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POLARIMETRIC ALOS/PALSAR-2 DATA FOR RETRIEVING ABOVEGROUND BIOMASS OF SECONDARY FOREST IN THE BRAZILIAN AMAZON

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ABSTRACT

Secondary forests (SFs) are one of the major carbon sink in the Neotropics due to the rapid carbon assimilating in their aboveground biomass (AGB). However, the accurate contribution of the SFs to the carbon cycle is a great challenge because of the uncertainty in AGB estimates. In this context, the main objective of this work is to explore polarimetric Alos/Palsar-2 data from to model AGB in the SFs of the Central Amazon, Amazonas State. Forest inventory was conducted in 2014 with the measured of 23 field plots. Multiple linear regression analysis was performed to select the best model by corrected AIC_w and validated by leave-one-out bootstrapping method. The best fitted model has six parameters and explained 65% of the aboveground biomass variability. The prediction error was calculated to be RMSEP = 8.8 ± 2.98 $Mg.ha^{-1}$ (8.75%). The main polarimetric attributes in the model were those direct related to multiple scattering mechanisms as the Shannon Entropy and the volumetric mechanism of Bhattacharya decomposition; and those related to increase in double-bounce as the co-polarization ratio (VV/HH) resulted of soil-trunk interactions. Such models are intended to improve accuracy for mapping SFs AGB in often cloudy environments as in the Brazilian Amazon.

Index Terms— SAR, Amazon Forest, Polarimetry, Scattering Decomposition, Second Growth.

1. INTRODUCTION

The areas undergoing regeneration partially counterbalance the carbon emissions from deforestation, forest degradation, forest fires, burning of fossil fuels, and other anthropogenic sources, accumulating carbon in their aboveground biomass (AGB). In the Brazilian Amazon, the secondary forests (SFs) have the potential to accumulate over 6 Pg C in 40 years [1]. This accounts for one third of Brazil's total CO_2 emissions [2]. So, carbon uptake by SFs is a key element in the global carbon cycle, which justifies the need to accurately estimate of the AGB stocks and their growth rates [3]. Historically, the AGB modeling in the Brazilian Amazon has been carried out through the information obtained by Radar (Radio-Detection and Range) data, due to two main reasons: the persistence of the cloud and to the greater sensitivity of the signal to the AGB. The Advanced Land Observing Satellite / Phased Array L-band Synthetic Aperture Radar-2 (Alos/Palsar-2), which operates on microwaves (L-band, 23.5 cm), are insensitive to weather conditions and capture images day and night [4].

When the microwave pulses reach the canopy layer they suffer multiple scatterings in all directions and the information recorded back to the sensor (backscatter) is result of the structure and geometric properties of the forest targets at the same wavelength. Thus, the higher the biomass density, the greater the backscatter recorded by the sensor [5]. With the rising of polarimetric SAR systems (operating in four polarizations), other levels of relationship with the forest targets are achieved allowing to decompose the recorded wave in three or more elementary scattering mechanisms that depend only on the targets properties [6]. Such polarimetric decompositions are useful to better characterize these complex targets, increasing, above all, the accuracy of biomass estimates [7]. The goal of this work is to evaluate the use of polarimetric Alos/Palsar-2 data to retrieve AGB of the SFs at Manaus study site, Central Amazonia, using multiple linear regression analysis.

2. METHODOLOGY

The study area comprises SFs formed on both sides of BR-174 highway, 70 km north of the city of Manaus. This area has 5,042 km² (2º33'11"S, 60º5'7'W) and includes protection areas

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and long-term ecological researches, such as the Biological Dynamics of Forest Fragments Project (BDFFP), started in 1979. This area was part of the international project REGROWTH-BR, completed in 2014, and carried out in partnership between the Institute of Tropical Scientific Research IICT/Lisbon, ISA/Lisbon Higher Institute of Agronomy, and the National Institute for Space Research (INPE) [8]. The process of deforestation in the region began with the construction of the BR-174 highway in the mid-1970s, where significant forest areas were suppressed around BR-174. However, due to the low agricultural aptitude and mainly due to the extinction of government subsidies, many of these areas were abandoned after 1984 [9]. This results in SFs over 16 years of age in 50% of the REGROWTH-BR project area [8].

