INTEGRATING ALOS PALSAR AND SPOT SATELLITE IMAGERY FOR TROPICAL FOREST BIOMASS ESTIMATION

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ABSTRACT: Due to the increasing interest in the amount of carbon stored in forest ecosystems and growing demand for accurate monitoring of carbon fluxes between vegetation and atmosphere for the purposes of the REDD+ scheme, remote sensing based methods are needed for forest biomass estimation. In this study we investigate the usability of a combination of SPOT 5 optical satellite imagery and ALOS PALSAR data for above ground biomass estimation in humid tropical forest. The study area covered around 2000 ha in the Central Nature Reserve of Singapore which is a protected area of humid tropical evergreen forests. Biomass was measured in 25 field plots and linear regression models were developed between ground biomass and remotely sensed parameters from SPOT 5 HRG and ALOS PALSAR satellite data using stepwise regression approach. Accuracy of the models was evaluated using an independent set of 10 field sample plots. The model considered to be most suitable for practical use which included NIR band from SPOT 5 and HV radar backscatter from ALOS PALSAR achieved adjusted r^2 of 0.46 and RMSE of 152 t/ha (36%) with essentially no bias. Based on the independent validation plots the model underestimated the average biomass of the plots by only 1%. Thereby, the results suggest that a combination of optical and radar remote sensing data can be used to produce reliable biomass estimates for large areas of humid tropical forests using empirical regression models in a rather homogeneous environment. However, the results also show that pixel level errors of the models may be large and that the use of mere optical data may enable similar level of results. Furthermore, the study highlights the unsuitability of empirical models for biomass estimation outside the vegetation type they have been developed for.

1. INTRODUCTION

Tropical deforestation and forest degradation are identified as one of the main contributors to global greenhouse emissions. Accurate quantification and monitoring of forest carbon stocks and carbon fluxes between vegetation and atmosphere are necessary for the implementation of schemes to reduce forest carbon emission such as the REDD+ (Reducing Emissions from Deforestation and Forest Degradation). Remote sensing based methods to estimate the distribution and amount of biomass stored in tropical forest have received much attention in recent years due to the relative ease and low cost of acquiring data over wide and often inaccessible areas compared to traditional approaches based on field measurements (Lu 2005, 2006). Optical remote sensing has been widely used to relate spectral reflectance to above ground vegetation biomass. However, such approach have been less successful for tropical forest as optical sensors mainly capture canopy information and the complex structure and species diversity of tropical forests result in a lack of strong relationship between changes in biomass to changes in reflectance (Foody et al. 2001, 2003). Radar backscatter, on the other hand, offers the possibility to obtain information on the structure of the vegetation cover and numerous studies have made use of Synthetic Aperture Radar (SAR) imagery to estimate forest biomass (Lu 2006). Previous research has indicated that although radar backscatter in the L-band has the most potential for forest biomass estimation, its sensitivity to biomass "saturates" at around 40-110 t/ha and thus has limited applicability in tropical forests where high level of biomass are common (Dobson 1992, Luckman et al. 1997). More recent studies have shown that a synergistic use of optical and SAR imagery has the potential to improve biomass estimation in tropical forests by taking advantage of the strengths of each data type and minimizing their limitations (Lu 2006, Wang et al. 2008). In this study we investigate the usability of the combination of SPOT 5 optical satellite imagery and ALOS PALSAR data for above ground biomass estimation in humid tropical forests using multiple regression modelling.

2. MATERIALS AND METHODS

2.1. Study Area

The study area for the research is the Central Nature Reserve (CNR) of Singapore, a forest area covering some 2000 ha in area located in the central part of the highly urbanised island of Singapore. CNR enjoys legal protection as a nature reserve and under the management of the National Parks Board of Singapore (NParks). Approximately 200 ha of nearly pristine patches of primary forest remain in fragments within CNR, engulfed by secondary forest in various stages of succession (Teo et al. 2003).

2.2. Field Measurements

A total of 36 permanent forest inventory plots (25 m radius circular plot) are maintained in the nature reserves for the purpose of monitoring forest health. 25 of these plots ranging from young secondary forest to primary lowland tropical forest were measured for this study. Ten of the remaining 11 permanent plots in the nature reserve were used for model validation. One clear outlier was removed from the dataset. The geolocation of each plots were determined using a high precision GPS receiver. For the 25 plots used in the model construction, all individual trees with a diameter at breast height (DBH) exceeding 5 cm were measured for DBH and the species were identified. For the 10 validation plots, only trees exceeding 9 cm DBH were identified and measured. The reason for the difference is that the sampling for the validation plots were not done for the specific purpose of this study but as standard measurement of the permanent sample plots. This difference was taken into account in the model validation process.

