CAMBODIAN FORESTS BIOMASS ESTIMATION USING ALOS PALSAR 50m MOSAIC DATA FOR REDD+ POLICIES IMPLEMENTATION

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ABSTRACT: Tropical countries like Cambodia require information about forest biomass for successful implementation of climate change mitigation policies related to reducing emissions from deforestation and forest degradation plus (REDD+). This study investigates the potential of Phased Array-type L-band Synthetic Aperture Radar fine beam dual (PALSAR FBD) 50m mosaic data to estimate above ground biomass in Cambodia. The radiometric and terrain corrections were applied to reduce the topographic effects. Above ground biomass (AGB) was estimated using bottom-up approach based on field calculated biomass and backscattering (σ^o) properties of PALSAR data. The relationship between the PALSAR σ^o HV and HH/HV with field based biomass was strong with R^2 = 0.67 and 0.56, respectively. PALSAR estimated biomass shows good results in deciduous forests because of less saturation as compared to dense evergreen forests. The validation result shows high coefficient of determination R^2 = 0.61 with RMSE = 21 t/ha using values up to 200 t/ha biomass. There are some uncertainty because of uncertainty in the field based measurement and saturation of PALSAR data. Above-ground biomass map of Cambodian forests will provide information about the successful implementation of forest management practices for the REDD+ assessment and policies implementation at national level.

1. INTRODUCTION:

Forests play an important role in global carbon cycling as they are potential carbon sinks and sources to the atmosphere CO_2 (Muukkonen, 2007). Tropical forests store about 40% of the terrestrial carbon (Page et al., 2009). According to the FAO (2010), the net change in global forest area is estimated to be -5.2 million ha per year for 2001-2010 and -8.3 million ha per year for 1990-2000. The International Panel on Climate Change (IPCC) has pointed out that reducing and/or preventing deforestation is the mitigation option for climate change. Clean Development Mechanism (CDM) under the Kyoto Protocol is not enough to mitigate climate change by adoption of afforestation and reforestation because deforestation releases more Green House Gases (GHGs) than afforestation and reforestation. Forest conservation is only one of many possible options by which permanent land-use change may be avoided. REDD+ avoids emissions of carbon into the atmosphere by conserving existing carbon stocks. The basic idea of REDD+ is to reward individuals, communities, projects and countries that reduce GHG emissions from the forests (Angelsen, 2008). Implementation of REDD+ policies require effective biomass and deforestation monitoring systems that are reproducible, provide consistent results, meet standards for mapping accuracy, and can be implemented at the national level (Defries, 2007).

There are various methodology for the biomass estimation but no methodology present a clear view on how to report carbon pools and their fluxes and what would be accuracy and uncertainty of biomass monitoring. Therefore biomass mapping has become an urgent need to assess and produce data on forest carbon stocks and change in stocks on a national level (Maniatis and Mollicone, 2010). Very recent biomass map (Sacchi et al., 2011) shows uncertainties of about 30-50% in Indo-China countries.

The most accurate way of calculating biomass is destructive sampling and forest inventory data using allometric equations. However, these traditional techniques are often time consuming, labor intensive, and difficult to implement, especially in remote areas and they cannot provide the spatial distribution of biomass in large areas. Moreover, the method cannot give historical information about forest if there were no existing forest inventory data. Therefore satellite remote sensing supplemented with low forest inventory data can provide cheap and fast estimation as well as historical information about forest biomass. Most of the remote sensing techniques are based on optical and synthetic aperture radar (SAR) systems. The disadvantages of optical sensors are not related to the plants structural parameters, acquisition of cloud free images in tropical countries, low saturation level of spectral bands and various indices (Gibbs et al., 2007). Therefore, dependency on SAR sensors has been increased because SAR can provide data without limitation of clouds and solar illumination. Penetration capability of SAR allows to give information about plants structural parameters hence have ability to measure biomass (Lu, 2006).

