SCIENCEFORECAST
Connecting Research to Drive Scientific Innovation

Research Article
Published: 08 May, 2020

SF Journal of Environmental and Earth Science

Relationship between Tropical Forest Biomass, Woody Volume and Backscattering Intensity of ALOS-2 SAR Data

Luong VN*, Tu TT, Thanh KTP and Son ML

Remote Sensing Application Department, Space Technology Institute, Vietnam Academy of Science and Technology, Hanoi, Vietnam

Abstract

The potential of Synthetic Aperture Radar (SAR) data based on ALOS-2 satellite operating in L-band radar was assessed for the estimation of biomass and woody volume in tropical dense forests in Vietnam by collecting *in situ* forest data in 2015. The effect of polarization and seasonality of the SAR data on the biomass and woody volume was analyzed. The combination of HH, HV, and HH/HV variables using multivariate linear regression did not improve the estimation of biomass and woody volume compared to using the HV channel independently, as the HH and HH/HV variables were not statistically significant (p-value>0.05). The dry season HV polarization could explain 65% and 58% variation of the biomass and woody volume respectively in the tropical forest with the biomass and woody volume as high as 447 Mg/ha and 493 m^3/ha respectively. The dry season HV backscattering intensity was highly sensitive to the biomass and woody volume compared to the rainy season backscattering intensity. The SAR data acquired in rainy season with humid and wet canopies were not very sensitive to the *in situ* biomass and woody volume. The strong dependence of the biomass and woody volume estimates with the season of SAR data acquisition confirmed that the choice of right season SAR data is very important for improving the satellite based estimates of the biomass and woody volume. We expect that the results obtained in this research will contribute to monitoring of forest biomass and woody volume in Vietnam and abroad.

Keywords: Forest biomass; Woody volume; SAR; ALOS-2; Backscattering intensity; Sensitivity analysis

OPEN ACCESS

****Correspondence:***
Luong Viet Nguyen, Remote Sensing Application Department, Space Technology Institute, Vietnam Academy of Science and Technology, Cau Giay, Hanoi, Vietnam.
Tel: *+84-437-562-895*
Fax: *+84-437-914-622*
E-mail: *nvluong@sti.vast.vn*

Received Date: *05 Apr 2020*
Accepted Date: *01 May 2020*
Published Date: *08 May 2020*

Citation: *Luong VN, Tu TT, Thanh KTP, Son ML. Relationship between Tropical Forest Biomass, Woody Volume and Backscattering Intensity of ALOS-2 SAR Data. SF J Environ Earth Sci. 2020; 3(1): 1035.*

ISSN 2643-8070

Copyright *© 2020 Luong VN. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.*

Introduction

Information on forest biomass and woody volume are essential for increasing understanding of the terrestrial carbon cycle and judicial management of forest resources. Forests sequestrate atmospheric carbon dioxide in the form of biomass during photosynthesis [1-3]. Therefore, forest biomass has an important role in the global carbon cycle [4-6]. Global total forest area is just over four billion hectares (31 per cent total land area of the Earth) and is unevenly distributed over the climatic regions. However, average forest area decreased by about 5.3 million hectares per year between 1999 and 2010; and deforestation is continuing everywhere [7-10]. When forests are destroyed, more carbon is added to the atmosphere which accelerates climate change. Deforestation and forest degradation contribute approximately 12-20 per cent of all greenhouse gas emissions [11,12]. The concentration of atmospheric carbon dioxide (CO_2) has already surpassed 400 parts per million which is larger than the ecological safety level of 350 parts per million [13]. Accurate monitoring of forest biomass and CO_2 sequestration rates are immensely important for increasing understanding of global carbon cycles, improving climate change forecasting models, and climate change mitigation and adaptation strategies [2,6,8,14-16]. Global monitoring of forest carbon is also urgently needed for the United Nation's program on Reducing Emissions from Deforestation and Degradation (REDD+), a financial payment mechanism for environmental services [16,17]. However, estimating woody volume and biomass from satellite data is challenging due to the diverse nature of forests and tropical forests [6,8,18-20].

Satellite remote sensing technology has many advantages for biomass estimates over traditional field survey based methods, particularly at larger scales. Therefore, it has been used by many researchers for biomass and woody volume estimates [6,19,21]. Satellite based estimation of woody volume and biomass are based on optical, radar, and more recently lidar techniques. Limitations on optical data based biomass estimates have been reported by researchers such as saturation over large biomass regions, very low correlation, and difficulties in detecting vertical structure [6,11,15,22-25]. To overcome such limitations, some researchers have tried multi-angular remote

sensing based bi-directional reflectance data for retrieving canopy structural information [26,27]. Some studies have combined spectral and textural features for biomass estimates using very high spatial resolution data and improved the accuracy of biomass and woody volume estimates [19]. However, due to complexities associated with high biological diversity, dense forests, multi-layer canopies, and unavailability of seasonal data due to clouds, estimation of biomass over tropical regions have been more challenging, especially with the optical data [6,19,20,22,28,29]. Lidar sensors have performed excellent estimates even in forests with high biomass and woody volumes by directly measuring the structure of the forest, i.e., canopy height and vertical distribution [18,23,30-37]. However, large scale application of lidar data is not economically feasible at present [6,19,25].

Radar remote sensing from satellites has high potential for biomass estimates at large scale because of its penetrability through clouds, applicability with night time, coverage at large scale, availability of seasonal data, and lower saturation in dense forests [6,20,21,38-44]. The long-wavelength SAR satellite is expected to have much promise for estimates of forest biomass [2,42,43]. The backscattering intensity of L-band and P-band SAR data have demonstrated sensitivity to structure, cover, volume, and biomass of the forests penetrating into the branches and stems of trees [40,45-48]. A number of previous studies have shown an impressive relationship between the SAR data and biomass [28,39,48-54]. On the other hand, several researchers have reported saturation problems with the L-band SAR backscattering over high biomass regions. However the level of biomass and woody volume at which backscattering intensity saturates are varying among the researchers: 40 Mg/ha [55], 60 Mg/ha [52], 120 Mg/ha [56], 150 Mg/ha [51], 200 m^3/ha [57], 150-200 Mg/ha [58], 136-182 Mg/ha [59], 250 Mg/ha [60-63], 297 Mg/ha [64], 310m3/ha [65], 357 Mg/ha [66]. The major techniques for SAR based estimates of woody volume and biomass attempted by a number of researchers so far are regression modelling [49,60,67,68], dual-wavelength SAR interferometry [47]; image texture analysis [69]; interferometric water cloud model [28], random volume over ground model [70], water cloud model [71], combination of forest structure and radiative transfer models [72],electromagnetic modelling [63], multivariate relevance vector regression [64]. SAR data have been used for estimating biomass and woody volume at different scales from local to regional/country level: pine plantation in Southwest Alabama [39], Mount Sharsta region of Northern California [73], plantation forest of the Landes forest in southwestern France [49], Brazilian Amazon [28,52] Nuuksio Natural Park in Southern Finland [57], Queensland in Australia [74], Mozambique in Zambézia province [68], Cambodia [58], and Cameroon [63]. However, the backscattering mechanisms in forests are very complex due to multi-level interaction of the scatterings with several horizontal and vertical components of the trees, and effect the environmental conditions. Different kinds of backscattering phenomena in forests such as diffused scattering from the ground, direct scattering from thin and dense vegetation parts, double bounce vegetation-ground interaction, direct backscattering from the canopy, volume scattering from within the forest canopy, and shadowing have been reported by researchers [38,61,75-78]. Backscattering intensity is also affected by a number of site conditions such as environmental temperatures [51,79], textures [80], moistures [81-86], roughness [81,83,87], terrain slopes [60,63,65, 88,89], forest stand age and canopy structure [69,90], forest species and cover [61,88,91-93]. As a result, potential of backscattering intensity for the estimation of forest biomass is influenced by the uncertainties coming from the heterogeneity of site conditions.

