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Above Ground Biomass Assessment from Combined Optical and SAR Remote Sensing Data

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Abstract- **Today the carbon content in the atmosphere is predominantly increasing due to green house gas emission and deforestation etc. Forest plays a key role in absorbing carbon dioxide from atmosphere and stores in form of wood biomass which contains nearly 70-80% of global carbon. Spatial distribution of biomass cannot be obtained by inventory techniques so the application of remote sensing in biomass assessment is introduced to solve the problem. Both optical (LANDSAT-8) and synthetic aperture radar (ALOS-2) remote sensing data are used for above ground biomass (AGB) assessment. Biomass that stores in branch and stem of tree can be called as above ground biomass. 20 ground sample plots of 30m*30m utilized for biomass calculation from allometric equations. Optical remote sensing calculates the biomass based on the spectral indices of SAVI and RVI by regression analysis (R^2=0.813). Synthetic aperture radar is an emerging technique uses high frequency wavelengths for biomass estimation. HV back scattering shows good relation (R^2=0.74) with field calculated biomass compared to HH (R^2=0.43) utilizes for biomass model generation by linear regression analysis. Combination of both optical spectral indices (SAVI, RVI) and HV SAR back scattering increases the plantation biomass accuracy to (R^2=0.859) compared to optical (R^2=0.788) and SAR (R^2=0.742).**

Keywords **– above ground biomass, Spectral indices, Backscattering, LANDSAT, ALOS-2**

I.INTRODUCTION

Every year an average of 9.9 billon metric tons of carbon is releasing into atmosphere. It causes lot of threats to the global environment. The carbon emission increased due to increase usage of fossil fuels, forest deforestation etc. Forest acts as a carbon sequestration because it stores lot of carbon in the form of biomass. Due to increase in anthropogenic activities like land cover change, burning lots of fossil fuel and deforestation there is a need to produce accurate biomass for future forest ecosystem management M.Lucas 2012 [1]. 30% of earth land that means 4 billion hectares is occupied by forest. For example according to Kyoto protocol [2] a forest is defined as an area of land having 0.5-1 hectares and crown cover greater than 10-30%. Biomass is the weight (or) mass of its living plant tissue generally expressed in metric ton. It is the organic matter present in the environment. Generally Biomass can be obtained in two forms 1. Raw biomass from different sources like agricultural, forestry, agricultural crops, municipal waste and animal dropping 2.secondary biomass obtained from primary biomass includes paper, cotton, natural rubber, card board etc. Energy released from biomass when it is burnt it converted into fuels called biomass energy. Biomass provides renewable energy that improves the economy, environment and energy source. Renewable energy is eco friendly and provides less harm to the environment. Traditional inventory method is most accurate method for biomass estimation but it consumes lot of time, cost and labor. The spatial distribution of biomass in huge large cannot be calculated by inventory technique. So In order to solve this problem remote sensing techniques are utilized for biomass estimation. Due to deforestation lot of carbon content is releasing in to the atmosphere and create threads to the global environment. In general the accurate land cover change mapping is needed for finding the deforestation areas and also helps to monitor the biomass changes with time. Therefore it is important to estimate the biomass content in the environment. The application of remote sensing data becomes the primary source for biomass estimation easy and quickly for a large area. The remote sensing data consists of both optical and SAR data. Previous studies estimate the biomass by using the vegetation indices of the optical sensor data like (LANDSAT [3], SPOT [4], MODIS [5]) images. Optical remote sensing has an ability to estimate the above ground biomass because the spectral response in optical sensor data is related to the interaction between the vegetation cover and sun radiance. The biomass is estimated by determining the correlation between the spectral response and the ground data obtained from the field plots. To remove the variability caused by canopy geometry, sun view angle on biomass estimation a relationship was developed between the vegetation indices and forest biophysical parameters. It has a potential benefits in biomass estimation ranging from medium to large scales. High spatial resolution data like IKONOS [6] and WORLDVIEW-2 [7] provides the accurate biomass at local scales. For regional scales a large volume of data like LANDSAT which is medium spatial resolution data is used. At national and global scales coarse spatial resolution data like MODIS have been found useful for biomass estimation. Optical remote sensing calculates the biomass from the spectral indices. It is successful in estimating forest biomass but it is not used in the regions of cloud cover. The limitation may be overcome by the use radar data which provides additional capability of cloud free images. Different bands P, L, S, C, K, X are used in SAR data. Out of all bands both P and L has higher wavelengths and scattered by trunks and branches of trees so they mostly used for biomass estimation. By SAR data biomass over a large area is calculated from the backscattering value. Previous studies calculate the biomass from SAR data (ALOS PALSAR-1[8], RADARSAT [9] [10], TERRASAR-X [11], ENVISAT [12], ALOS-2[13]). Compared to all SAR data ALOS PALSAR is most commonly used because it has higher wavelength L band that penetrates more through the canopy of trees and produce high accuracy biomass .Higher wavelengths and cross polarization (HV&VH) of SAR data shows good results in biomass estimation. Application of multi frequency SAR data [14] increases the saturation effect and accuracy of biomass estimation. Dual polarization-L band (HH&HV) is most commonly used for tropical forest biomass estimation [15]. Different regression models are applied to generate biomass prediction model by correlating both ground data and backscatter value of SAR data. Interferometric is an emerging SAR technique and application of polarimetric [16] with interferometric increases the biomass estimation. The combination of optical remote sensing with SAR data increases the accuracy level of biomass [17]. Therefore by application of different optical and SAR techniques in biomass estimation leads to understand the forest ecosystem management. The objective of this study is 1. Land cover map of study area from landsat-8 2. Biomass model generation by regression analysis of optical spectral indices and filed calculated biomass 3.Biomass map from SAR data. 4. Biomass map from combined optical and SAR remote sensing data.