The successful launch of the Advanced Land Observing Sattelite's (ALOS) PALSAR in 2006 has increased the potential to use radar to measure biomass, as this is the first long-wavelength (L-band, 23-cm wavelength) synthetic aperture radar (SAR) satellite sensor to have the capability of collecting single, dual, full and Scan-SAR mode with cross-polarized (HV, horizontal-transmit, vertical receive) and co-polarized (HH, horizontal-transmit, horizontal receive; VV, vertical-transmit, vertical receive) data. The HV polarization is useful because it interacts with trees and produces a strong response (Mitchard 2011).

Various studies have analyzed the retrieval of AGB using radar data in tropical regions (Mitchard et al., 2009; Gama et al., 2010; Englhart et al., 2011). Longer wavelengths SAR have proven to be more useful because of an increasing backscatter range with changing biomass (Dobson et al., 1992; Luckman et al., 1997; Castro et al., 2003; Lu, 2006). These biomass estimations are valid up to a certain threshold where saturation occurs, (Lucas et al., 2007; Mitchard et al., 2009). In general, saturation level of SAR depends on the frequency of SAR systems as well as forests structure. The sensitivity of SAR decreases with the increase of biomass in the dense forests (Imhoff, 1995; Kasischke et al., 1997). This study is an attempt to overcome the saturation problem of PALSAR to some extent. The main aim of this study is to estimate national level biomass using PALSAR 50m mosaic data based on bottom-up approach to support REDD+ and forest management practices in Cambodia.

2. STUDY AREA:

Cambodia has an area of 181,035 square kilometers in the southwestern corner of Indo-China countries, bordered by Vietnam to the east, Thailand to the west, Lao P.D.R. to the north and Gulf of Thailand to the south. The average temperature ranges from 21° to 35°C and experiences tropical monsoons. Southwest monsoons blow inland bringing moisture-laden winds from the Gulf of Thailand and Indian Ocean from May to October. Cambodia is a tropical country with the rainy season from May to October and dry season from November to April.

Cambodia has one of Asia's highest rates of forest loss. Cambodia has lost 29% of its primary forests during 2000 to 2005. The deforestation rate is highest in Cambodia among Indo-China countries (FAO, 2010). Logging activities, combined with rapid development, population growth, urbanization, agricultural expansion has been the primary reason for Cambodia's forest loss (Gaughan et al., 2009). Cambodia has signed REDD+ policies in 2009 therefore study of forest cover is necessary for REDD+ policies implementation.

3. METHODOLOGY:

3.1 Field data: The study area was visited in November 2010 and January 2011 to collect forest inventory data (Diameter at breast height (DBH), tree height, species, tree density and forest types). Seventy nine sampling plots were selected on the basis of analysis of land use/land cover map (LULC), Landsat ETM+ 2009, 2010 data and SRTM-DEM data. During the selection of sampling plots spatial homogeneity, eco-climatic conditions and forest types were kept in mind. Most of the sampling plots were selected in the plane area to minimize topographic effects of SAR data. 30x60m and 30x30m sampling plots were used depends on the homogeneity of the site. The sampling plots were located using GPS (Garmin 62s). The AGB in kg for each tree was calculated using allometric equation as derived by Kiyono et al., (2010). We used Kiyono et al., (2010) allometric equations because Anglesen (2008) has mentioned that country specific allometric equation is better than global allometric equation other reason, we compared the Kiyono et al., (2010) allometric equation based biomass with the Brown (1997) and Kenzo et al., (2009) allometric equations based biomass then we found that the Brown (1997) allometric equation based biomass estimation shows over estimation and Kenzo et al., (2009) shows under estimation. The biomass value obtained from each tree using allometric equation were summed and normalized by the area of the plots to produce the AGB in t/ha. In this biomass estimation, we have considered the tree ≥ 10cm DBH, which are likely to comprise of most of the woody mass of the plots.