The Advanced Land Observing Satellite-2 (ALOS-2), a Japanese satellite launched in 2014, which operates in L-band radar and collects very high spatial resolution data (1-3 m per pixel) is considered useful technology for biomass and woody volume estimates particularly over dense tropical forests.

The collection of biometry data via field inventory in dense tropical forests is very difficult, time-consuming, and costly. The *in situ* biomass data calculated from incomplete sampling methods without representing the total forest, and lack of correct allometric equations to convert the field measured tree variables into biomass, and no validation and cross checks with repetitive measurements cannot correctly evaluate the potential of SAR data for biomass estimates. Moreover, the non-coincidence of the field inventory date and acquisition of the radar data is another challenge for deriving models for accurate estimation of the forest biomass.

Therefore, this research was conducted in a tropical dense forest to assess the current uncertainties associated with the estimation of biomass by collecting *in situ* biometry data by the authors. This research attempted to answer whether the ALOS-2 based SAR data are really capable of estimating the biomass and woody volume in such high biomass regions, and whether biomass estimates vary with the season of SAR data acquisition. Moreover, this research was conducted in Vietnam with more than 40% forest cover which is one of the nine countries chosen for implementing United Nations' program on Reducing Emissions from Deforestation and Degradation (REDD+).

Study Area and Data

Study area

This research was carried out in Yok Don National Park, the largest national park in Vietnam which is located in the Central Highlands region. This park is very rich in biodiversity where 474 vascular plant species have been recorded [94]. This park is one of the most important protected areas in Southeast Asia providing important habitat for conservation of globally endangered species such as Indochinese tiger and Asian elephant.

This park has two major types of forest: deciduous broadleaf forest and evergreen broadleaf forest [94-98]. The dominant tree species in the deciduous broadleaf forest are *Dipterocarpus tuberculatus*, *Dipterocarpus obtusifolius*, *Terminalia tomentosa*, and *Shorea obtuse*. The evergreen broadleaf forest mainly comprises of *Michelia mediocris*, *Cinamomum iners*, *Syzygium zeylanicum, Syzygium wightianum, Garruga pierrei, Gonocaryum lobbianum, Schima superba, Camellia assamica,* and *Lithocarpus fenestratus*. The forest inside the park has diverse types of soils including brown, red-yellow, and black soils [99]. This park contains relatively plain topography and is located at an altitude of 200-300 m above sea level [100]. The location map of the Yok Don National Park is shown in Figure 1.

The climate of this region is tropical monsoon type which has a well-defined dry season between October and April, and typical rainy season between May and November. The mean annual rain falls is 1540 mm, and mean monthly temperature is around 25°C. The well-defined distinction of the climate between the dry and rainy season found in this forest provides an ideal site to analyze how the backscattering intensity varies with the seasons, and to know how the seasonal variation of the backscattering intensity affects the

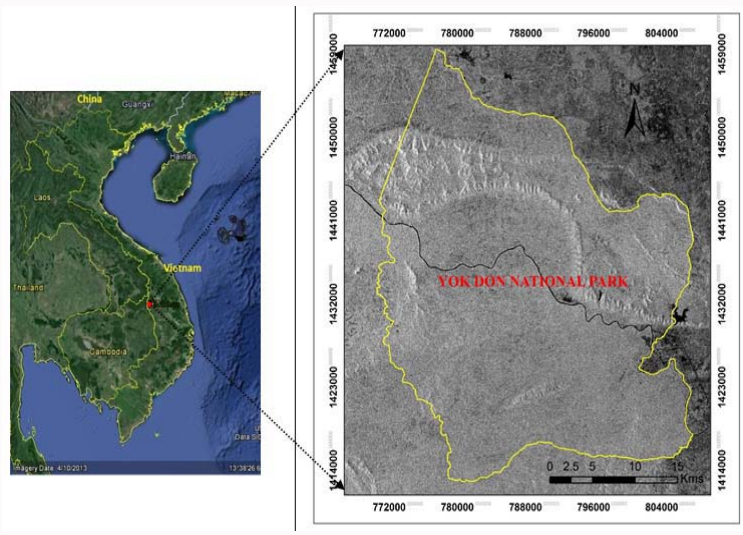

Figure 1: Location map of the study area displaying the boundary of Yok Don National Park (yellow polygon) in Central Highlands region, Vietnam.

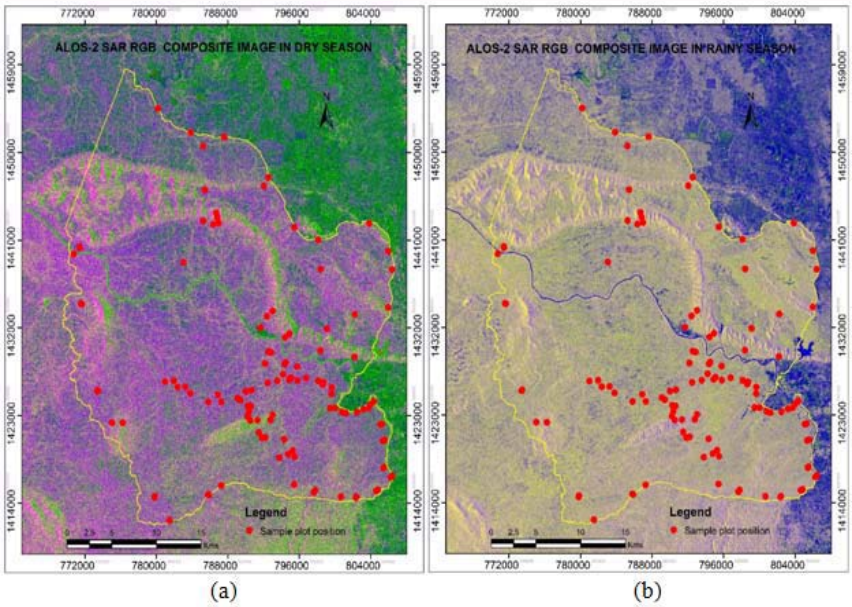

Figure 2: The distribution of the location of sample plots established during field survey over the RGB color composite images: (a) Dry season RGB image, and (b) Rainy season RGB image. The RGB color composite image was created by using the HH channel for red (R), HV channel for green (G), and the ratio HH/HV for blue (B).

estimation of woody volume and biomass. Moreover, this forest with dense and multi-strata canopies consisting of diverse tree species in tropical monsoon setting provides an opportunity to analyze how the backscattering intensity is sensitive to large woody volume and biomass. The analysis on sensitivity of backscattering intensity is required for improving the SAR based estimates of the woody volume and biomass particularly in the dense and multi-strata tropical rain forests.

