USE OF OPTICAL, THERMAL IR AND RADAR SATELLITE DATA TO ESTIMATE ABOVE GROUND BIOMASS IN MONTANE FORESTS OF SRI LANKA

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ABSTRACT: Above Ground Biomass (AGB) has received a greater attention as one of the immediate reduction of atmospheric carbon dioxide by carbon sequestration. As a tropical country, Sri Lanka consisted with different forest types having very high biomass and productivity. Variety of approaches have been developed to derive aboveground biomass by many scientists, however, methods differ in procedure, complexity and time requirement depending on the specific aim of these estimations. Currently, Remote Sensing (RS) is popular approach as a nondestructive method of biomass estimation since it can reduce the measurements and monitoring in the field to a considerable extent, minimizing the cost.

This study focused to estimate above ground biomass of Montane Forests located in Horton Plains National Park and surrounding areas of Sri Lanka. Initially, field based biomass estimation was done by data collecting in 55 field sampling plots (size 30x30m). The forest stand parameters; diameter at breast height (dbh), total tree height, and canopy cover percentage, slope of land and GPS locations of each sampling plots were collected.

Six allometric equations were used to estimate AGB using correlation with dbh and height data of the field sampled plots and observed the best fit models for the local conditions. The observed biomass data were correlated with Back Scatter Coefficient values (HH and HV) of ALOS PALSAR image; Vegetation Indices (VI) derived from Landsat 8 OLI image (Normalized Difference VI, Soil Adjusted VI, Advanced VI and Ratio VI) and land surface temperature generated form Landsat Thermal Infra-Red Sensor (TIRS) image. The relationship between satellite data and field estimated biomass was done by observing the Pearson's correlations through statistical analysis.

The results observed, a positive linear correlation between field's estimated AGB and NDVI was relatively high compared to other VI's. There is a negative linear correlation observed in Back Scatter Coefficient with the AGB. The land surface temperature from the TIRS observed the strong correlation with forest canopy cover percentage rather than AGB of the forest. Accordingly, the average montane forest biomass content derived as follows; from NDVI (42 t/ha), backscatter HH (38 t/ha) and HV (32 t/ha) and TIRS (48 t/ha).

The accuracy of the AGB estimation from remote sensing methods varies from 61 - 72 percent and this applications can be used for other forest types also to estimate AGB as a less time consuming, economical and non-destructive method.

INTRODUCTION

Biomass estimates provide a means of calculating the amount of carbon dioxide that could be removed/fixed from the atmosphere by re-growing vegetation. Many efforts have been made to evaluation vegetation biomass and use of existing forest inventory can be identified as a key method. Researchers have developed various methods for the quantification of sequestered carbon (Brown *et al,* 1989).

Inventory of forest parameters based on fieldworks is often difficult, costly and time consuming to conduct in large areas and complexity of forest structure and inaccessible nature of many tropical forest limits the feasibility of ground based inventory. Remote sensing is one of the practicable ways to acquire forest stand parameter information at a reasonable cost with an acceptable accuracy. Advanced new remote sensing techniques such as multi-sensor data fusion, increased spatial and spectral resolution and integration possibility with Geographical Information Systems (GIS) have made the remotely sensed data a primary source for many forestry applications.

Observation and measurements by satellite based remote sensing have currently become one of the key sources of information in estimating AGB in tropical forest (Lu, 2006). A number of studies have evaluated remote sensing techniques for mapping of forests and forest stand parameters, including height, age, density, biomass and leaf area index, using optical remote sensing (Boyd *et al*., 1999; Foody *et al*., 2001, 2003; Lu, 2005; Steininger, 2000; Thenkabail *et al*., 2004). Vegetation indices are the most widely used approach (Foody *et al*., 2003). Most indices depend on the relationship between red and near-infrared wavelengths to enhance the spectral contribution from green vegetation while minimizing contributions from the soil background, sun angle, sensor view angle, vegetation and the atmosphere (Huete *et al*., 1985; Tucker, 1979). However, vegetation indices have achieved only moderate success in tropical and subtropical regions where biomass levels are high, the forest canopy is closed, with multiple layering, and greater species diversity (Foody *et al*., 2001; Lu, 2005; Nelson *et al*., 2000).