3.2 Satellite data: LULC map based on ASTER 2005 data, SRTM-DEM data, Landsat ETM+ 2009, 2010 data were used for selection of sampling sites. PALSAR FBD 50m mosaic data was downloaded from Japan Aerospace Exploration Agency (JAXA). The processing of PALSAR data was started with the terrain corrections using Akatsuka et al., 2009 and Shimada et al., 2010 methodology to minimize the topographic effects of PALSAR in mountainous area. This methodology was not very effective because of highly rugged topography in the area. The digital number (DN) was converted to the normalized radar cross section (NRSC or σ^o). The backscattering coefficient was calculated using the following equation (Shimada 2009).

$$\sigma^o = 10 \times \log_{10}(DN^2) - 83 \qquad (1)$$

The PALSAR data was co-registered with Landsat ETM+ orthorectified data. We have not considered the climatic conditions of PALSAR 50m mosaic data because these information's was not available.

3.3 Statistical Analysis: Multi-linear regression (MLR) analysis using the stepwise forward method was conducted relating the σ^o of PALSAR to corresponding field calculated biomass. We used 3x3 pixels window size analysis for MLR model development and this MLR model has been applied to the PALSAR 50m mosaic data to estimate biomass of whole Cambodia. Finally validation was used to evaluate the accuracy of the model by comparing PALSAR estimated to the field derived AGB. The detailed methodology is shown in the flow chart (figure 1).

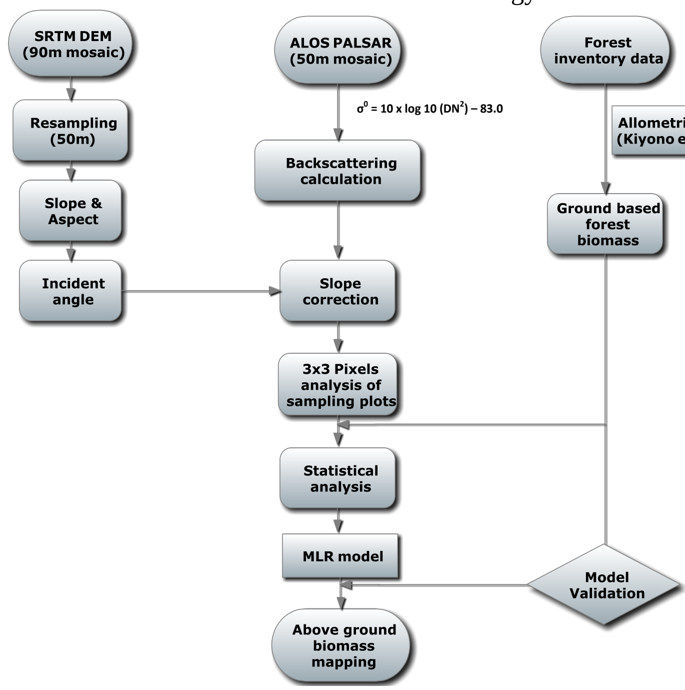

Figure 1. Flow chart of the methodology

4. RESULTS AND DISCUSSION:

Statistical analysis has been made to relate the forest inventory data. Figure 2a and b show the relationship of biomass with the stem density and basal area respectively. Figure 2a does not show good correlation (R^2 = 0.2) between biomass and tree density because the tree density depends on the tree species, site conditions, forest types etc. Figure 2b shows strong correlation (R^2 = 0. 9) between biomass and basal area because basal area is a function of tree density and DBH. A total seventy nine plots data has been analyzed. Fifty one plots were used for the MLR model development and 23 plots were used for model validation. Five plots were excluded from the analysis because the location of the plots was near to the road as well as some degradation activity.