The biomass of each tree was calculated using the allometric model (Equation 1) developed by Chave et al. (2005) for moist tropical forest, based on field sampling of tropical forest in Malaysia and Indonesia:

$$\boxed{AGB = \rho \times \exp(-1.499+2.148\ln(D)+0.207\ln(D))^2-0.0281(\ln(D))^3} \quad (1)$$

Where ρ is the wood density (oven dry mass divided by green volume) (g/cm^3) of the tree species and D is the DBH (cm) of the tree. Wood density values were obtained from the Global Wood Density Database collated by Zanne et al. (2009), the largest wood density database to date.

2.3 Remotely Sensed Data

A set of remote sensing data from both optical and microwave remote sensing sensors were compiled for this study. Two multispectral optical images from SPOT 5 (satellite from the Satellite Pour l'Observation de la Terre programme) acquired on 14 April 2010 and 20 May 2010 and a Synthetic Aperture Radar (SAR) scene in L-band HH and HV polarization from ALOS PALSAR acquired on 1 July 2010 were used.

SPOT 5 imageries have a spatial resolution of 10 m and comprises of four wavelength bands; green (Band 1; 0.50 – 0.59 µm), red (Band 2; 0.61 – 0.68 µm), near infra-red (Band 3; 0.79 – 0.89 µm) and shortwave infra-red (Band 4; 1.58 – 1.75 µm). The raw digital numbers (DN) from both images were first converted to top of the atmosphere (TOA) and then corrected for Rayleigh scattering and molecular absorption using routines in the 6S package (Vermote et al. 1997), assuming a standard tropical atmosphere with considerations of the spectral response of each spectral band of the sensor. The images were than merged and resampled using the nearest neighbour method to form a single cloud-free image over the study area. In addition to wavelength bands a set of other parameters were derived from the optical dataset (Table 1).

Table 1: Remotely sensed parameters tested for biomass estimation.

Image Parameter	Description
SPOT 5 HRG Bands 1 to 4	Atmospherically corrected SPOT 5 HRG band values converted to surface reflectance measures.
NDVI	$\frac{B3-B2}{B3+B2}$, Band numbers refer to SPOT 5 bands.
SAVI	$\frac{B3-B2}{B3+B2+L}(1+L)$, Band numbers refer to SPOT 5 bands.
2-band EVI	$\frac{2.5*(B3-B2)}{(\mathrm{B3}+2.4*\mathrm{B2}+1)}$, Band numbers refer to SPOT 5 bands.
Albedo	B1+B2+B3+B4, Band numbers refer to SPOT 5 bands.
PCA	1^{st} PC of PCA
Occurrence Texture Measures	Data range, mean, variance, entropy, and skewness measures in the optical (SPOT 5) data within 5x5 pixel kernel.
Co-Occurrence Texture Measures	Mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment, and correlation measures in the optical (SPOT 5) data within 5x5 pixel kernel.
HH backscatter	HH backscatter of ALOS PALSAR sensor presented in sigma-nought values.
HV backscatter	HV backscatter of ALOS PALSAR sensor presented in sigma-nought values.

For the ALOS PALSAR data, the Level 1.0 images (HH and HV) were first multi-looked by a factor of three in the azimuth direction. They were then geo-registered (using a nearest-neighbour scheme to preserve the original data values) to the same image geometry as the SPOT

5 mosaic to facilitate later comparison. Using SRTM DEM data to calculate the local incidence angle at each pixel, topographic normalization was carried out, before obtaining the final output data in σ^0 (normalized radar backscatter cross-section, also called sigma-nought) values, with units in dB (decibels). Table 1 presents the processed remote sensing parameters that were used for this study.