The climate is classified as Am (Köppen), with an annual mean temperature of 26.7 °C and an annual average rainfall of 2200 mm. The dry season occurs from July to September with rainfall below 100 mm in this period. The vegetation is considered as Terra Firme moist forest, with canopy height between 25 and 35 m and some emergent trees reaching 40 m in favorable sites [10]. The inventory was carried out in August 2014 with the measurement of 23 field plots. The field plots were randomly selected in the SFs after cutting with ages varying from 12 to 34 years according to the land-use history obtained by the REGROWTH-BR project [8]. The method consisted of nested transects with different sizes, ranging from 10 x 100 m for the measurement of small arboreal individuals with diameters at breast height DBH ≥ 5 cm, up to 60 x 100 m to measure large-trees (DBH ≥ 20 cm). The arboreal individuals were identified by species and botanical family by an experienced parataxonomist the field and had its scientific names conferred by the site: www.theplantlist.org [11].

2.1. Aboveground-biomass (AGB)

The aboveground biomass equation for living trees at Manaus study site was described by Brown et al. (1989) (1):

$$AGB_{live} = e^{(-2.17 + 1.02 \ln(DBH^2) + 0.39 \ln(h))} \quad (1)$$

where AGB is the aboveground dry mass in kg, DBH is the diameter at breast height, in cm, ρ is the wood density in g cm^{-3}, h is the total tree height, in meters, obtained by hypsometric equations adjusted by ecological species group [11]. The AGB from standing dead trees and palm trees were estimated by different methodologies, as described in Cassol et al. [12]. The total AGB was extrapolated to the hectare by the sum of the individual tree weights in each plot, given by Megagrams per hectare (Mg ha^{-1}).

2.2. Alos/Palsar-2 data processing

Two full-polarimetric scenes were acquired for the study area in CEOS SAR format, processing level 1.1. (Single Look Complex) in slant range and High Sensitive mode. The acquisition dates were 04 and 18 April 2016, obtained in the ascending orbit to the right of the antenna at 4:15. The angle of incidence ranged from 33.8 to 36.5° to the dates of April 4 and April 18, respectively.

The pre-processing steps were the follow: multilook, filtering, extraction of attributes derived from covariance and coherence matrices, polarimetric decompositions, calibration, and geocoding. The multilook process is a resampling step towards the azimuth that is intended to produce images with regular dimensions, as well as to reduce the speckle effect [4]. The range and azimuth resampling factor was set at 1:2, resulting in a nominal spatial resolution of approximately 6.25 m. The speckle was reduced by Refined Lee filter (11x11 pxl size), which was considered optimal for our analysis. This filter size was considered as a trade-off between the gain obtained by the indiscriminate increase of the filter size and the loss of relevant radiometric information caused by the smoothing [12]. The polarimetric decomposition involved the extraction of 125 polarimetric attributes from coherence [T] and covariance [C] matrices, and used as predictors of multiple linear regressions models. The list of attributes can be accessed in Cassol et al. [12].

The conversion of the digital numbers from the SLC image to the backscatter coefficient σ° (sigma-naught, in dB) in the four polarizations HV = VH was performed by (2):

$$\sigma^{\circ}_{slc} = 10 \log_{10} (I^2 + Q^2) + CF \quad (2)$$

where I is the In-phase image and Q is the phase Quadrature of the SLC image, and CF is the calibration factor and has the value of -83 dB [12].

After calibration and extraction of polarimetric attributes, the geocoding was performed by the operation known as Range-Doppler Terrain Correction. This process performs orthorectification of the SAR image with the precise transformation of slant-range to ground-range using a Digital Elevation Model (DEM).