Figure 3a shows the relationship between PALSAR σ^o (HH) and (HV) with biomass. Field measured biomass shows a significant relationship with the σ^o HV (R^2 = 0.67) as compared to σ^o HH (R^2 = 0.05). High σ^o HH in low biomass region has been noticed because of the high surface scattering from the plots covered by dry leaves and grasses, which increases the surface roughness. The reason why σ^o HV polarization produces better correlation than HH is because of the volume scattering in forest areas enhances the cross-polarization returns as increase in biomass. Other studies also reveal that the σ^o HV is more sensitive to the forest biomass compared to σ^o HH (Le Toan et al. 1992; Harrell et al. 1995). We have observed different backscattering properties from the same biomass region (Figure 3a at biomass 100-150 t/ha) because of difference in canopy and their distribution. Evergreen forest having multi-story tree structure shows high backscattering as compared to deciduous forests of same biomass class. A loss in sensitivity of PALSAR signal has been appeared to occur at approximately 150-200 t/ha biomass (Figure 3a). Figure 3b shows the strong relationship between PALSAR σ^o HH/HV with biomass (R^2 = 0.56). Therefore, polarization ratio is useful parameter for biomass estimation. Figure 3c shows the poor relationship between PALSAR σ^o HH and HV with the stem density (R^2 = 0.06 and 0.32) respectively. This is mainly because tree density depends on the forest types, tree species and site conditions etc. Figure 3d also shows poor relationship between σº HH/HV with tree density ($R^2 = 0.3$).

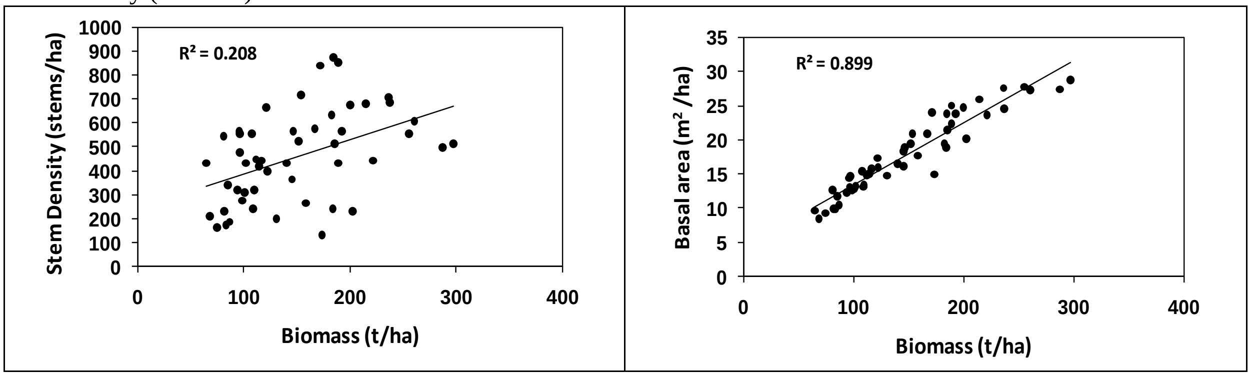

Figure 2. Biomass value for the filed plots against (a) stem density (b) basal area