Acquisition and processing of ALOS-2 data

We used Synthetic Aperture Radar (SAR) data from ALOS-2 satellite which has been operating since May 2014 and provides SAR data in L-band. We used ALOS-2 version 2.1 polarized SAR data in HH and HV polarizations with pixel resolution of 6.25 m and it was available as a geometrically corrected product. The Digital Number (DN) values of the SAR images in both the HH and HV polarizations were calibrated by calculating the backscattering intensity using the Equation (1) [101].

$$\sigma^o = 10x\log_{10}(DN^2)+CF \qquad (1)$$

In Equation (1), the σ^o is the sigma-naught backscattering intensity in the units of decibels (dB), and CF is the calibration factor which is currently set as -83 [101]. We used two scenes of the ALOS-2 data covering our study area and representing each of the rainy (October) and dry season (February). The details on the ALOS-2 SAR images used in this research are described in Table 1. Both dry and rainy season SAR images were used, acquired with the same off-nadir angle (32.9°) in descending modes in order to avoid bias related to observation angles.

Methodology

In situ measurements

The sensitivity analysis of the backscattering intensity with different seasons for the estimation of forest structural parameters such as woody volume and biomass requires ground truth data. Therefore, the authors organized an intensive field campaign during dry season of April, 2015 to collect the ground truth data. Field survey is important for collecting in situ data required for accuracy analysis of the satellite based estimates.

The *in situ* measurements were conducted by establishing the sample plots according to the inventory guideline available for the Central Highlands region [102,103]. All 115 sample plots were established by meeting the criteria of representativeness of different forest types across the study areas. The authors carefully designed the sample plots in such a way that they were at least 100-m apart from trails, roads, streams, and rivers to avoid the signals from unwanted surface types for sensitivity analysis.

Each sample plot established during the forest inventory was (50mx50m) with an area of 0.25 ha. The authors measured the diameter at breast height (D) and total tree height (H) of all the trees larger than 5 cm diameter at breast height located inside the sample plots. The tree diameter and height were measured by using laser diameter and laser height instruments respectively. The central geo-location (latitude and longitude) of each sample plot was recorded by using GPS instruments.

The authors also recorded the types of tree species during the field inventory following the Vietnam Flora book [104]. All species were recorded and the taxonomy used was the Flora of Vietnam book). The sample plots represent 28.75 hectares forest area which is 0.02% of the total study area.

Several studies have focused on importance of careful selection of the sample plots by incorporating relatively homogenous areas and large sample plots [1,6,17,102,105-107]. Many researchers have also reported that the minimum size for forest plot should be 1 ha [108,109]. In the case that size of sample plots established based on national inventory guidelines are relatively smaller, the variation of the backscattering intensity was analyzed to choose the sample plots that represent large homogenous forests. The mean backscattering intensity of the HV polarization from a sample plot with the size of 50mx50m, equivalent to 8x8 pixels of SAR image was analyzed with the mean backscattering of a plot with the size of 100mx100m equivalent to 16x16 pixels. If the backscattering ratio between two different plot sizes were near to 1 (0.75-1.25), the plots were considered to represent large homogenous forests. In this way, 77 representative plots out of 115 plots in the field were chosen for the analysis.

The distribution of sample plots used in this research is shown in Figure 2 using RGB color composite of the SAR images. Distinct variation between the rainy season and dry season RGB images in Yok Don National Park were observed as demonstrated in Figure 2.

Estimation of biomass/woody volume

The authors converted the individual tree biometry data: diameter at breast height (D) and total tree height (H) measured during the forest inventory into Above Ground Biomass (AGB) using the allometric equations. We used separate allometric equations for calculating the AGB of the deciduous and evergreen forests (Tan Vu et al., 2012). The allometric equations used for calculating the AGB of deciduous and evergreen forest types are given in Equation (2) and Equation (3) respectively.

$$AGB = 0.14xD^{2.31} \quad (2)$$

$$AGB = 0.098xexp(2.08xLn(D)+0.71xLn(H)+1.12xLn(WD)) \quad (3)$$

In Equation (2) and Equation (3), AGB is the above ground biomass of a tree in kilograms (kg); D is the diameter at breast height measured at 1.3-m above the ground level in meters (m); H is the total height of tree in meters (m); WD is the wood density of tree in tones dry matter per fresh cubic meters (ton/m^3). The species-specific Wood Density (WD) data were obtained from the forest carbon measurement guidelines prepared by the IPCC [1]. The species-specific wood density data were used for calculating the AGB in evergreen forests due to large number of tree species present in these forests with varying amount of AGB. The allometric equations of the AGB in Equation (1) and Equation (2) gives the total biomass of a tree including all the stems, branches and leaves.

The woody Volume (V) of each tree was calculated by using Equation (4) [2,14,102] which uses the basal area of a tree at breast height (G) in squared meters (m^2), total tree height (H) in meters (m) and the conversion factor (F). The woody volume (V) in Equation (4) also includes the volume of branches and twigs, which is usually 10% of total woody volume (V) [102].

$$V = FxGxH \quad (4)$$

Sensitivity analysis

We calculated the averages of the forest structural parameters: diameter at breast height (D), Basal Area (BA), tree height (H), density of trees (N), Above Ground Biomass (AGB), and woody volume (V) for representing each sample plot. The backscattering intensity from the SAR data was calculated as the mean of 8x8 pixels for each sample plot. In this way, we carried out the relationship between the woody volume/biomass and backscattering intensity. The sensitivity of the backscattering intensity on the biomass and woody volume was statistically analyzed by using simple linear regression and multivariate linear regression analysis. The coefficient of determination (R^2) and Root Mean Square Error (RMSE) were used as the metrics for evaluating the relationships. The results of this analysis are presented in the section below.

Results and Discussions

Forest biometry results

The relationship between different canopy structural parameters was analyzed to confirm the accuracy of the field inventory based data. The comparison result is shown in Figure 3. The coefficient of determination (R^2) between tree height (H) and diameter at breast height (D), density of trees (N) and diameter at breast height (D), density of trees (N) and tree height (H), woody volume (V) and Basal Area (BA), and Above Ground Biomass (AGB) and Basal Area (BA) were 0.71, 0.48, 0.41, 0.93, and 0.84 respectively. The above analysis shows for the purpose the clearly the structure of the forest in the study area. Though the calculation of woody volume (V) and Above Ground Biomass (AGB) relied on allometric equations suggested by different sources, the higher relationship (R^2= 0.88) was obtained between them. Tropical forest is a complex mixture of heterogeneous trees species, hence the accuracy of *in situ* biomass/woody volume data are crucial for linking with the satellite based data.

Table 1: Description of the ALOS-2 PALSAR-2 data used in this research.