II. STUDY AREA

The study area is located in Mueang Surat Thani which is capital district of Surat Thani province Thailand and geographically located on western shore of the gulf of Thailand. The geographical area of Mueang Surat Thani is 233.8 sq km and spatial co-ordinates lies between 90 43' 24.08" N 980 58' 48.06 "E and 8016'44.65" N 990 16' 43.79" E. The Mueang Surat Thani flourishes with lands of fertile soil, good rainfall and balanced climatic conditions.Tapi and Phum Daung are the major rivers in this area. The Study area is selected with 9 Tombons of Mueang surat Thani district because this research is mainly focused on the estimation of biomass from plantations so the occurrence of plantation area in these regions is more.

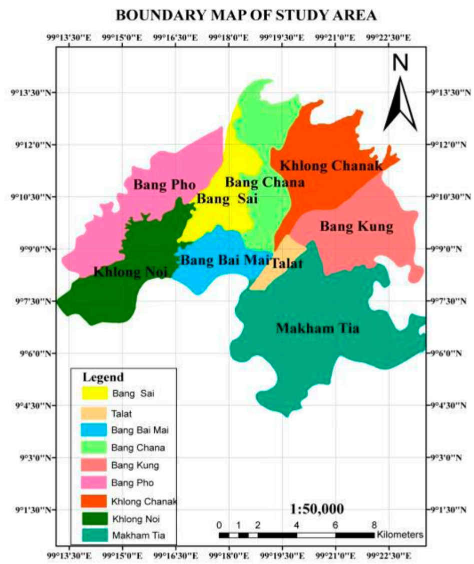

Figure 1 Represents boundary map of study area

III. DATA COLLECTION

A. Field data

In this study for designing of sample plots the remote sensing image is considered because the biomass results are obtained from both field measurements and satellite image. From optical image LANDSAT 8 the pixel size is 30m*30m so in this study, 30m*30m size of 20 square plots are utilized for collecting the field data of DBH (Diameter at Breast height of tree) and height of tree for each tree in sample plot.

B. Satellite data

Now a day's satellite image plays a key role for solving problems because we can acquire majority of useful information from it. The accuracy of the results mainly depends on the quality of input data. In this research LANDSAT 8 optical sensor data of spatial resolution 30m available on October 2015 is downloaded freely from USGS website for biomass assessment. Fine beam dual polarization (HH&HV) of October 2015 ALOS-2 image with pixel spacing of 6.25m and an incident angle of 38.8o is downloaded from JAXA website.

IV. METHODOLOGY

A. Biomass from optical sensor data

Raw satellite data cannot be used directly for land cover classification so intially it has to be processed by ERDAS softwrae image and transformed its co-ordinates to WGS 84 47N.