Difficulties to acquire cloud free images in tropical region is one of the key challenges in optical remote sensing data under Sri Lankan condition.
Space borne synthetic aperture radar (SAR) sensors such as the L-band ALOS PALSAR, the C-band ERS/SAR, RADARSAT/SAR or ENVISAT/ ASAR and the X-band Terra SAR-X instrument are active systems, transmitting microwave energy at wavelengths from 3.0 (X-band) to 23.6 cm (L-band). The major advantage of SAR systems is their weather and daylight independency. In addition, the ability to penetrate into the volume of the object (canopies) which depend on the wavelength is another important character. The degree of penetration depends on the wavelength so the sensors ability to estimate biomass. The ability to measure biomass is additionally affected by the polarization and the incidence angle of the sensor, and land cover and terrain properties (Lu, 2005).

Objectives

This study attempts to estimate the above ground biomass in Montane forest of Sri Lanka using vegetation index from IRS LISS III (2008) optical and Infra-red data; thermal infrared band of Landsat OLI (2013) and backscatter coefficient of ALOS PASLAR (HH, HV) (2010) imageries.

METHODOLOGY

Study area and sampling sites: Montane forest located in Horton Plains National Park (HPNP) and surrounding area in the Nuwara Eliya District of the Central Province of Sri Lanka selected for the study (Figure 1) and the total area accounting to 3162 ha. The tree canopy is dominated by species such as *Calophyllum walkeri, Michelia nilagirica, Syzygium rotundifolium, S. revolutum, Elaeocarpus montanus, E. glandulifer, E. coriaceous, Ilex walkeri, Cinnamomum ovalifolium, Litsea ovalifolia* and *Photinia integrifolia.* The forest understory is somewhat darker but easy to access due to the low density of seedlings, saplings and herbaceous plants. Many bryophytes, epiphytes (orchids, lichens, bryophytes and ferns) and filmy ferns grow on the stems and branches of trees (DWC, 2007).

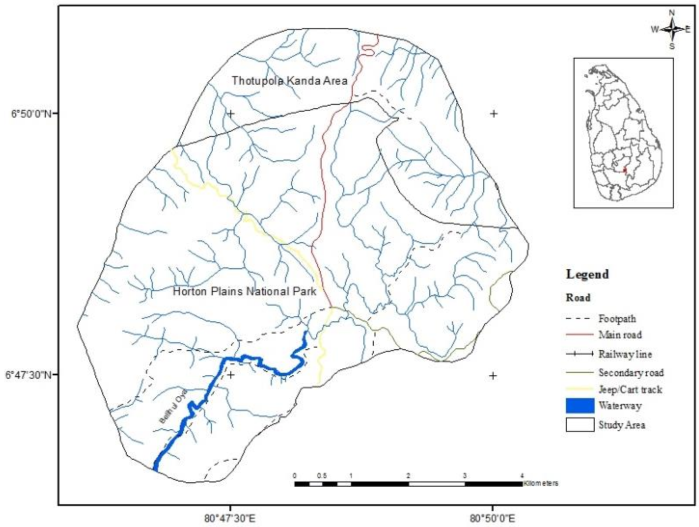

Figure 1. Location map of the study area

Data, materials and other information: The primary data used in the study was Landsat 8 TIRS (30th August 2013), IRS LISS III (2008) and ALOS PALSR (HH, HV) dual polarization image (21st June 2010), and Google Earth software was used for visual interpretation. Demarcation and identification of sampling sites were carried out using 1:10,000 topographic maps of Sri Lanka Survey Department and differential GPS receiver was used to identify the geographical locations.

