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

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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

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

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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

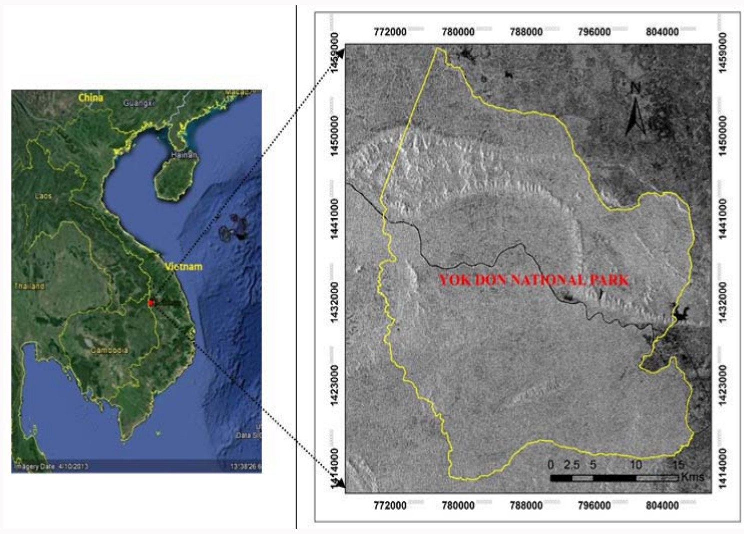

Figure 1: Location map of the study area displaying the boundary of Yok Don National Park (yellow polygon) in Central Highlands region, Vietnam.

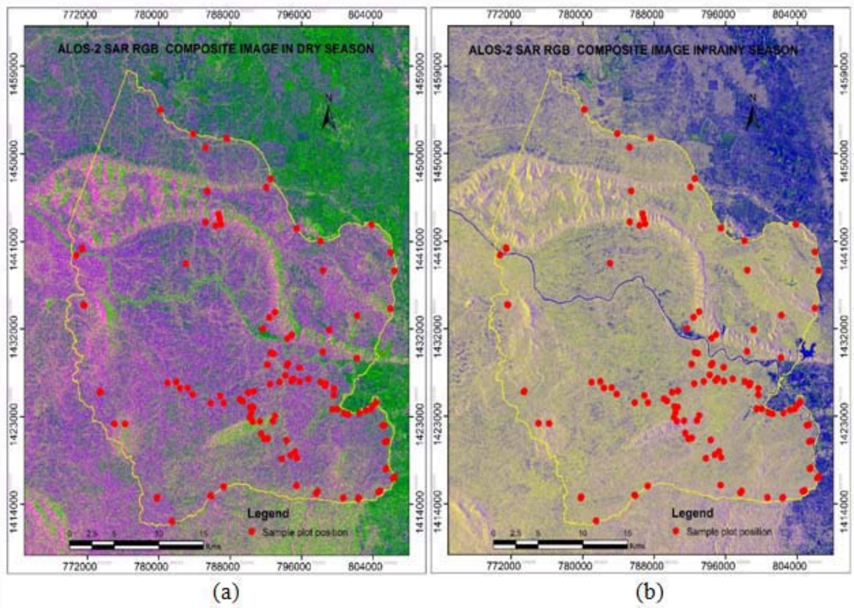

Figure 2: The distribution of the location of sample plots established during field survey over the RGB color composite images: (a) Dry season RGB image, and (b) Rainy season RGB image. The RGB color composite image was created by using the HH channel for red (R), HV channel for green (G), and the ratio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

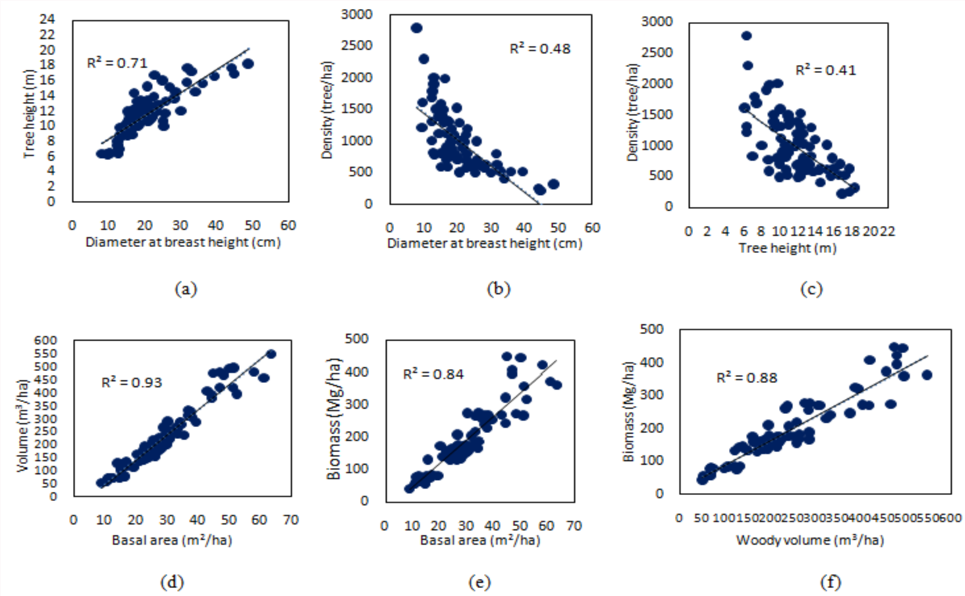

Figure 3: Cross-comparison between different structural parameters: (a) tree height (H) and diameter at breast height (D), (b) density of trees (N) and diameter at breast height (D), (c) density of trees(N) and tree height (H), (d) woody volume (V) and basal area (BA), (e) above ground biomass (AGB)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