No.	Observation date (time)	Scene ID	Polarizations	Obs. angle	Season
1	2014-10-05 (16:56:51)	ALOS2019900240-141005-FBDR2.1GUA	HH, HV	32.9°	Rainy
2	2014-10-05 (16:56:51)	ALOS2019900250-141005-FBDR2.1GUA	HH, HV	32.9°	Rainy
3	2015-02-22 (16:56:50)	ALOS2040600240-150222-FBDR2.1GUA	HH, HV	32.9°	Dry
4	2015-02-22 (16:56:50)	ALOS2040600250-150222-FBDR2.1GUA	HH, HV	32.9°	Dry

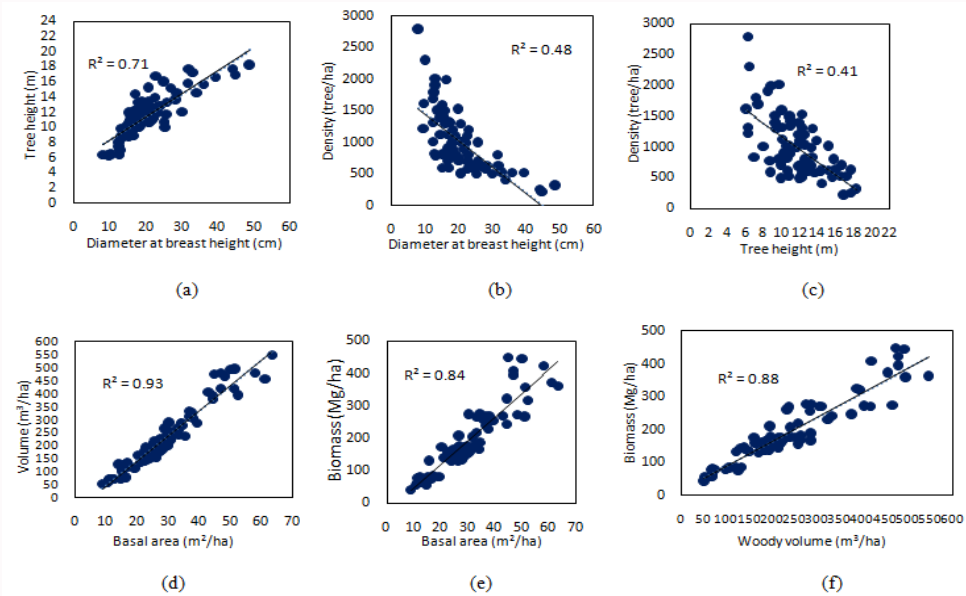

Figure 3: Cross-comparison between different structural parameters: (a) tree height (H) and diameter at breast height (D), (b) density of trees (N) and diameter at breast height (D), (c) density of trees(N) and tree height (H), (d) woody volume (V) and basal area (BA), (e) above ground biomass (AGB) and basal area (BA), and (f) woody volume (V) and above ground biomass (AGB).

Effect of SAR polarization on forest biomass/volume

The sensitivity of biomass and woody volume with the backscattering intensity of the HH and HV polarizations for the dry season was analyzed using the coefficient of determination (R^2) and Root Mean Square Error (RMSE). As shown in Figure 4, the HV polarization was highly related to both the biomass (R^2=0.65, RMSE=57.75 Mg/ha) and woody volume (R^2=0.58, RMSE=79.79 m^3/ha); whereas the HH polarization did not show a significant relationship with the above ground biomass (R^2=0.35, RMSE=79.08 Mg/ha), and woody volume (R^2=0.32, RMSE=101.44 m^3/ha).

Similarly, the sensitivity of biomass and woody volume with the backscattering intensity of the HH and HV polarizations for the rainy season is shown in Figure 5. The HV polarization was related to biomass (R^2=0.41, RMSE=74.14 Mg/ha) and woody volume (R^2=0.42, RMSE=93.79 m^3/ha) better than the HH polarization for both the biomass (R^2=0.21, RMSE=87.25Mg/ha) and woody volume (R^2=0.17, RMSE=112.50 m^3/ha).

The high sensitivity of the HV polarization towards biomass and woody volume was found for both the dry and rainy season SAR data. This result highlighted the importance of HV polarization for the estimates of biomass and woody volume. Similar results have been obtained by previous researchers with high sensitivity of the HV polarization with tree height and diameter [48,51,56].

Effect of SAR seasonality on biomass/volume

The sensitivity of the SAR data (HV and HH polarizations) acquired during dry season and rainy season on biomass and woody volume was analyzed. The relationship between woody volume/biomass and dry season SAR data is shown in Figure 4; and the relationship between woody volume/biomass and rainy season SAR data is shown in Figure5. The dry season backscattering intensity of the HH and HV polarizations was highly sensitive to the biomass and woody volume than the rainy season backscattering intensity. The higher relationship between the dry season HV polarization and biomass (R^2=0.65, RMSE=57.75 Mg/ha), and the woody volume (R^2=0.58, RMSE=79.79 Mg/ha) was obtained. However, the relationship between the rainy season HV polarization and biomass was relatively lower (R^2=0.41, RMSE=75.14 Mg/ha) than the dry season. The relationship between rainy season HV polarization and woody volume was also lower (R^2=0.42, RMSE=93.79 m^3/ha). This analysis suggests that dry season SAR data is more important for estimating the biomass/volume than the rainy season data. The effect of seasonality for the SAR data was clearly observed in this research.

We also analyzed multivariate linear regression between the SAR data (HH, HV, and HH/HV) and woody volume and biomass. For dry season SAR data, the adjusted coefficient of determination (R^2) between the biomass and three independent variables (HH, HV, and HH/HV) was 0.66, however the *p*-value of the HH was 0.31 (>0.05) and HH/HV variables was 0.30 (>0.05) which were not significant; whereas only the HV variable with *p*-value 3.6E-19 (<0.05) was significant. The R^2 between the woody volume and three independent variables (HH, HV, and HH/HV) was 0.58 and the *p*-value of the HH was 0.14 (>0.05), and HH/HV variables was0.14 (>0.05) which were not significant; whereas only the HV variable with *p*-value 2.2E-15

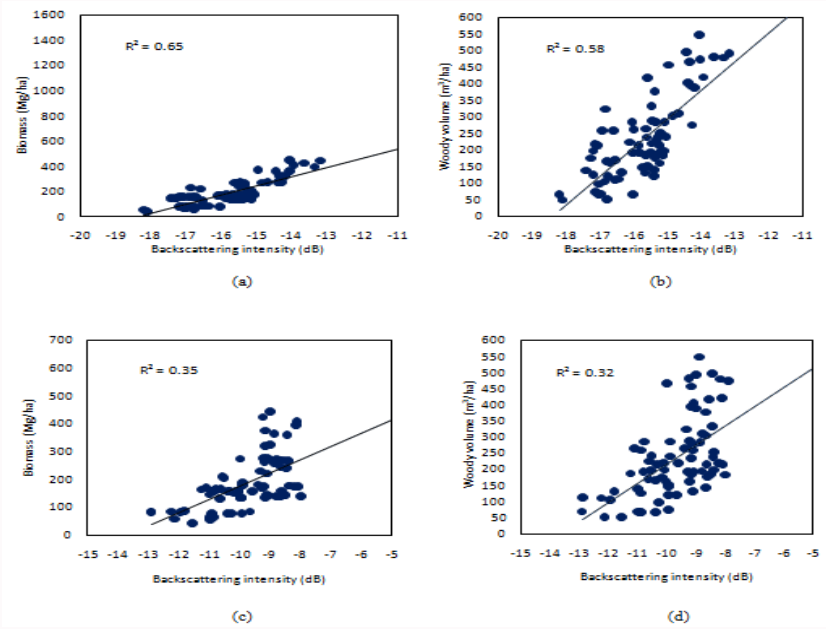

Figure 4: The relationship between biomass, woody volume, and backscattering intensity during dry season: (a) Biomass versus backscattering intensity (HV), (b) Woody volume versus backscattering intensity (HV), (c) Biomass versus backscattering intensity (HH), and (d) Woody volume versus backscattering intensity (HH).