Optical Image Classification

Remote sensing image classification can be viewed as a joint venture of both image processing and classification techniques. Generally, image classification, in the field of remote sensing is the process of assigning pixels or the basic units of an image to classes (Lu, 2006). Supervised and unsupervised classification were used to extracting ground cover information from satellite images in study area.

Development of Vegetation Indices with Optical and Near Infrared Imageries

Vegetation Indices (VIs) are combinations of surface reflectance at two or more wavelengths designed to highlight a particular property of vegetation. They are derived using the reflectance properties of vegetation. Each of the VIs is designed to accentuate a particular vegetation property. Normalize Difference Vegetation Index (NDVI), Ratio Vegetation Indices, Transformed VI, and Soil Adjusted vegetation index are widely used for estimation of biophysical parameters of the natural vegetation (Densheng *et al*, 2004). Among that, NDVI is the widely used vegetation index than other VI's for estimation of biomass and this study also used NDVI calculated IRS LISS III imagery.

Normalize Difference Vegetation Index (NDVI): This is the most widely used index for biomass calculation of vegetation, measure leaf area index, and has extensively used to monitor vegetation vigor (Panda, 2005). NDVI formula is the combination of red and near infrared spectra reflectance from the vegetation canopy which shown in Equation 1

$$NDVI = (NIR - Red) / (NIR + Red) \quad \text{(Equation 1)}$$

Developing Land Surface Temperature using Thermal Infrared band of Landsat 8 OLI

Land surface temperature (LST) is related to surface energy and water balance, at local through global scales, with principal significance for a wide variety of applications, such as climate change, urban climate, the hydrological cycle, and vegetation monitoring (Wan *et al*, 2004). Landsat-8 was launched on 11 February 2013 and deployed into orbit with two instruments on-board: (1) the Operational Land Imager (OLI) with nine spectral bands in the visual (VIS), near infrared (NIR), and the shortwave infrared (SWIR) spectral regions; and (2) the Thermal Infrared Sensor (TIRS) with two spectral bands in the LWIR. The spatial resolution of TIRS data is 100 m (resampled in to 30m originally) with a revisit time of 16 days (Rozenstein *et al*, 2014). In this study, TIRS bands were used to develop the land surface temperature map to find the relationship with AGB and surface temperature (Rozenstein *et al.*, 2014). This might be the first study on estimation of AGB in the Sri Lanka using TIRS form Landsat 8.

Calculation of backscattering coefficient using ALOS PALSAR image

Cloud-free synthetic aperture radar (SAR) has the potential to be an important data source for tropical forest mapping and there is no comprehensive study that uses PALSAR data to generate a biomass in Sri Lanka for any vegetation type yet. Previous studies showed that a longer radar wavelength (e.g. L-band SAR) is more suitable to the delineation of forest than shorter wavelengths because of its greater penetration through the tree canopy (Baghdadi *et al*., 2009). The Phased Array Type L-band Synthetic Aperture Radar (PALSAR) onboard the Advanced Land Observing Satellite (ALOS) was launched by the Japan Aerospace Exploration Agency (JAXA) in January of 2006 and provided polarimetric radar images for the global land surface that have been used for forest mapping (Almeida *et al*.,2009) ALOS –PALSAR images with HH polarization and HV polarization was used to calculate the backscattering coefficient. The DN (Digital Number) of the HH and HV polarized images were converted into backscattering coefficient values using the Equation 2 (Shimada *et al.*, 2009).

$$\sigma^\circ = 10*\log10\,(DN^2)-83. \quad \text{(Equation 2)}$$

σ^o= Backscattering Coefficient

Field data collection

Ground survey was done to collect information on forest stand parameters from 55 selected locations (plot size 30x30 m) in montane forest region of Sri Lanka. Area of canopy cover, ground vegetation cover, Diameter of Breast Height (DBH), total tree height and ground opening areas were measured. Field data collection was done during 2011-2013.