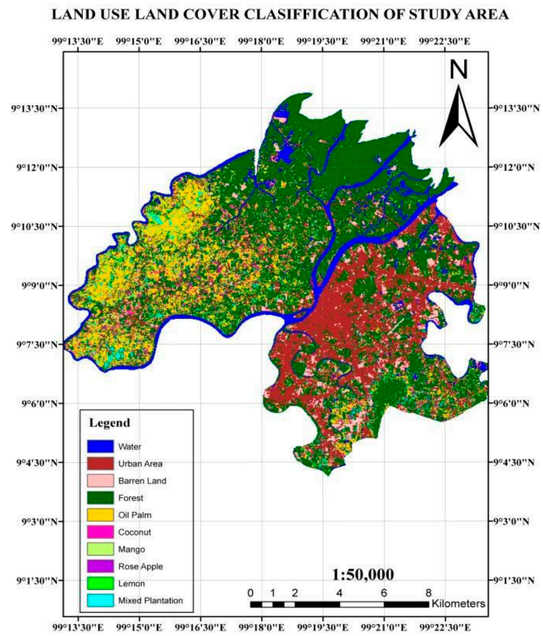

Figure 2 Represents Land cover map of study area

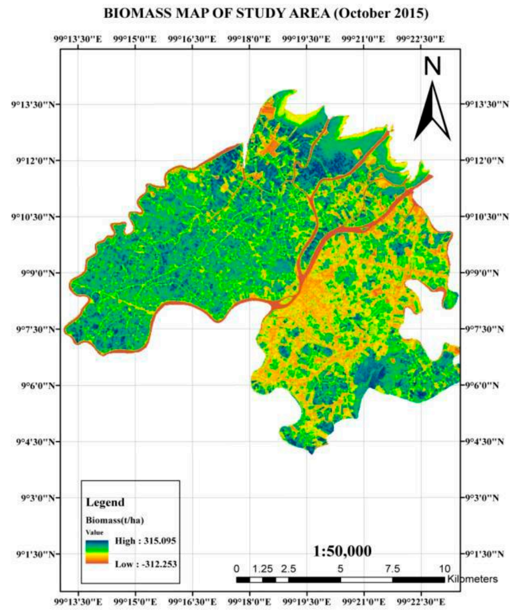

Figure 3 Represents biomass map from LANDSAT data

Both Geometric and atmsospheric corrections are applied to acquire accurate reflectance values which helps to improve the classification accuracy. Maximum likehood classification technique is applied to satellite imagery which produce overall classification accuracy of 91.13%. Forest has high land coverage (83.94sq km) fallowed by urban land (33.89 sq km), oil palm (26.92 sq km),water(13.94 sq km), coconut (6.35 sq km) and mixed plantation (5.17 sq km).Similarly mango, lemon and rose apple shows less area coverage of (0.03-0.07 sq km). Different allometric equations are applied for DBH and height of tree for calculating biomass of oil plam, mango,coconut and mixed plantations. Compared to all values of field calculated biomass only oil palm plantations shows high biomass values ranging from 140-219 (tons/ha). Spectral indices of Optical sensor data is widely used for the biomass asssessment. Four different spectral indices(NDVI,SAVI,RVI and EVI) are calculated form LANDSAT data and compare with the biomass calculated from field data to genrate biomass regression model. SAVI(R^2=0.711), RVI(R^2=0.79) and EVI(R^2=0.74) shows good relation with field calculated biomass compared to NDVI (R^2=0.64). Biomass model of SAVI and RVI (R^2=0.81) provides good accuracy compared to EVI and SAVI (R^2=0.75).

$$AGB= -238.341+353.062*SAVI+19.491*RVI(R^2=0.813)$$

B. Biomass from SAR data

The application of Synthetic radar aperture data is a Promising Technique which uses high frequency wavelengths to estimate above ground biomass. Initially SAR data has to be process by both terrain correction and radiometric calibration for calculating backscattering values. To reduce noise reduction in SAR images mean adaptive filtering is applied. In order to compare SAR backscattering values with field calculated biomass values the pixel spacing is to resample to 30m. Linear regression analysis is used to develop biomass model by comparing backscattering values and field biomass. HV backscattering (R^2=0.77) shows good relation with field biomass compared to HH (R^2=0.4). Finally accurate biomass map is produced with HV backscattering as best fit model.

