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Above Ground Biomass Assessment from Combined Optical and SAR Remote Sensing Data in Surat Thani Province, Thailand

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Abstract

Today the carbon content in the atmosphere is predominantly increasing due to greenhouse gas emission and deforestation. Forest plays a key role in absorbing carbon dioxide from atmosphere by process of sequestration through photosynthesis and stores in form of wood biomass which contains nearly 70% - 80% of global carbon. Different forms of biomass in the environment include agricultural products, wood, renewable energy and solid waste. Therefore, it is essential to estimate the biomass content in the environment. In olden days, biomass is estimated by forest inventory techniques which consume lot of time and cost. The spatial distribution of biomass cannot be obtained by traditional inventory forest techniques so the application of remote sensing in biomass assessment is introduced to solve the problem. Overall accuracy of classified map indicates that land features of Surat Thani on map show an accuracy of 91.13% with different land features on ground. 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 is called as above ground biomass. Twenty ground sample plots of 30 m × 30 m utilized for biomass calculation from allometric equations. Optical remote sensing calculates the biomass based on the spectral indices of Soil Adjusted Vegetation Index (SAVI) and Ratio Vegetation Index (RVI) by regression analysis (R^2 = 0.813). Synthetic aperture radar (SAR) is an emerging technique that uses high frequency wavelengths for biomass estimation. HV backscattering of ALOS-2 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 (ALOS-2) SAR backscattering increases the plantation biomass accuracy to (R^2 = 0.859) compared to optical (R^2 = 0.788) and SAR (R^2 = 0.742).

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Keywords

Above Ground Biomass, Spectral Indices, Backscattering, LANDSAT 8, ALOS-2

1. 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 [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 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 into the atmosphere and creates 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 consist 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 benefit in biomass estimation ranging from medium to large scales. High spatial resolution data like IKONOS [6] and WORLDVIEW-2 [7] provide 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 provide additional capability of cloud free images. Different bands P, L, S, C, K, and X are used in SAR data. Out of all bands both P and L have 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 the 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 show 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 the 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 of the biomass estimation. The combination of optical remote sensing with SAR data increases the accuracy level of biomass [17]. Therefore, application of different optical and SAR techniques in biomass estimation leads to understand the forest ecosystem management. The objectives of this study are: 1) land cover map of study area from landsat-8; 2) biomass model generation by regression analysis of optical spectral indices and field calculated biomass; 3) biomass map from SAR data; and 4) biomass map from combined optical and SAR remote sensing data.

2. 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 9˚43'24.08"N 98˚58'48.06"E and 8˚16'44.65"N 99˚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 Mueang Surat Thani is located at the mouth of Tapi River, which consists of eleven Tambons. The Study area is selected with 9 Tombonsof Mueang Surat Thani district because this research mainly focused on the estimation of biomass from plantations so the occurrence of plantation area in these regions is more. In this area, forest has been converted to plantations such as Oil palm, coconut and mango farms in last twenty years. Therefore it is important to estimate the spatial distribution of biomass in Surat Thani province (**Figure 1**).

3. Data Collection

3.1. 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 output results mainly depends on the quality of input data utilized. In this research both optical (LANDSAT 8) and SAR (ALOS-2) data are used for biomass assessment. LANDSAT 8 optical sensor data of spatial resolution 30 m acquired on October 2015 is downloaded freely from USGS website. Fine beam dual polarization HH (Horizontal Horizontal) & HV (Horizontal Vertical) of ALOS-2 acquired on October 2015 with pixel spacing of 6.25 m and an incident angle of 38.8˚ is downloaded from JAXA website.