Estimation of biomass through field sampling

Many regression models available for estimation of AGB developed by many scientists considering dbh, wood density and tree height (Zanne *et al.,* 2009), Chave *et al.* (2005), Bao HUY *et al.* (2012) and Brown and Lugo (1982). The evaluation of above-ground carbon of woody plants was concentrated only to tree species which are having DBH of ≥10 cm, excluding lianas, and non-woody monocots. The following allometric regression model (Brown, 1989) was applied for individual plants to convert the inventory data into the above ground biomass for 27 tree dominated plots. The allometric regression models were selected based on published literature which revealed that it is more suitable to be used for tropical forests and biogeographic zone of the present investigation.

$$AGB = 13.2579-4.8945(DBH) +0.6713(DBH)^{2}- \quad \text{(Equation 3)}$$

AGB = above-ground tree biomass (t)   DBH = tree diameter at breast height

The selected allometric model is only applicable to estimate AGB in tree dominated plots in natural forests. Therefore, low dense vegetation (scrubland and grasslands having <10 cm DBH) areas AGB were estimated through the previously derived direct application remote sensing indices as

Grassland	y = -61+16300 (NDVI)	(Equation 4)
	Y= above ground live biomass (kg)	
Scrublands	y = 9.17 + 3.00 Ln (NDVI)	(Equation 5)
	Y= above ground live biomass (t)	(Foster et *al*, 2012, Aranha *et al.*, 2008)

Correlations of estimated biomass with NDVI, Land Surface Temperature (LST) and backscattering coefficient derived from satellite data

The dense and moderately dense vegetation areas identified through image classification were subjected to estimation of biomass using standard allometric equations. It was attempted to correlate these estimated biomass with the NDVI derived using IRS LISS III, land surface temperature derived with Landsat 8 OLI, and backscattering coefficient (HH, HV Polarization) derived from ALOS PALSAR data. The Pearson's correlation coefficient was calculated (Table 1).

RESULTS AND DISCUSSION

Development of land cover map of study area: The land over map of the study area was derived using supervised classification of IRS LISS III (2008) satellite image with the support of field samplings. Accordingly, four levels of vegetation types were identified as dense forest (850 ha), moderately dense vegetation (1,957 ha), low dense vegetation (554 ha) and grasslands (655 ha) (Figure 2). The overall accuracy of land cover map reach 78% and the highest accuracy was achieved in dense forest and grasslands.

Biomass estimation through field sampling: The highest estimated plot AGB was observed as 81.68 t/ha in while lowest was observed in (4.599 t/ ha) and mean AGB was calculated as 50.17 t/ha. The AGB estimations made by Eskil *et al*. (2012) by forest inventory data observed as 43 – 50 t/ha and similar study conducted by Forest Carbon Asia Country Profile estimation was 14.2 t/ha.

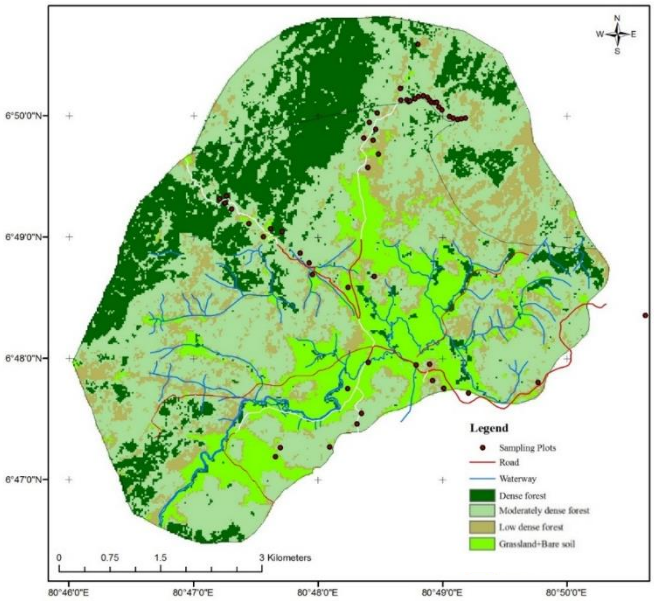

Figure 2. Land cover map developed using unsupervised classification of IRS LISS III image

Relationship between estimated biomass with NDVI from IRS LISS III image

The relationship between NDVI with estimated AGB is observed as following equation No 3.

$$AGB = 10{,}077 * NDVI - 2{,}936.8 \qquad \text{(Equation 3)}$$

AGB maps were prepared for the tree dominated dense and moderately dense vegetation using this model. However, derived equation cannot be applied for the grassland and scrub dominated vegetation due to extreme over estimation of AGB because of represent higher NDVI values.