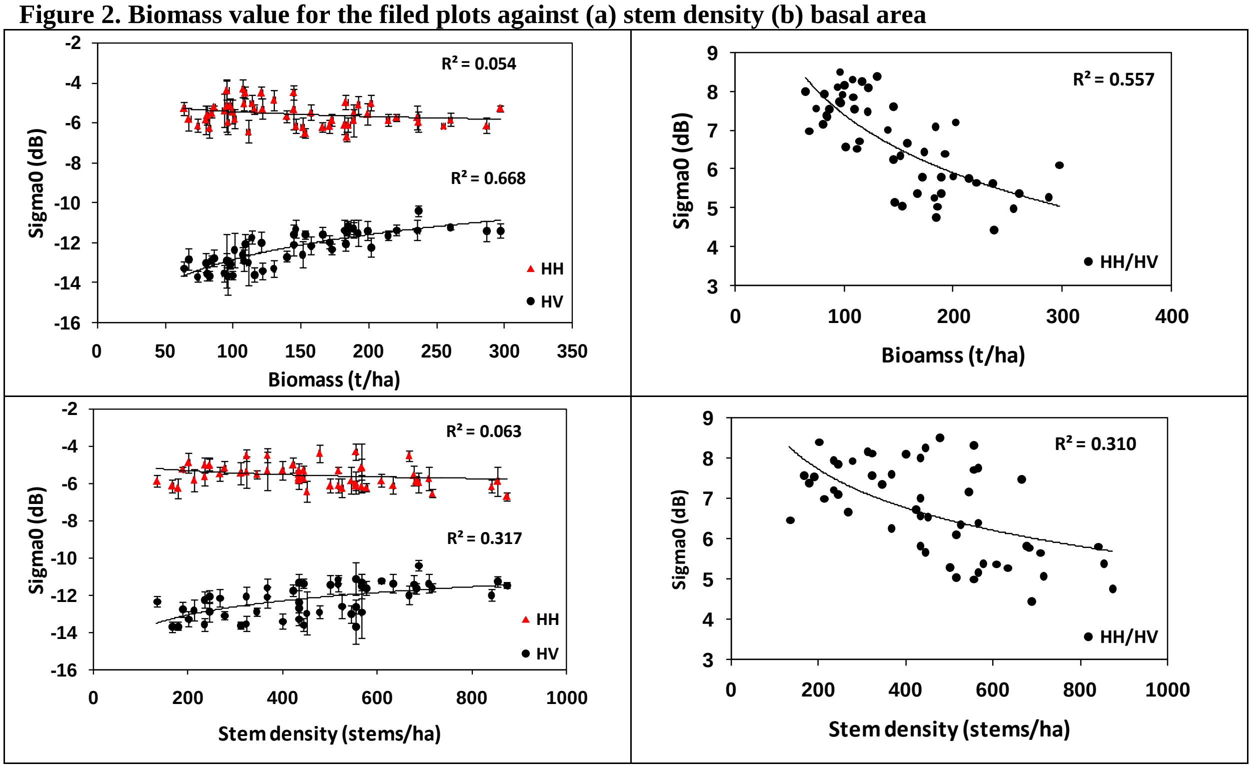

Figure 3. PALSAR 2009 σº HH, HV and HH/HV plotted against biomass (a, b) and stem density (c, d)

We have used PALSAR σº HV and HH/HV to generate MLR model because HV and HH/HV shows strong correlation with biomass. The MLR model has been applied to the PALSAR 50m mosaic data to generate national level biomass map. Figure 4a shows the biomass map of the Cambodia. The biomass values were classified into 8 classes. Deforested area shows the zero biomass value. Figure 4b shows the LULC map of the same biomass region. If we compared the biomass map (fig. 4a) with the LULC map (fig. 4b) then the high biomass region (>200 t/ha) mostly falls into the evergreen high and medium low class of the LULC map. However, in mountainous area (northern part) the biomass map shows variation because of the topographic effects. The results from this study are preliminary, but it shows the potential of PALSAR 50m mosaic data that is freely available.

Figure 5 shows the validation results of PALSAR derived biomass. The accuracy of PALSAR predicted AGB decreases as the biomass increases because of saturation of PALSAR signal. It shows a significant coefficient of correlation $R^2 = 0.61$. The overall root mean square error (RMSE) for these data is 63 t/ha; however this decreases to 19 t/ha if only values below 100 t/ha are considered and to 21 t/ha using values up to 200 t/ha. The high variation in errors are present in the high biomass region i. e. >200 t/ha. We have predicted two types of uncertainties a) calculating biomass from field data using allometric equation because we have not used species specific allometry as well as small plot size and trees having DBH < 10 cm was not considered and b) saturation of PALSAR signal at high biomass region as well as topographic effects.