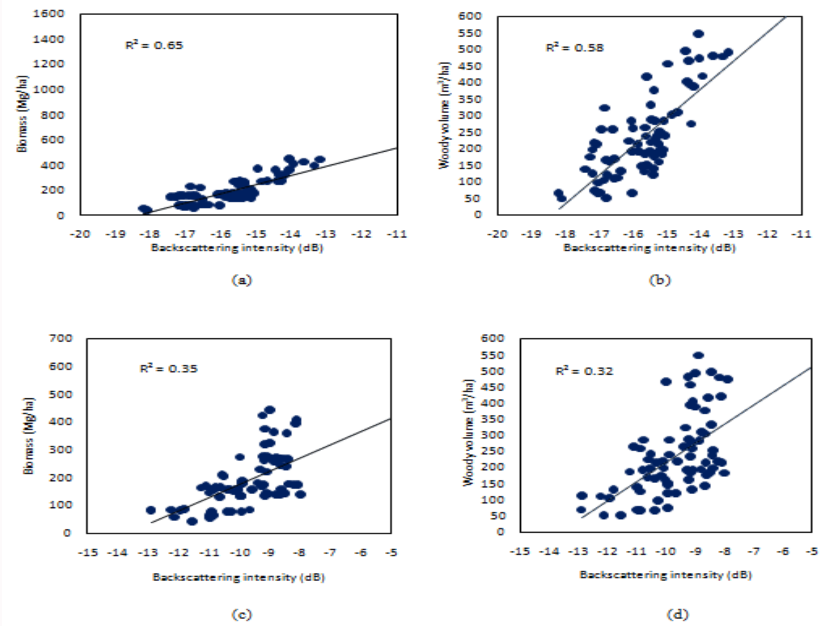

Figure 4: The relationship between biomass, woody volume, and backscattering intensity during dry season: (a) Biomass versus backscattering intensity (HV), (b) Woody volume versus backscattering intensity (HV), (c) Biomass versus backscattering intensity (HH), and (d) Woody volume versus backscattering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

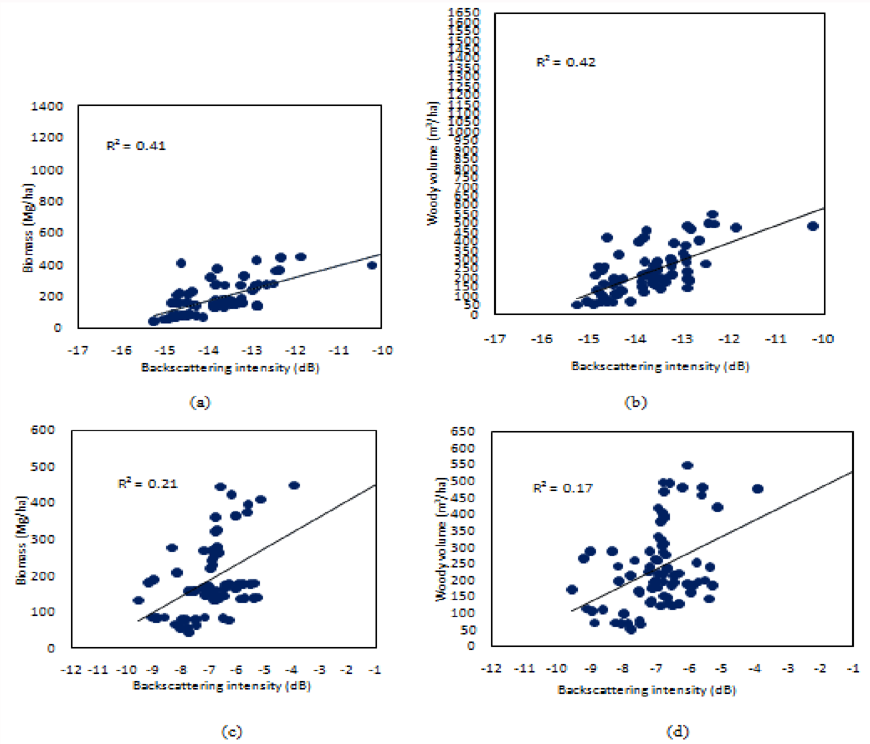

Figure 5: The relationship between the woody volume, biomass, and backscattering intensity during rainy season: (a) Biomass versus backscattering intensity (HV), (b) Woody volume versus backscattering intensity (HV), (c) Biomass versus backscattering intensity (HH), (d) Woody volume versus backscattering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

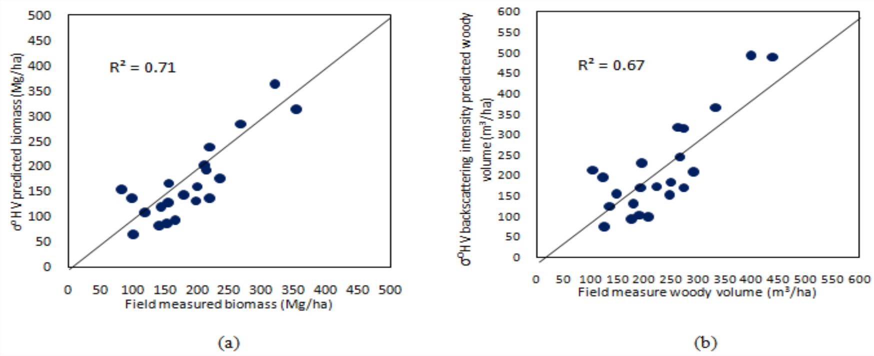

Figure 6: The validation of the SAR data based predicted results: (a) above ground biomass, and (b) woody volume. The 1:1 plot between the predicted and field data are shown.

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.

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