2.3. Multiple Linear Regression (MLR) Models

In the multiple linear regression models, the AGB (Y) dependent variable is estimated by multiple independent variables (X) from the Alos/Palsar-2 images by a linear relationship between these variables (3):

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_{p-1} X_{i,p-1} + \varepsilon_i \quad (3)$$

where Y_i is the AGB in the i-th observation in Mg ha^{-1}, β_0, β_1, β_2,…, β_{p-1} are the model parameters, X_{i1}, X_{i2},…$X_{i,p-1}$ are the p-1 explanatory variables of the model in the i-th observation and the ε_i is the random error.

The analysis was performed by using the exhaustive selection package of variables "glmulti" implemented in R through the ordinary least squares method. The model selection was performed by the AIC criterion, where the models with Δ AIC < 2 were chosen, and the best was determined by the weights given to the set of explanatory variables in the model – Akaike weights (w_i) [13]. According to the authors, w_i is the relative likelihood of the model, given the data. These are normalized to sum to 1 and interpreted as probabilities. So, the ratio of Akaike weights w_i / w_j can be judged in favor of the best model.

The evaluation of the best MLR model was performed using the following criteria and statistical analyzes, defined by [14]: i) the significance, standard error (Sy), and Variance Inflation Factor (VIF) of the regression parameters; ii) the distribution of the standardized residuals to verify the absence of outliers; (iii) the Akaike information Criterion (AIC) and weights (w_i); and iv) the Breusch-Pagan test for the homoscedasticity of the residuals. The validation of the regression models was evaluated by the coefficient of determination (R^2) between the values predicted by the regression and the values from the validation samples and by the distribution error of prediction, i.e., by Root Mean Square Error of the Prediction (RMSEP) [14] (4):

$$RMSEP = \sqrt{bias^2 + \sigma^2_{bias}} \quad (4)$$

where bias is the difference between the expected value from MLR and the observed values from validation samples.

In addition, the distribution of the deviations of the prediction and the null hypothesis of bias deviation equal to zero (without trend) was analyzed by the t-test. The selection of the best MLR model was given by the highest w_i value and lowest RMSEP. The bootstrapping method with 100 repetitions was used to refine the model, maintaining the separation of 80% for training samples and 20% for validation.

3. RESULTS

Ten attributes were chosen as best predictors of the AGB. The selected attributes were manifested by the multiple scattering mechanisms from canopy, such as the Bhattacharya and Yamaguchi volumetric scattering components, the Shannon Entropy (SE) and the cross-polarization ratio (R_{cross}). The attributes from the VV channel, whose responses are related to the double-bounce scattering components such as and co-polarization ratio (R_{cop}), become larger as the AGB increases. The other attributes are related to the structure of the SFs, which, due to the orientation of the multiple scatters, changes the signal phase return and causes depolarization between the polarimetric channels (Table 1).

The selected model (1) was able to explain 65% of AGB variability of SFs at Manaus study site (R^2aj. = 0.65; RMSE = 35.93 Mg.ha^{-1}); and did not show evidence of multicollinearity by VIF (Table 2). However, the relative standard error of the parameter estimation was higher than Sy = 20%, except for the regression parameter of the Bhattacharya volumetric scattering component (Sy = 11.5%, Table 2).

Table 1. Model description of ΔAIC < 2 selected by the exhaustive "glmulti" package. w_i are the weights given by the relative likelihood amongst models [13].

N	MLR Model	Nº (p)	LogLik	AIC	w_i
1	~1+TVSM_phi_s1+Bhattacharya_Vol+SE_P_norm+T12_imagC+T13_realC+R_{co}	6	-896.5	1809.0	0.12
2	~1+TVSM_phi_s1+Bhattacharya_Vol+SE_P_norm+SE_norm+T12_imagC+T13_realC+R_{co}	7	-895.8	1809.5	0.09
3	~1+I_C33+TVSM_phi_s1+Bhattacharya_Vol+SE_norm+T12_imagC+T13_realC+R_{co}	7	-896.2	1810.3	0.06

The selected model shown good distribution of the residuals when plotted versus each predictor parameter (not shown), and does not shown evidence of heterocedasticity (BP: 3.38, p-valor = 0.067).