Table. 1. Correlations between estimated biomass with vegetation indices, Land surface temperature and backscattering coefficient derived from satellite data

	NDVI	HH	HV	LS T
Pearson's Correlation	.712	.587	.441	-.594
Sig. (2-tailed)	.000	.001	.021	.001
N (No of plots)	27	27	27	27

Accordingly, the AGB in tree dominated areas were calculated as 41.76 t/ha which show 17% underestimation with field estimated biomass. Figure 3 (a) presents the AGB distribution in dense and moderately dense vegetation areas. Some satellite driven models were developed by many scientists to estimate above ground biomass for different vegetation types. Roy and Ravan (1996) used Landsat TM derived NDVI and Middle Infrared Ratio (MIR) to predict biomass content of natural forests in India and obtained 90% accuracy. Lue *et al.* (2003) found the relationship between multi-angular satellite remote sensing (AVHRR and MODIS) and forest inventory data for carbon stock and sink capacity estimation.

For scrublands which were having DBH less than 10 cm and for the grasslands, AGB was estimated separately using direct use of NDVI without correlation of field sampling data (Foster et *al.*, 2012 and Aranha *et al.*, 2008). Though the accuracy of this method is much lower than the field sampling technique, this method can consider as quick and low cost way of estimating AGB. Distribution of Grassland and Scrubland AGB in study area mapped in Figure. 3 (b and c).