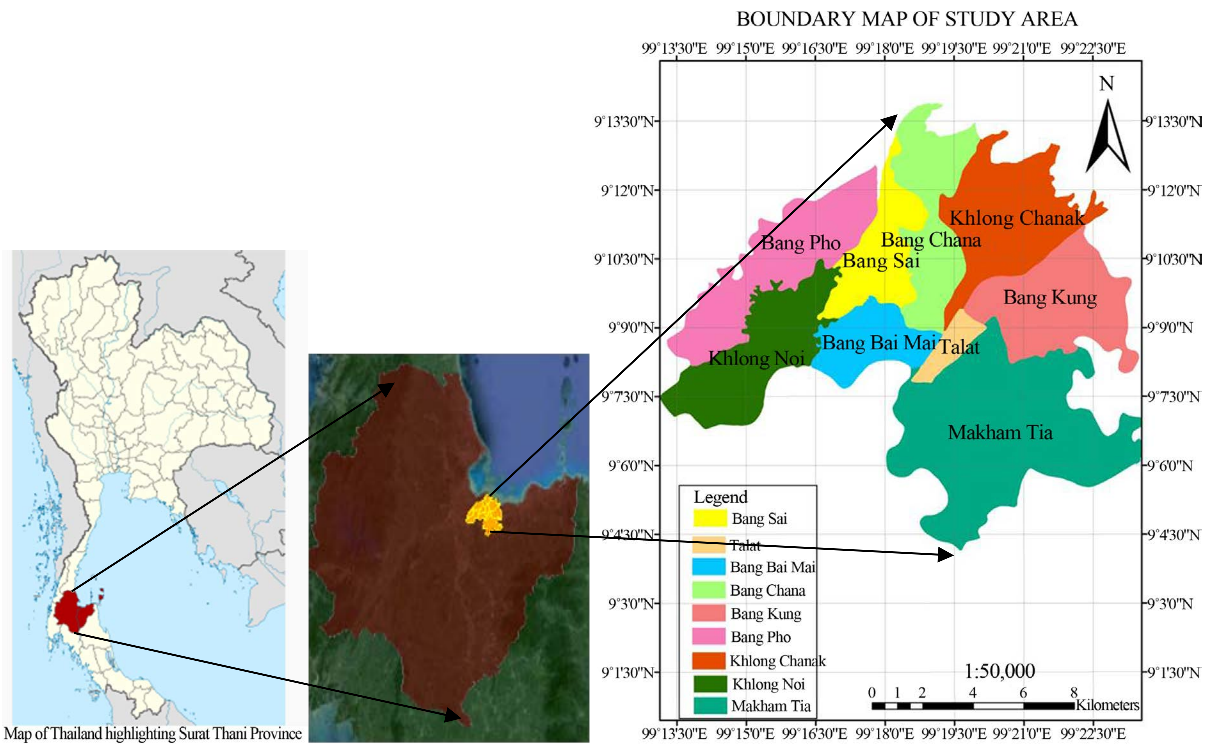

Figure 1. Location map of study area in Surat Thani province.

3.2. Field Data

In this research the field data collection plays a key role in biomass estimation because the accuracy of the calculation mainly depends on the relation between satellite images and field data. The sample plots are selected in such a way it represents the whole area. The sample plot selected should be easily accessible by car or walk. In this study, random sampling method applied for selection of sample plots. For designing of sample plots the remote sensing image pixel size is considered because the biomass results are obtained from both field measurements and satellite image. From optical image (LANDSAT 8) the pixel size is 30 m × 30 m so in this study, 30 m × 30 m size of 20 square plots are utilized for collecting field data of both DBH (Diameter at Breast height of tree) and height of tree for each tree in square sample plot.

4. Methodology

4.1. Land Cover Classification

Raw satellite data cannot be used directly for land cover classification so initially it has to be processed by ERDAS software imagine because the satellite data collected from USGS is in different projection so it has to be transformed to WGS 84 north 47N projection. In satellite data the complete information about the land surface is not stored in single band it was stored in different bands so stacking of all layers makes into a single image. Both Geometric and atmospheric corrections are applied to acquire accurate reflectance values which helps to improve the classification accuracy of image. For atmospheric correction of LANDSAT 8 image the FLAASH Atmospheric correction Model in ENVI 5.1 software is used. In this research only supervised classification is used because it extracts both quantitative and qualitative information accurately form the remote sensing image data compared to unsupervised classification. Maximum likelihood classification technique of supervised classification uses training sites which are selected for each land cover during field survey and also Google Earth as a reference to classify the satellite imagery data which produce overall classification accuracy of 91.13% and Kappa Coefficient of 0.8947. Overall accuracy of map indicates land features on map shows 91.13% accurate with different land features on ground. From the supervised classification forest has high land coverage (83.94 sq 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) (**Figure 2**, **Figure 3**).