Table 2. Statistics of the selected MLR model to estimate AGB of secondary forests at Manaus study site. Sy – standard error; Sy – relative standard error (%), VIF – variance inflation factor.

Polarimetric attribute	Estimator	Sy	Sy (%)	p-valor	VIF
(Intercept) ~1	-60.64	20.6	-34.0	0.0037	
TVSMphi_s1	0.71	0.3	46.1	0.0314	4.06
BhattacharyaVol	272.76	31.2	11.5	< 0.0001	2.26
SE_P_norm	34.77	14.8	42.6	0.0202	2.41
T_{12_imagC}	910.79	274.1	30.1	0.0011	4.14
T_{13_realC}	733.02	237.4	32.4	0.0024	1.03
R_{co}	58.31	23.3	40.0	0.0134	1.38

However, there is a tendency to overestimate low AGB values < 50 Mg.ha^{-1} and super estimate AGB > 150 Mg.ha^{-1} (Figure 1A), which is reflected in the positive and non-zero bias by the t-test: μ_{bias} = 1.3 Mg.ha^{-1}, t = -2.21, p-value = 0.02 (Figure 1B). On the other hand, the error of prediction was considered low and represents 8.75% of mean observed AGB (RMSEP = 8.8 ± 2.98 Mg.ha^{-1}). The bias of the estimate was 1.3 ± 36.5 Mg.ha^{-1}.

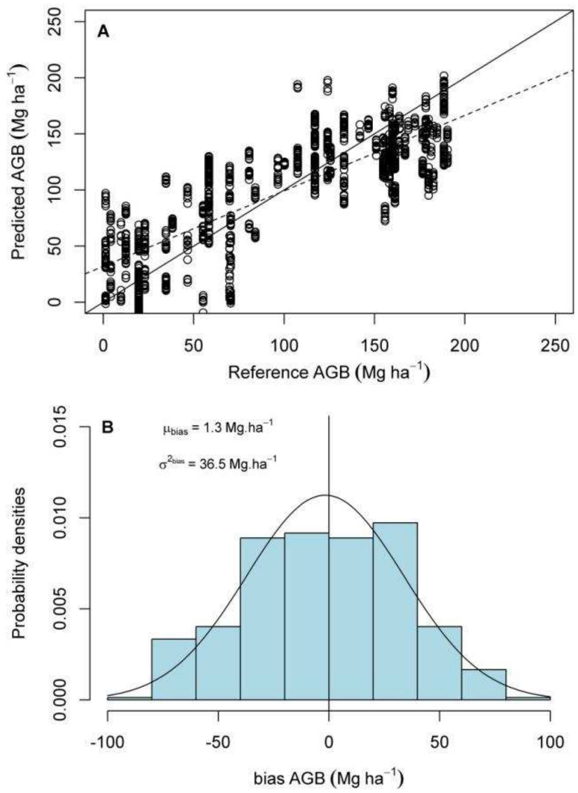

Figure 1. Cross-validation of MLR for AGB estimation at Manaus study site. A) Biomass distribution after bootstrapping cross-validation between the estimated and observed AGB values. The solid line represents the perfect 1:1 fit and the dotted line the adjustment after cross validation $R^2 = 0.65$; RMSEP = 8.8 ± 2.98 Mg ha^{-1}. B) Probability density histogram of AGB bias after bootstrapping.

4. CONCLUSIONS

The selected MLR model with six parameters estimator was able to explain 65% of the biomass variability in the secondary forests north to Manaus city, Central Amazonia. Prediction errors, obtained by cross-validation, were only 8.75% (8.8 Mg ha^{-1}). We also observed that the regression parameters involved unusual polarimetric decompositions and attributes obtained from covariance and coherence matrices. This model can help us understand how the secondary forests interact with the different polarimetric attributes from the Alos/Palsar-2 data, and especially to increase the accuracy of biomass and carbon estimates in these areas, often covered by clouds.

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