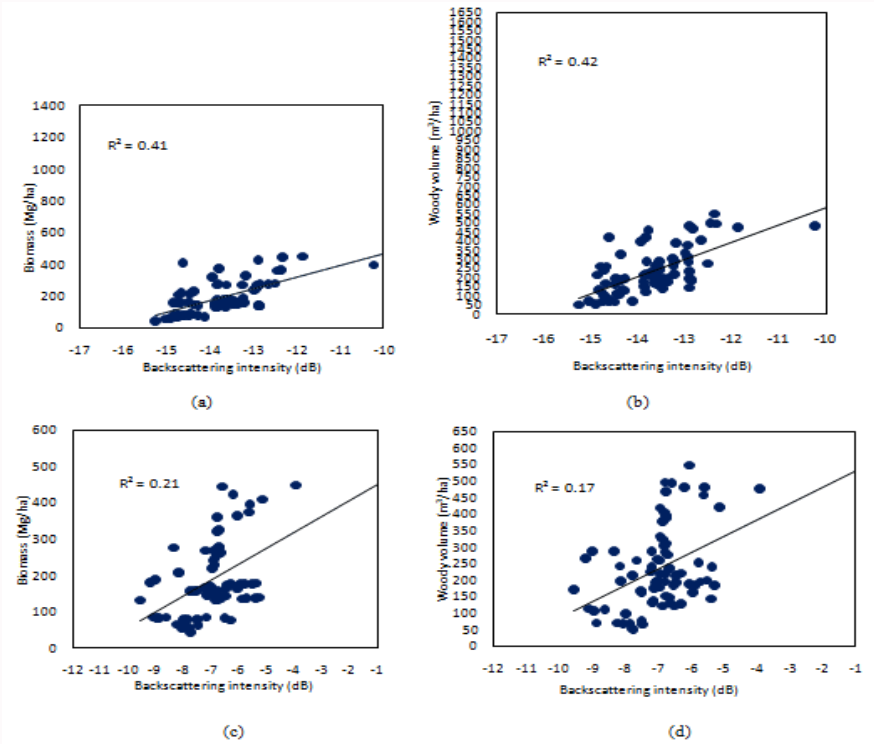

Figure 5: The relationship between the woody volume, biomass, and backscattering intensity during rainy season: (a) Biomass versus backscattering intensity (HV), (b) Woody volume versus backscattering intensity (HV), (c) Biomass versus backscattering intensity (HH), (d) Woody volume versus backscattering intensity (HH).

(<0.05) was significant.

Similar results were obtained for the rainy season SAR data. Though the adjusted (R^2) between the biomass, and three independent variables (HH, HV, and HH/HV) was 0.43, only the HV variable was statistically significant with *p*-value of 3.6E-10 (<0.05). Other HH (*p*-value 0.07) and HH/HV (*p*-value 0.07) variables did not show statistically significant relationship with biomass. While analyzing the multivariate linear regression between woody volume and SAR variables (HH, HV, and HH/HV) has R^2=0.45 and *p*-value of the HH was 0.2 (>0.05) and HH/HV was 0.19 (>0.05) and only the *p*-value of HV was 3.6E-10 (<0.05) and 1.1E-09 (<0.05) respectively. From all results above, only the HV variable was statistically significant for both the dry and rainy season data. Therefore, the estimates of the

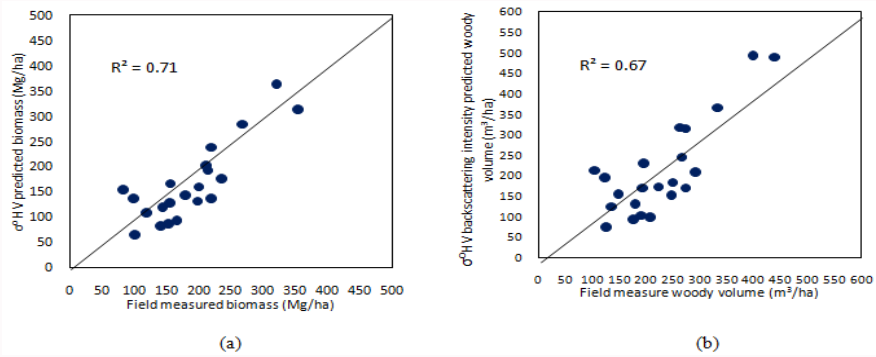

Figure 6: The validation of the SAR data based predicted results: (a) above ground biomass, and (b) woody volume. The 1:1 plot between the predicted and field data are shown.

woody volume and biomass could not improve by using multivariate linear regression in this research.

Validation results

We used above ground biomass and woody volume data from national forest inventory program of Vietnam in 2014. This data was provided by Forest Inventory and Planning Institute (FIPI) and The Ministry of Agriculture and Rural Development (MARD) for the validation of the results obtained in this research. For this purpose, 22 sample plots data that were available in the same study areas were compared against the predicted biomass and woody volume. As shown in Figure 6, our model could explain 71% variation of the biomass (R^2=0.71, RMSE=24.06 Mg/ha) and 67% variation of the woody volume (R^2=0.67, RMSE=28.50 m^3/ha).

Conclusion

In this research, the authors collected forest biometry data at the tropical forest conducting forest inventory in 2015. The sensitivity of the woody volume and biomass to the polarizations of ALOS-2 SAR data, and to the season of the acquisition of the SAR data were analyzed.

The authors achieved a promising relationship between the ALOS-2 based HV polarization backscattering intensity and field measured biomass and woody volume since 65% variation in forest biomass and 58% variation in woody volume could be explained by the HV polarization data. The combination of the HH, HV, and HH/HV channels by multivariate linear regression did not improve the estimates of the biomass and woody volume than using HV channel independently since the HH and HH/HV variables were not statistically significant (p-value>0.05).

The study has found strong dependence of the biomass and woody volume estimates with the season of SAR data acquisition. None of the biomass and woody volume correlated with the rainy season HV polarization data as highly as the dry season HV polarization data. Therefore, this research concluded that the choice of right season in which SAR data is acquired is a very important consideration for satellite based estimates of the biomass and woody volume. In tropical forests where the dry and rainy season are well-defined as in case of our study area, the rainy season with frequent and plenty of rainfall and cloudy sky keeps the forest canopy wet and humid. Since the SAR backscattering intensity is highly sensitive to the surface moisture, the SAR data acquired in the rainy season is not very sensitive to the in situ biomass and woody volume.

The national park as the study area in this research supports wider variation of the forests representative to a specific ecological zone therefore provides an important site for establishing the satellite based models for biomass and woody volume estimates, and has important implications for estimating the large amount of carbon stocks protected by the national parks. The relationship established between the ALOS-2 SAR data and biomass and woody volume in this research could contribute to the monitoring of the biomass and the woody volume in other regions of Vietnam and other counties as well. The authors expect that the results obtained in this research would be useful for promoting emission reduction programs in forestry sector, and achieving sustainable forest management goals.

Acknowledgements

The authors are grateful to the VT-UD. 05/17-20 project under National Research on, Space Science and Technology Program of Vietnam (2016-2020) for financial support to this research.