$$AGB= 679.326+35.307*\sigma^\circ \text{ [dB] HH } (R^2 =0.775)$$

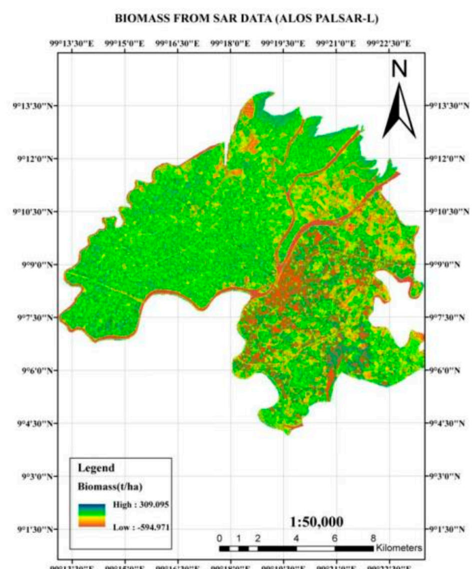

Figure 4 Represents biomass map from SAR data

C. Biomass from combined optical and SAR data

Both spectral indices and backscattering values are utilized for new biomass model generation. Multi linear regression is used to develop biomass model by comparing both spectral indices (SAVI, RVI) and HV backscattering values with field calculated biomass. Accurate biomass equation is produced with SAVI, RVI and HV SAR backscattering as best fit model (R^2=0.87) applied to total study area.

$$AGB= 101.819+17.866* \sigma^{\circ} [dB]\ HV+442.344*SAVI +9.113*RVI\ (R^2=0.870)$$

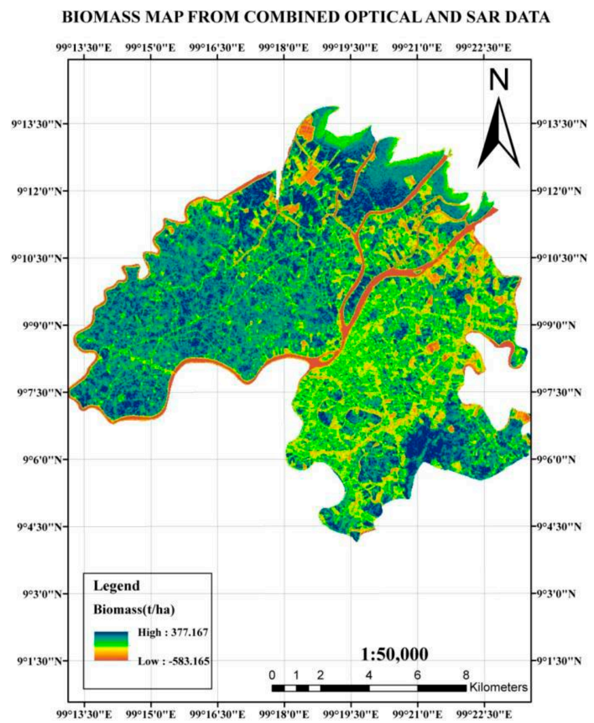

Figure 5 Represents biomass map from combined SAR and LANDSAT data

V. RESULTS

Accuracy assessment for all biomass models has to be checked with 20 field sample plots. Biomass map generated from spectral indices shows good accuracy (R^2=0.788) with RMSE of 26.054(t/ha). SAR backscattering biomass map accuracy was not higher (R^2=0.74) than spectral regression map. Combination of both optical (spectral indices) and SAR (HV backscattering) increases biomass accuracy to (R^2=0.859) with RMSE of 21.20(t/ha) compared to regression models of optical and SAR data.

TABLE I ACCURACY RESULTS

S.NO	DATA	R^2	RMSE
1	Optical	0.788	26.054(t/ha)
2	SAR	0.742	28.736(t/ha)
3	combined	0.859	21.207(t/ha)

VI. CONCLUSION

The overall accuracy of classified map indicates different land features on map shows 91.13% accuarte with the original land features on the ground. Biomass map developed from Spectral indices of both SAVI and RVI shows good accuracy compared to NDVI and EVI spectral indices. Only HV backscattering (R^2=0.77) of ALOS-2 shows good relation with the field biomass compared to HH backscattering (R^2=0.4). Application of combined optical and SAR data provides high accurate biomass map (R^2=0.859) which leads to implementation of different techniques in biomass research.

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