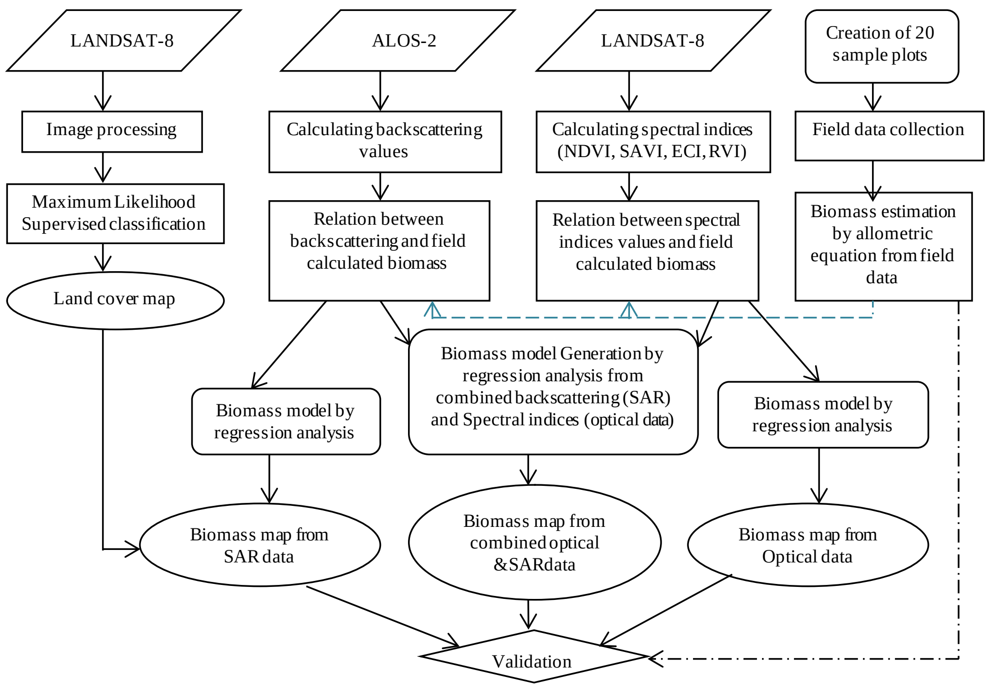

Figure 2. Overall methodology of research study.

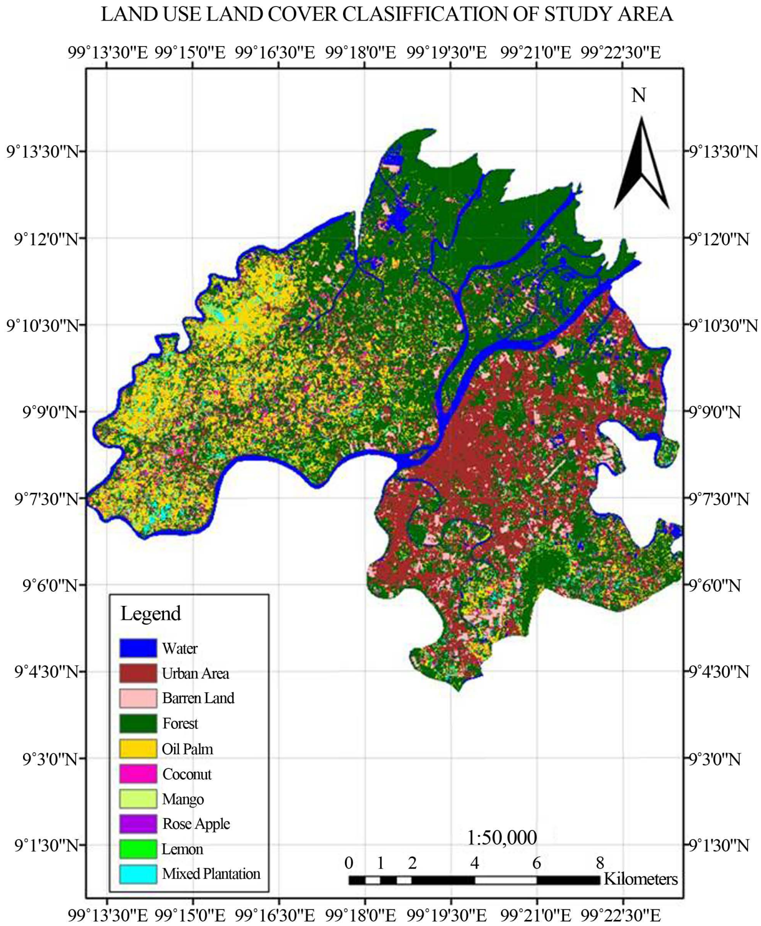

Figure 3. Land cover map of study area.