References

1. IPCC. Good Practice Guidance for Land Use, Land-Use Change and Forestry. IPCC National Greenhouse Gas Inventories Programme. ISBN. 2003.
2. FAO. Terrestrial Essential Climate Variables for climate change Assessment, Mitigation and Adaption. Biomass. 2009.
3. Way AD, Pearcy RW. Sunflecks in trees and forests: from photosynthetic physiology to global change biology. Tree Physiology. 2012; 32: 1066-1081.
4. Brown S. Estimating biomass and biomass change of tropical forests: a primer. Food & Agriculture Org. 1997.
5. IPCC. Guidelines for National Greenhouse Gas Inventories. 2006.
6. Gibbs HK, Brown S, Niles JO, Foley JA. Monitoring and estimating tropical forest carbon stocks: Making REDD a reality. Environ Res Lett. 2007; 2: 4.
7. Angelsen A. Moving ahead with REDD: Issues, Options and Implications. CIFOR. 2008.
8. FAO. Global Forest Resources Assessment 2010-Main Report. FAO Forestry Paper 163. 2010.
9. D'Annunzio R, Lindquist E, MacDicken KG. Global forest land-use change from 1990 to 2010: an update to a global remote sensing survey of forests. Food and Agriculture Organization of the United Nations. 2014.
10. Busch J, Engelmann J. The Future of Forests: Emissions from Tropical Deforestation with and without a Carbon Price, 2016-2050. CGD Working Paper 411. 2015.

11. Sukhdev P, Prabhu R, Kumar P, Bassi A, Patwa-Shah W, Enters T, et al. REDD+ and a green economy: Opportunities for a mutually supportive relationship. UN-REDD Programme Policy Brieff. 2010.

12. Agrawal A, Nepstad D, Chhatre A. Reducing Emissions from Deforestation and Forest Degradation. Annual Review of Environment and Resources. 2011; 36: 373-396.

13. NOAA.2015.

14. FAO. Estimating Biomass and Biomass Change of Tropical Forests: a Primer. FAO Forestry Paper 134. 1997.

15. Secretariat GCOS. Systematic Observation Requirements for Satellite-based Products for Climate. Supplemental details to the satellite-based component of the Implementation Plan for the Global Observing System for Climate in Support of the UNFCCC (GCOS-92). 2006.

16. Stone S, León CM. Climate Change & the Role of Forests A Community Manual. Conservation International 2011 Crystal Drive Arlington. 2011.

17. UN-REDD Vietnam. Guidelines on Destructive Measurement for Forest Biomass Estimation. UN-REDD Vietnam Programme. 2012.

18. Lefsky AM, Warren BC, Geoffrey GP, Harding JD. Lidar Remote Sensing for Ecosystem Studies: Lidar, an emerging remote sensing technology that directly measures the three-dimensional distribution of plant canopies, can accurately estimate vegetation structural attributes and should be of particular interest to forest, landscape, and global ecologists. BioScience. 2002; 52: 19-30.

19. Lu D. The potential and challenge of remote sensing-based biomass estimation. Int J Rem Sens. 2006; 27: 1297-1328.

20. Sinha S, Jeganathan C, Sharma LK, Nathawat MS. A review of radar remote sensing for biomass estimation. Int J Environ Sci Technol. 2015; 12: 1779-1792.

21. Ghasemi N, Sahebi MR, Mohammadzadeh A. A review on biomass estimation methods using synthetic aperture radar data. International Journal of Geomatics and Geosciences. 2011; 1: 776-788.

22. Ripple WJ, Wang S, Isaacson DL, Paine DP. A preliminary comparison of Landsat Thematic Mapper and SPOT-l HRV multispectral data for estimating coniferous forest volume. Int J Remote Sensing. 1991; 12: 1971-1977.

23. Vincent MA, Saatchi SS. Comparison of remote sensing techniques for measuring carbon sequestration. JPL. 1999.

24. Gonzalez P, Asner GP, Battles JJ, Lefsky MA, Waring KM, Palace M. Forest carbon densities and uncertainties from Lidar, QuickBird, and field measurements in California. Remote Sens Environ. 2010; 114: 1561-1575.

25. Brewer KC, Monty J, Johnson A, Evans D, Fisk HD. Forest carbon monitoring: A review of selected remote sensing and carbon measurement tools for REDD+. 2011.

26. Chopping M, Schaaf CB, Zhao F, Wang Z, Nolin AW, Moisen GG, Bull M. Forest structure and aboveground biomass in the southwestern United States from MODIS and MISR. Remote Sens Environ. 2011; 115: 2943-2953.

27. Sharma CR, Kajiwara K, Honda Y. Estimation of forest canopy structural parameters using kernel-driven bi-directional reflectance model based multi-angular vegetation indices. ISPRS Journal of Photogrammetry and Remote Sensing. 2013; 78: 50-57.

28. Santos JR, Lacruz MP, Araujo LS, Keil M. Savanna and tropical rainforest biomass estimation and spatialization using JERS-1 data. Int J Remote Sensing. 2002; 23: 1217-1229.

29. Foody GM, Boyd DS, Cutler ME. Predictive relations of tropical forest biomass from Landsat TM data and their transferability between regions. Remote Sens Environ. 2003; 85: 463-474.

30. Drake JB, Dubayah R.O, Knox RG, Clark DB, Blair JB. Sensitivity of large-footprint lidar to canopy structure and biomass in a neotropical rainforest. Remote Sens Environ. 2002; 81: 378-392.

31. Popescu SC, Wynne RH, Nelson RF. Measuring individual tree crown diameter with lidar and assessing its influence on estimating forest volume and biomass. Can J Remote Sensing. 2005; 29: 564-577.

32. Bortolot ZJ, Wynne RH. Estimating forest biomass using small footprint LiDAR data: An individual tree-based approach that incorporates training data. ISPRS Journal of Photogrammetry and Remote Sensing. 2005; 59: 342-360.

33. Beets PN, Reutebuch S, Kimberley MO, Oliver GR, Pearce SH, McGaughey RJ. Leaf area index, biomass carbon and growth rate of radiata pine genetic types and relationships with LiDAR. Forests. JRNL. 2011; 2: 637-659.

34. Moskal LM, Zheng G. Retrieving forest inventory variables with terrestrial laser scanning (TLS) in urban heterogeneous forest. Remote Sensing. 2011; 4: 1-20.

35. Kankare V, Vastaranta M, Holopainen M, Räty M, Yu X, Hyyppä J, et al. Retrieval of forest aboveground biomass and stem volume with airborne scanning LiDAR. Remote Sens. 2013; 5: 2257-2274.

36. Sheridan RD, Popescu SC, Gatziolis D, Morgan CL, Ku NW. Modeling Forest Aboveground Biomass and Volume Using Airborne LiDAR Metrics and Forest Inventory and Analysis Data in the Pacific Northwest. Remote Sens. 2014; 7: 229-255.

37. Hansen EH, Gobakken T, Bollandsås OM, Zahabu E, Næsset E. Modeling Aboveground Biomass in Dense Tropical Submontane Rainforest Using Airborne Laser Scanner Data, Remote Sens. 2015; 7: 788-807.