2.4 Above Ground Biomass Estimation Procedure

Vegetation biomass is a comprehensive parameter that is related to many factors such as vegetation stand structure, vegetation density and vegetation species composition. The differences in these factors are captured by remote sensing data in the form of varying spectral reflectance or radar backscatter patterns. Simple linear and multiple regression models were tested to empirically relate measured field biomass values to the remote sensing parameters. The remotely sensed parameter values were derived by calculating the mean values of image pixels within each of the 25 biomass plots. Using field biomass values as the dependant variable and the mean parameter value of each plot as the independent variable, stepwise regression analysis was used to find the best parameter combination to estimate forest biomass. The performance of the model was tested against the 10 independent validation plots.

3. RESULTS AND DISCUSSION

Results from the stepwise analysis indicated that Band 3 (near infra-red) mean occurrence texture measure using 5x5 kernel was the best individual parameter for the regression model (adjusted $r^2 = 0.49$), explaining 49% of the variance in field biomass data and producing a root mean square error (RMSE) of 149 t/ha or 35% of the sample plots' mean biomass values. As only one parameter was identified, this indicates that addition of other parameters did not contribute significantly to the success of the model. Assessment of the model using the validation plots revealed that the difference between the biomass predicted by the model and actual biomass can be quite significant, reaching as high as 113% for a validation plot, however

Table 2. Example of the size of plot level errors and overall bias of the model used for biomass estimation in the study area when applied to independent validation plots.

Biomass Plot	**Estimated Biomass**	**Actual Biomass**	**%Difference**
1	764.910	359.459	-113
2	602.898	788.476	24
3	656.217	705.636	7
4	522.063	474.651	-10
5	532.052	365.105	-46
6	361.518	367.678	2
7	302.326	521.531	42
8	265.834	223.614	-19
9	281.073	536.073	48
10	468.678	298.876	-57
		Estimation Bias	2.5%

the estimation bias (i.e. the percentage difference between average biomass of the plots and the estimated biomass of the plots) was only 2% (Table 2). The results indicate that the performance of the model is low when applied on plot level basis and thus inappropriate for biomass estimation at the micro level, however when applied on large contiguous forest areas such as the entire CNR, the biomass estimate can be expected to be accurate and reliable.

Estimation bias is not taken into account for when comparison between regression models is made based merely on the r^2 values. In this study we also evaluated the best performing regression models selected with stepwise regression for their estimation bias performance using the 10 independent validation plots. Table 3 summarises the tested regression models, together with their statistical parameters and the bias of the model.

Among the tested regression models which all performed on a similar level according to r^2, Model 1 (adjusted r^2 = 0.46 and RMSE = 152 t/ha) was considered the most suitable for practical use having nearly as small bias as Model 3 but more simple parameters reducing the amount of computation in the execution of the method. Note that the results suggest that the radar reduces the bias slightly in biomass estimation. This very minor improvement may be due to the ability of the radar sensor to penetrate through the canopy and thereby obtain information on the vegetation type. In any case, the penetration is not deep enough for the radar signal alone to derive meaningful estimations of above ground biomass in high volume tropical forests (shown by the weak correlation of HV backscatter and biomass of r^2 = 0.23).

Table 3. Models compared in the final stage of model selection for the CNR biomass estimation. Band 3_mean5x5 refers to the co-occurrence mean texture measure in 5x5 kernel.

Regression Models	**Adjusted r^2**	**Variables**	**Beta value**	**Bias (%)**
Model 1 2848.029-6196.912*band3+25.071*HV	0.462	Band3	-0.594	-1.0
		HV	0.206	
Model 2 2826.491-7180.492*band3	0.451	Band 3	0.688	1.5
Model 3 3236.006-84.115*Band3_mean5x5 +15.145*HV	0.474	Band3_mean5x5	-0.644	0.8
		HV	0.124	
Model 4 3299.722-93.026* Band3_mean5x5	0.486	Band3_mean5x5	-0.712	2.5

4. CONCLUSION

The results of the study suggest that a combination of optical and radar remote sensing data supported by field sampling can be used to produce reliable biomass estimates for large areas of humid tropical forests using empirical regression models in a rather homogeneous environment. However, the results also show that at the pixel level, errors of the models may be large. Within CNR, there were also small pockets of areas where the model failed to give reasonable estimates as these areas consist of vegetation types that were not represented in any of the model construction plots. This highlights that caution must be taken when applying biomass models outside the area and vegetation types they have been developed for. These types of empirical biomass estimation models have a range of scale and area of suitability where they can be reliably applied to, but the suitability of such models for areas outside this range should be examined in case-by-case bases using local field data.

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