4.2. Biomass from Optical Sensor Data

The accuracy of estimated biomass mainly depends on the selection of appropriate allometric equations for different plantations. Allometric equations may not be same for all types of trees it changes based on 1) Species of trees and 2) selection of field data variables. In this research only two variables DBH (Diameter at breast height of tree) and tree height (H) are utilized for calculating field biomass from allometric equations because majority allometric equations are based on these two variables. From the below **Table 1** allometric equations for different plantations can be noticed.

Different allometric equations are applied for DBH and height of each tree for calculating biomass of 20 Sample plots (oil palm, mango, coconut, santol, lemon 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) (**Table 2**).

Spectral indices of Optical sensor data are widely used for the biomass assessment. Four different spectral indices Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), Ratio Vegetation Index (RVI) and Enhanced Vegetation Index (EVI) are calculated form LANDSAT-8 data and compare with the biomass calculated from field data to generate biomass model. 15 sample plots are utilized for biomass model generation by finding relation with the spectral indices of optical sensor data. Regression analysis is utilized to find new biomass model from the spectral indices of optical data which shows good relation with the field calculated biomass. 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). So NDVI is not considered in biomass model and regression analysis is applied to SAVI, RVI and EVI. Biomass model generated from combined SAVI and RVI (R^2 = 0.81) shows good accuracy compared to SAVI and EVI (R^2 = 0.75) (**Figure 4**).

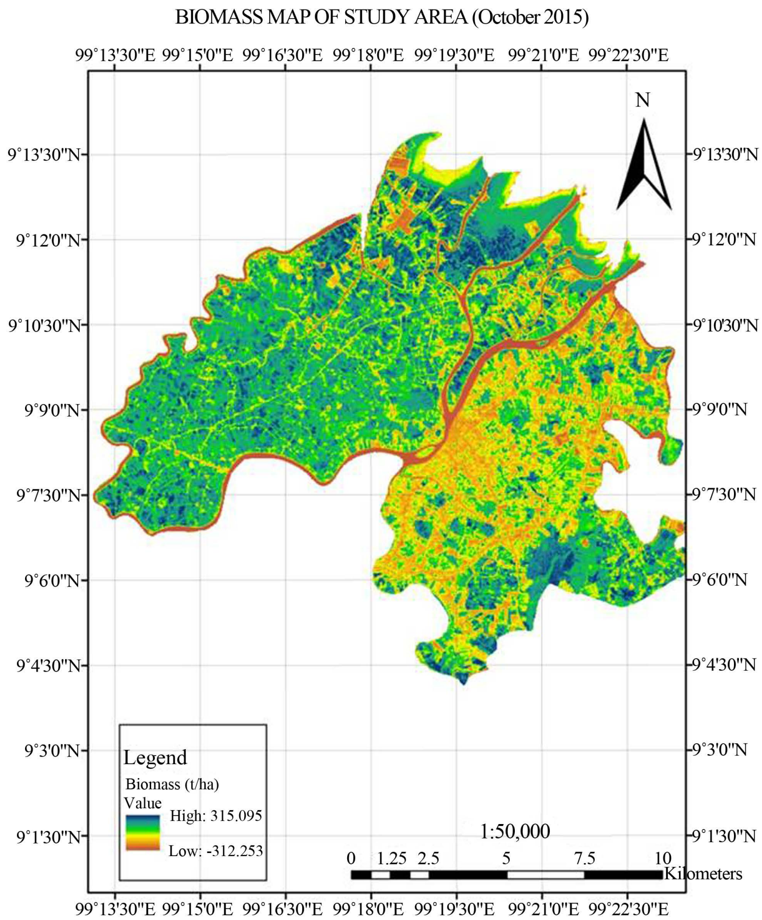

Figure 4. Biomass Map from LANDSAT-8 data.