38. Ulaby FT, Moore RK, Fung AK. Microwave remote sensing: active and passive. Reading, MA: Addison-Wesley. 1981.

39. Wu ST. Potential application of multipolarization SAR for pine-plantation biomass estimation. IEEE . 1987; 25: 403-409.

40. Jensen JR. Remote sensing of the environment: An earth resource perspective. Pearson Education India. Third Indian reprint. 2005.

41. Kellndorfer J, Walker W, Pierce L, Dobson C, Fites JA, Hunsaker C, Clutter M. Vegetation height estimation from shuttle radar topography mission and national elevation datasets. Remote Sens Environ. 2004; 93: 339-358.

42. Ramankutty N, Gibbs HK, Achard F, Defries R, Foley JA, Houghton RA. Challenges to estimating carbon emissions from tropical deforestation. Global Change Biology. 2007; 13: 51-66.

43. Le Toan T, Quegan S, Davidson MWJ, Balzter H, Paillou P, Papathanassiou K, et al. The BIOMASS mission: Mapping global forest biomass to better understand the terrestrial carbon cycle. Remote Sens Environ. 2011; 115: 2850-2860.

44. Brolly M, Woodhouse IH. A "Matchstick Model" of microwave backscatter from a forest. Ecological Modelling. 2012; 237: 74-87.

45. Sun G, Ranson JK, Kharuk IV. Radiometric slope correction for forest biomass estimation from SAR data in the Western Sayani Mountains, Siberia. Remote Sens Environ. 2002; 79: 279-287.

46. Balzter H. Forest mapping and monitoring with interferometric synthetic aperture radar (InSAR). Progress in Physical Geography. 2001; 25: 159-177.

47. Balzter H, Rowland CS, Saich P. Forest canopy height and carbon estimation at Monks Wood National Nature Reserve, UK, using dual-wavelength SAR interferometry. Remote Sens Environ. 2007; 108: 224-239.

48. Mitchard ETA, Saatchi SS, Lewis LS, Feldpausch TR, Woodhouse IH, Sonke B, et al. Measuring biomass changes due to woody encroachment and deforestation/degradation in a forest-savanna boundary region of central Africa using multi-temporal L-band radar backscatter. Remote

Sens Environ. 2011; 115: 2861-2873.

49. Le Toan T, Beaudoin A, Riom J, Guyon D. Relating forest biomass to SAR data. IEEE Trans Geosci Remote Sens. 1992; 30: 403-411.

50. Dobson MC, Ulaby FT, Le Toan T, Beaudoin A, Kasischke ES, Christensen N. Dependence of radar backscatter on coniferous forest biomass. IEEE Trans Geosci Remote Sens. 1992; 30: 412-415.

51. Ranson KJ, Sun G. Mapping biomass of a northern forest using multifrequency SAR data. IEEE Trans Geosci Remote Sens. 1994; 32: 388-396.

52. Luckman A, Baker J, Kuplich MT, Yanasse FCC, Frery CA. A study of the relationship between radar backscatter and regenerating tropical forest biomass for spaceborne SAR instruments. Remote Sens Environ. 1997; 60: 1-13.

53. Sandberg G, Ulander LM, Fransson JES, Holmgren J, Le Toan T. L-and P-band backscatter intensity for biomass retrieval in hemiboreal forest. Remote Sens Environ. 2011; 115: 2874-2886.

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

55. Imhoff LM. Radar Backscatter and Biomass Saturation: Ramifications for Global Biomass Inventory. IEEE Trans Geosci Remote Sens. 1995; 33: 511-518.

56. Suzuki R, Kim Y, Ishii R. Sensitivity of the backscatter intensity of ALOS/PALSAR to the above-ground biomass and other biophysical parameters of boreal forest in Alaska. Polar Science. 2013; 7: 100-112.

57. Mika K, Ulla P, Kirsi K, Juha H. Forest biomass estimation using ALOS PALSAR images in challenging natural forest area in Finland. In ALOS PI 2008 Symposium. ESA Special Publication. 2009.

58. Avtar R, Suzuki R, Takeuchi W, Sawada H. PALSAR 50 m Mosaic Data Based National Level Biomass Estimation in Cambodia for Implementation of REDD+ Mechanism. PloS One. 2013.

59. Motohka T, Shimada M, Isoguchi O, Ishihara M, Suzuki SN. Relationships between PALSAR backscattering data and forest above ground biomass in Japan. IEEE International. 2011.

60. Englhart S, Keuck V, Siegert F. Aboveground biomass retrieval in tropical forests - The potential of combined X- and L-band SAR data use. Remote Sens Environ. 2011; 115: 1260-1271.

61. Le Toan T, Mermoz S, Bouvet A, Villard L. K&C Phase 3 Forest cover change and Biomass Mapping. K&C Initiative. 2013.

62. Ni W, Zhang Z, Sun G, Guo Z, He Y. The Penetration Depth Derived from the Synthesis of ALOS/PALSAR InSAR Data and ASTER GDEM for the Mapping of Forest Biomass. Remote Sens. 2014; 6: 7303-7319.

63. Mermoz S, Réjou-Méchain M, Villard L, Le Toan T, Rossi V, Gourlet-Fleury S. Decrease of L-band SAR backscatter with biomass of dense forests. Remote Sens Environ. 2015; 159: 307-317.

64. Sharifi A, Amini J, Tateishi R. Estimation of forest biomass using multivariate relevance vector regression. Photogrammetric Engineering and Remote Sensing. 2015.

65. Kim C. Quantitative analysis of relationship between ALOS PALSAR backscatter and forest stand volume. Journal of Marine Science and Technology. 2012; 20: 624-628.

66. Gonçalves FG, Santos JR, Treuhaft RN. Stem volume of tropical forests from polarimetric radar. International Journal of Remote Sensing. 2011; 32: 503-522.

67. Morel CA, Saatchi SS, Malhi Y, Berry JN, Banin L, Burslem D, et al. Estimating aboveground biomass in forest and oil palm plantation in Sabah, Malaysian Borneo using ALOS PALSAR data. Forest Ecology and Management. 2011; 262: 1786-1798.

68. Carreiras JMB, Melo JB, Vasconcelos MJ. Estimating the above-ground biomass in Miombo Savanna woodlands (Mozambique, East Africa) using L-band synthetic aperture radar data. Remote Sens. 2013; 5: 1524-1548.

69. Champion I, Dubois-Fernandez P, Guyon D, Cottrel M. Radar SAR images texture as a function of forest stand age. Int J Remote Sensing. 2008;29: 1795-1800.

70. Hajnsek I, Kugler F, Lee SK, Papathanassiou KP. Tropical-forest-parameter estimation by means of Pol-InSAR: The INDREX-II campaign. IEEE Trans Geosci Remote Sens. 2009; 47: 481-493.

71. Cartus O, Santoro M, Kellndorfer J. Mapping forest aboveground biomass in the Northeastern United States with ALOS PALSAR dual-polarization L-band. Remote Sens Environ. 2012; 124: 466-478.

72. Brolly M, Woodhouse IH. Long Wavelength SAR Backscatter Modelling Trends as a Consequence of the Emergent Properties of Tree Populations. Remote Sensing. 2014; 6: 7081-7109.

73. Richards J, Sun GQ, Simonett DS. L-band radar backscatter modeling of forest stands. IEEE Trans Geosci Remote Sens. 1987; 25: 487-498.