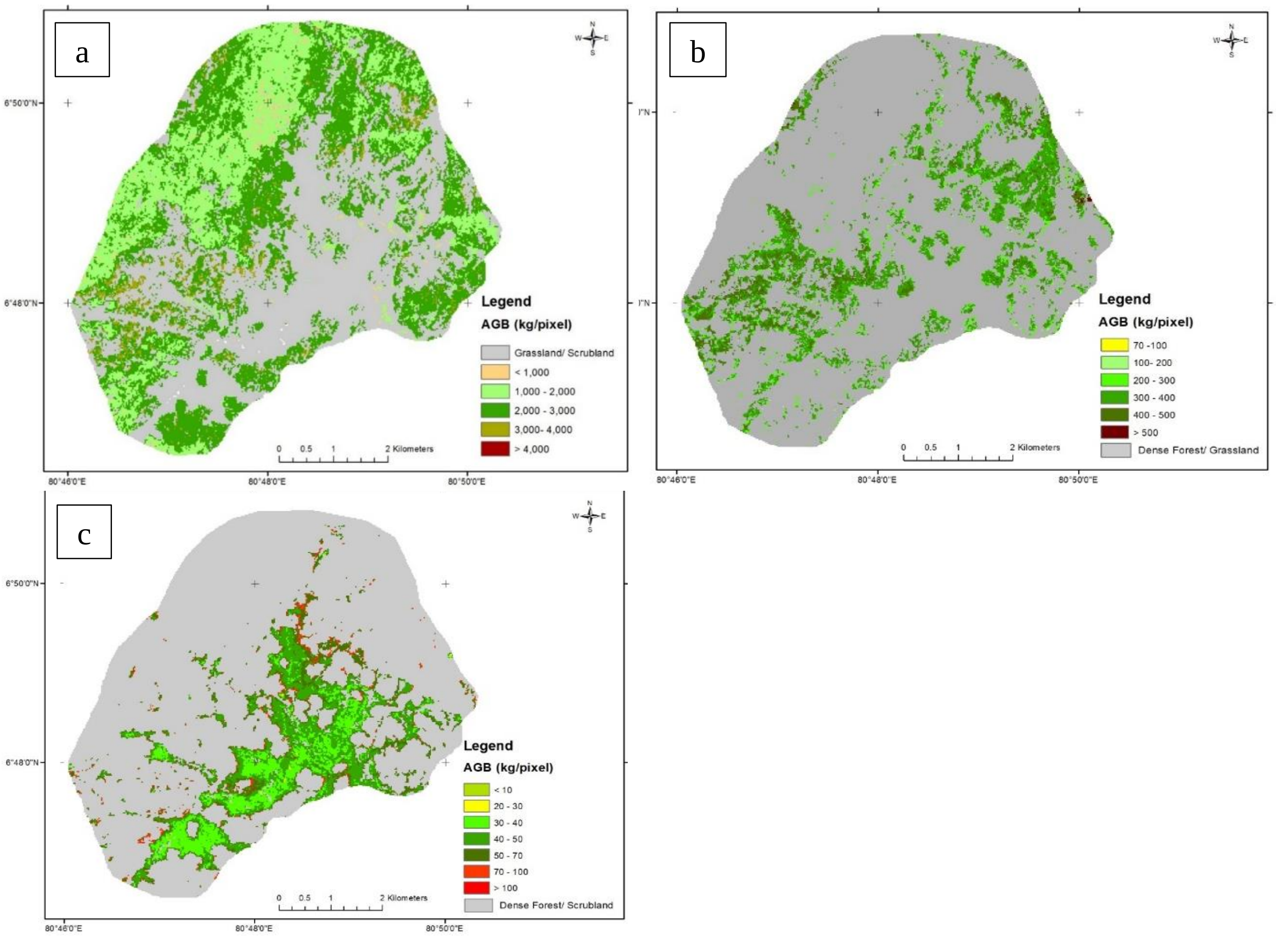

Figure 3. (a) Distribution of AGB with in dense and moderately dense vegetation derived from NDVI of IRS LISS III data and distribution of AGB within grassland (b) scrubland (c) dominated vegetation

Relationship between estimated biomass with backscattering coefficient of ALOS PALSAR image

Backscattering coefficient derived from ALOS PALSAR data are correlated with estimated AGB in tree dominated plots. A weak negative correlation was observed between the two variables. According to the derived equations, the average AGB (dense and moderately dense vegetation) calculated as form HH (38.9 t/ha) and HV (32.5t/ha).

Relationship between estimated biomass with land surface temperature derived from Landsat 8 TIRs band

The derived land surface temperature values were correlated with the estimated biomass and vegetation types to investigate any possible relationship. Accordingly, a poor negative correlation was observed between the two variables with a R^2 value of 0.35. The AGB calculation was carried out with the derived relationship (AGB = -634.58 LST +14,502). According to the relationship it is evident that the when the biomass content is high, them the surface temperature of the vegetation areas are low indicating good canopy cover.

Accuracy Assessment

Accuracy assessment was done by obtaining field biomass estimations from another 8 post random sampling plots representing dense and moderately dense vegetation. The overall accuracy of AGB estimation using NDVI was identified as 72.3 %. With backscattering coefficient of HH polarization, the accuracy was identified as 71% and with HV polarization it was 68%.

CONCLUSIONS

Three remote sensing based parameters were used to explore a correlation between above ground biomass estimated in dense and moderately dense vegetation's using field sampling techniques (51.7 t/ha). The study identified that NDVI is the most suitable vegetation index to estimate AGB in dense and moderate dense vegetation areas. The amount of dense and moderately dense vegetation biomass estimated for the HPNP using NDVI (41.76 t/ha), TIRS (62.72 t/ha), form HH (38.9 t/ha) and HV (32.5t/ha). According to the derived equations form ALOS PALSAR imagery, the average AGB (dense and moderately dense vegetation) calculated as form HH (38.9 t/ha) and HV (32.5t/ha).

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