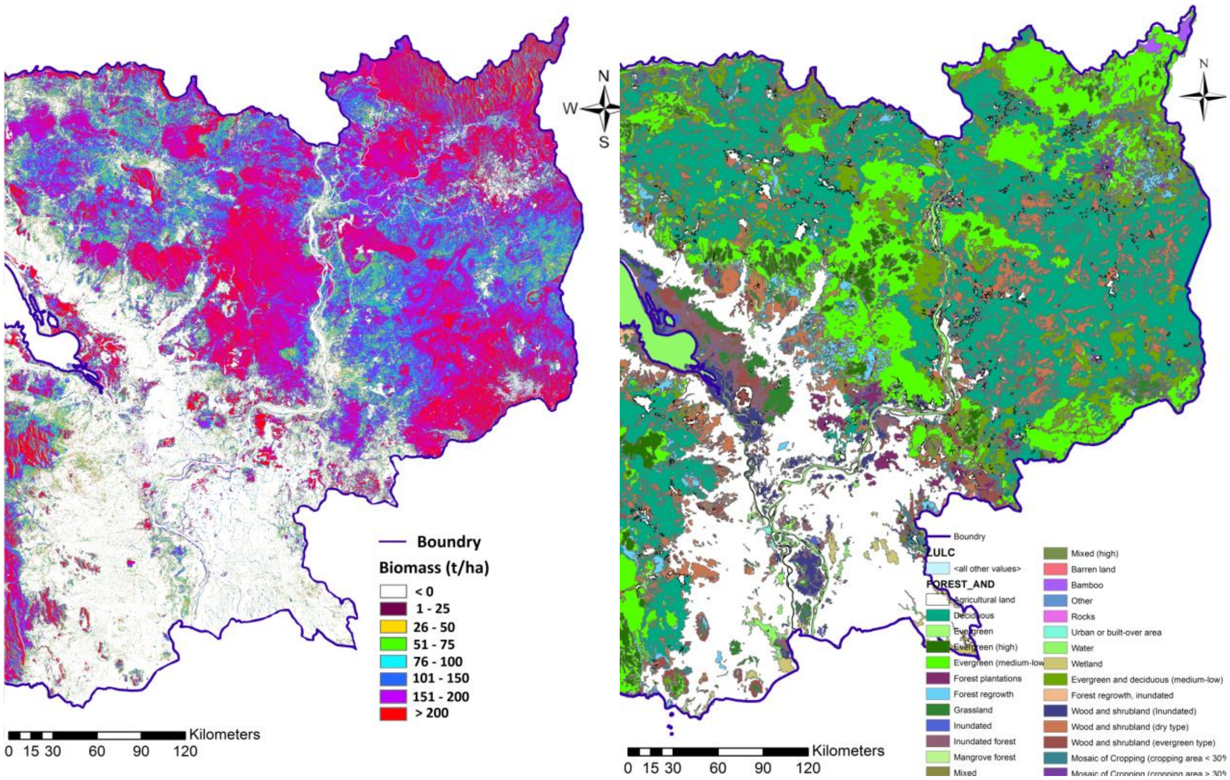

Figure 4. (a) PALSAR derived biomass map of Cambodia (b) LULC map of the area

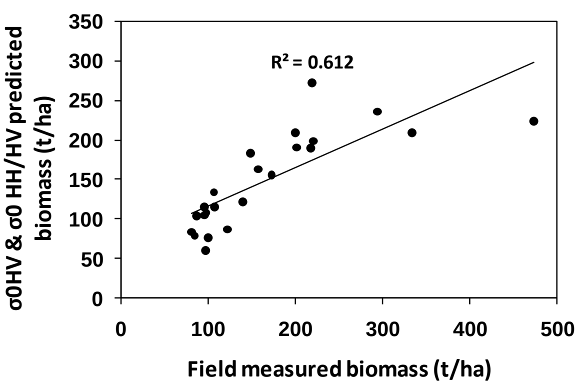

Figure 5. Relationship between PALSAR predicted biomass plotted against field measured biomass

5. CONCLUSION:

This study demonstrates that a combination of PALSAR (L-band SAR) and field data can provide biomass map. However at high biomass region the PALSAR become saturated. Such biomass map is not very exact but it can provide information about biomass distribution which is needed for forest management practices. For more precise estimation we must look forward for the P-band SAR or DESDynl satellite system in the future.

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