Table 1. Allometric equations for calculation of Above ground biomass.

S. No.	Type	Scientific name	Equation AGB	Reference
1	Oil palm	*Elaeis guineensis*	$71.797*H - 7.0872$ (kg/tree)	Mazzueen Md. Khalid *et al*. 2013) [18]
2	Banana	*Musa acuminata*	0.030D2.13 (kg/tree)	Van Noordwijik M *et al*. 2010) [19]
3	coconut	*Cocos nucifera*	$4.5 + 7.7*H$ (kg/tree)	Hairiah K *et al*. (2010) [19]
4	Mango (D < 25 cm)	*Magnifera indica*	$-2.43 + 0.154*D + 0.193*H$ (kg/tree)	BalbhimChavan *et al*. 2012) [20]
5	Mango (D = 25 - 65 cm)	*Magnifera indica*	$-26.6 + 0.614*D + 1.39*H$ (kg/tree)	BalbhimChavan *et al*. 2012) [20]
6	Mango (D ≥ 65 cm)	*Magnifera indica*	$-115 + 1.59*D + 3.38*H$ (kg/tree)	BalbhimChavan *et al*. 2012) [20]
7	Lemon	Citrus	$-6.64 + 0.279*BA + 0.000514*BA^2$ (kg/tree)	Jackson Mwamba Bwalya 2012 [21]
8	Santol	*Sandoricum koetjape*	$\rho*\text{Exp}(1.239 + 1.980*\text{In}(DBH) + 0.207*\text{In}(DBH)^2 - 0.0281*\text{In}(DBH)^3)$ (kg/tree)	J. Chave *et al*. 2005 [22]

$$\text{AGB} = -238.341 + 353.062 \times \text{SAVI} + 19.491 \times \text{RVI} \; \left(R^2 = 0.813\right) \tag{1}$$

4.3. Biomass from SAR Data

The application of Synthetic radar aperture data is a Promising Technique in Remote Sensing which uses high frequency wavelengths to estimate above ground biomass. Initially SAR data has to be process by both terrain

Table 2. Field calculated biomass from allometric equations.

S. No.	Plantation scientific name	No of trees	Mean DBH (cm)	Mean height (m)	Mean biomass (kg/tree)	Biomass (t/ha)
1	Lemon Citrus	24	10.466	2.445	22.512	6.003
2	Rose Apple Syzygiumjambos	25	40	4.117	28.11	5.03
3	Mango Magnifera Indica	24	99.401	6.191	112.327	29.954
4	Oil Palm Elaeis Guineensis	20	231.6	8.537	605.843	134.631
5	Coconut Cocos Nucifera	40	91.3	18.577	147.542	65.574
6	Coconut Cocos Nucifera	36	91.44	9.744	79.534	31.813
7	Banana, ca, Mango Musa Magnifera Indi Acuminata Mango	63	51.44	4.657	112.048	78.433
8	Mixed (Oil Elaeis Guineensis, Palm, Mango Magnifera Indica, Santol) Sandoricum Koetjape	19	198.342	6.27	267.13	107.93
9	Oil Palm Elaeis Guineensis	19	249.97	8.57	608.57	128.47
10	Mixed Musa acuminate, (Lemon, Sandoricum, Koetjap	24	45.97	5.46	281.70	75.14
	Santol, Koetjape, Citrus Banana)					
11	Mixed Cocos Nucifera, (Mango, Magnifera Indica Coconut)	21	81.818	10.83	84.10	20.55
12	Oil Palm Elaeis Guineensis	16	274.518	5.77	407.54	72.45
13	Oil Palm Elaeis Guineensis	16	364.36	5.63	397.34	70.63
14	Oil Palm Elaeis Guineensis	16	289	10.05	714.90	127.09
15	Oil Palm Elaeis Guineensis	17	261.176	13.08	932.01	176.04
16	Mixed Musa Acuminata, (Banana, Cocos Nucifera Coconut)	65	47.99	4.81	104.50	75.47
17	Oil Palm Elaeis Guineensis	25	255.6	11.105	790.21	219.50
18	Oil Palm Elaeis Guineensis	25	211.4	3.32	231.49	64.30
19	Oil Palm Elaeis Guineensis	16	245.75	8.16	579.35	102.99
20	Oil Palm Elaeis Guineensis	17	282.78	7.29	516.74	97.60