74. Lucas R, Armston J, Fairfax R, Fensham R, Accad A, Carreiras J, et al. An evaluation of the ALOS PALSAR L-band backscatter-Above ground biomass relationship Queensland, Australia: Impacts of surface moisture condition and vegetation structure. IEEE. 2010; 3: 576-593.

75. Richards J, Sun GQ, Simonett DS. L-band radar backscatter modeling of forest stands. IEEE Trans Geosci Remote Sens. 1987; 25: 487-498.

76. Lo CP. Applications of imaging radar to land use and land cover mapping. Manual of Remote Sensing. 1988.

77. Touzi R, Deschamps A, Rother G. Wetland characterization using polarimetric RADARSAT-2 capability. Can J Remote Sensing. 2007; 33: S56-S67.

78. Ordonez FY, Ruiz SJ, Leblon B. Forest Inventory Using Optical and Radar Remote Sensing. Advances in Geoscience and Remote Sensing. 2008.

79. Ranson KJ, Sun G. Effect of environmental temperatures on SAR forest biomass estimates. IEEE International. 1997; 4: 1722-1724.

80. Joseph TA, Van der Velde R, O'Neill EP, Lang R, Gish T. Effects of corn on C- and L-band radar backscatter: A correction method for soil moisture retrieval. Remote Sens Environ. 2010; 114: 2417-2430.

81. Shi J, Wang J, Hsu AY, O'Neill PE, Engman ET. Estimation of bare surface soil moisture and surface roughness parameter using L-band SAR image data. IEEE Trans Geosci Remote Sens. 1997; 35: 1254-1266.

82. Bindlish R, Barros AP. Parameterization of vegetation backscatter in radar-based, soil moisture estimation. Remote Sens Environ. 2001; 76: 130-137.

83. Baghdadi N, Holah N, Zribi M. Calibration of the Integral Equation Model for SAR data in C-band and HH and VV polarizations. Int J Remote Sens. 2006; 27: 805-816.

84. Kasischke ES, Bourgeau-Chavez LL, Rober AR, Wyatt KH, Waddington JM, Turetsky MR. Effects of soil moisture and water depth on ERS SAR back scatter measurements from an Alaskan wetland complex. Remote Sens Environ. 2009; 113: 1868-1873.

85. Koyama NC. Quantitative Estimation of Surface Soil Moisture in Agricultural Landscapes using Spaceborne Synthetic Aperture Radar Imaging at Different Frequencies and Polarizations. University of Cologne. 2011.

86. Huang W, Sun G, Zhang Z, Ni W. Sensitivity of multi-source SAR backscatter to changes of forest aboveground biomass. Remote Sens. 2015; 7: 9587-9609.

87. Panciera R, Tanase M, Lowell K, Walker JP. Evaluation of IEM, Dubois, and Oh radar backscatter models using airborne L-Band SAR. IEEE Trans

Geosci Remote Sens. 2014; 52: 4966-4979.

88. Park SE, Moon WM. Assessing Vegetation Scattering Mechanisms of L-band AIRSAR Data on Sloping Forest Area. IEEE International Conference 2006.

89. Park SE, Moon WM, Pottier E. Assessment of scattering mechanism of polarimetric SAR signal from mountainous forest areas. IEEE: Trans Geosci Remote Sen. 2012; 50: 4711-4719.

90. Champion I, Da Costa JP, Godineau A, Villard L, Dubois-Fernandez P, Le Toan T. Canopy structure effect on SAR image texture versus forest biomass relationships. EARSeL eProceedings. 2013; 12: 25-32.

91. Wang C, Qi J. Biophysical estimation in tropical forests using JERS -1 SAR and VNIR imagery. II. Aboveground woody biomass. Int . Remote Sens. 2008; 29: 6827-6849.

92. Lewis SL, Sonké B, Sunderland T, Begne SK, Lopez-Gonzalez G, Van Der Heijden GM, et al. Above-ground biomass and structure of 260 African tropical forests. Philosophical Transactions of the Royal Society B. 2013.

93. Iizuka K, Tateishi R. Simple Relationship Analysis between L-Band Backscattering Intensity and the Stand Characteristics of Sugi (Cryptomeria japonica) and Hinoki (Chamaecyparis obtusa) Trees. Advances in Remote Sensing. 2014; 3: 219-243.

94. Nguyen NT, Nguyen AD, Anh VT, Nguyen TKT, Nguyen TD. Update Information of Flora and Plant's Resources of Yok Don National Park, Daclak Province. 2008.

95. UNESCO. International Classification and Mapping of Vegetation. United Nations Educational, Scientific and Cultural Organization. 1973.

96. Trung TV. The Vegetation Cover in Vietnam. Chapter IV, V, 2nd Edition. Science and Technics Publishing House. 1978.

97. Trung TV. The Tropical Forest Ecosystem in Vietnam, Chapter IV. Science and Technics Publishing House. 1998.

98. Phung NL, Phan NH, Trieu VH, Nguyen NT, Le CT. Natural forest ecosystems Viet Nam. Ministry of Agriculture and Rural Development of Vietnam (MARD). 2006.

99. MARD. Soil map in Highlands's region in 2010. National Institute for Agricultural Planning-Remote Sensing Center, Ministry of Agriculture and Rural Development of Vietnam (MARD). 2010.

100. Nguyen XC, HaQQ, Luu TA, Nguyen VL. Report on Conservation Planning and Sustainable Development of Yok Don National Park in 2010-2020. Ministry of Agriculture and Rural Development (MARD). 2009.

101. ALOS-2. Calibration Result of JAXA standard products. Japan Aerospace Exploration Agency, Earth Observation Research Center. 2014.

102. Vo VH, Tran VH, Pham NB. Handbook for Vietnam forest inventory. Ministry of Agriculture and Rural Development of Vietnam (MARD). 2006.

103. Tan VP, Nguyen VX, Thinh TD. PART B-6 Tree allometric equations in Evergreen broadleaf, Deciduous, and Bamboo forest in Central Highland region, Vietnam. UN-REDD Vietnam Programme. 2012.

104. Pham H. Handbook of Reliability Engineering. 2003.

105. Kieth H, Barrett DJ, Keenan R. Review of Allometric Relationships for Estimating Woody Biomass for New South Wales, the Australian Capital Terriory, Victoria, Tasmania and South Australia. National Carbon Accounting System Technical Report. 2000.

106. Chave J, Andalo C, Brown S, Cairns MA, Chambers JQ, Eamus D, et al. Tree allometry and improved estimation of carbon stocks and balance in tropical forests. Oecologia. 2005; 145: 87-99.

107. Fassnacht FE, Hartig F, Latifi H, Berger C, Hernández J, Corvalán P, et al. Importance of sample size, data type and prediction method for remote sensing-based estimations of aboveground forest biomass. Remote Sens Environ. 2014; 154: 102-114.

108. Wagner F, Rutishauser E, Blanc L, Herault B. Effects of plot size and census interval on descriptors of forest structure and dynamics. Biotropica. 2010; 42: 664-671.

109. Réjou-Méchain M, Muller-Landau HC, Detto M, Thomas SC, Toan TL, Saatchi SS, et al. Local spatial structure of forest biomass and its consequences for remote sensing of carbon stocks. Biogeosciences Discussions. 2014; 11: 5711.