correction and radiometric calibration for calculating backscattering values. Radiometric calibration converts SAR data from DN (digital number) to backscattering coefficients (σ°) calculated in [dB] decibel values was mainly used for biomass model generation from SAR data. The SAR backscattering value calculated for both HH and HV polarization bands of ALOS-2 to generate new biomass model by comparing with biomass calculated from field data. To reduce noise reduction in SAR image mean adaptive filtering of kernel size 5 × 5 applied to increase the accuracy in biomass estimation. In order to compare the SAR backscattering values with field-calculated biomass the pixel size of ALOS-2 increased from 6.25 m to 30 m because sample plot size in study area is 30 m. Linear regression analysis is utilized to find new biomass model from HH and HV backscattering coefficients of ALOS-2 SAR data which shows good relation with the field calculated biomass. HH backscattering coefficient was not considered in biomass model because it shows less relation ($R^2 = 0.405$) with field calculated biomass compared to HV backscattering coefficients ($R^2 = 0.775$). Finally accurate biomass map is produced with HV backscattering as best fit model (Figure 5).

$$\mathrm{AGB} = 679.326 + 35.307 \times \sigma^{\circ}\,[\mathrm{dB}]\,\mathrm{HH}\left(\mathrm{R}^2 = 0.775\right) \tag{2}$$

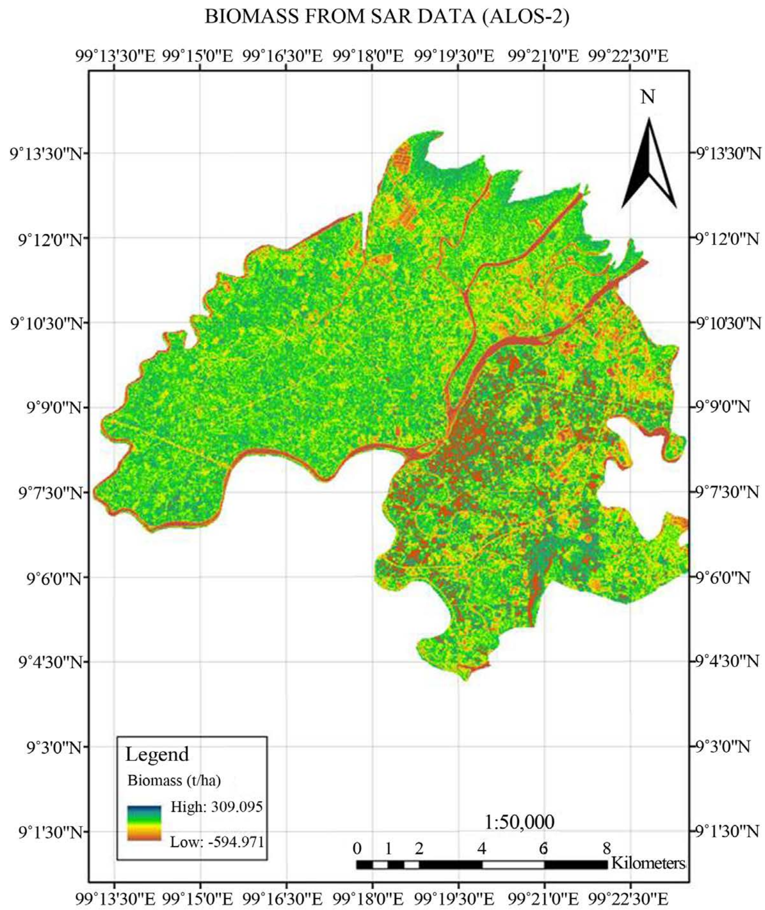

Figure 5. Biomass map from SAR (ALOS-2) data.

4.4. Biomass from Combined Optical and SAR Data

Combination of both optical and SAR remote sensing data leads to new techniques in biomass estimation. Both optical (LANDSAT 8) and SAR (ALOS-2) remote sensing data applied to develop new biomass model by finding relation with field-calculated biomass. Multi linear regression is used to develop high accuracy biomass model (R^2 = 0.87) by comparing both spectral indices (SAVI, RVI) of LANDSAT 8 and HV backscattering values of ALOS-2 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 (**Figure 6**).

$$\text{AGB} = 101.819 + 17.866 \times \sigma^\circ [\text{dB}]\text{HV} + 442.344 \times \text{SAVI} + 9.113 \times \text{RVI}\left(R^2 = 0.870\right) \quad (3)$$

5. Results

Accuracy assessment for all biomass models has to be checked with total 20 field sample plots. Linear regression analysis is applied for accuracy validation of each biomass map by checking the biomass value of 20 field sample plots with the biomass value obtained from satellite imagery. From the results it shows that biomass map generated from spectral indices of Optical sensor data 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 biomass 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 biomass models of optical and SAR data (**Table 3**).

6. Conclusion

In this study the application of remote sensing in biomass assessment is introduced. Both optical (LANDSAT-8)

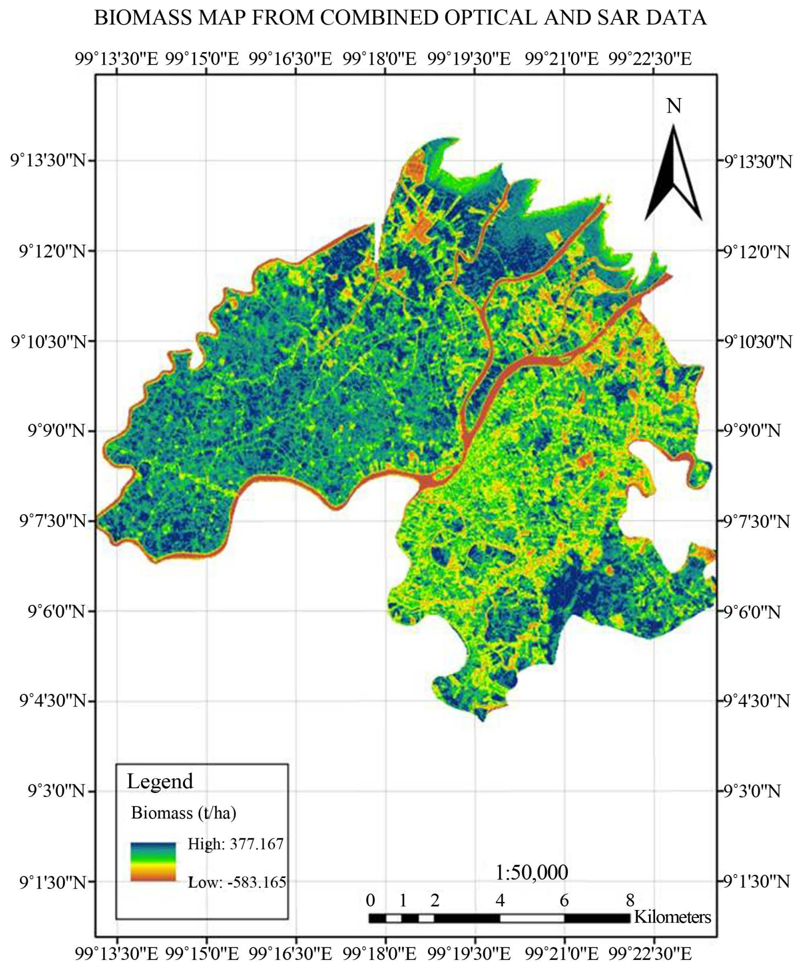

Figure 6. Biomass map from combined SAR and optical data.

Table 3. Accuracy results of biomass models.

S.NO	Data	R^2	RMSE
1	Optical (LANDASAT-8)	0.788	26.054 (t/ha)
2	SAR (ALOS-2)	0.742	28.736 (t/ha)
3	Combined (Optical & SAR)	0.859	21.207 (t/ha)

and synthetic aperture radar (ALOS-2) remote sensing data are used for above ground biomass (AGB) assessment. The overall accuracy of classified map from optical data (LANDSAT-8) indicates that different land features on map show an accuracy of 91.13% with the original land features on the ground. Biomass map developed from spectral indices of both SAVI and RVI shows good accuracy (R^2 = 0.81) compared to SAVI and EVI (R^2 = 0.75) 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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