Improvement in Estimation of Above Ground Biomass of *Albizia lebbeck* using Fraction Reflectance of Landsat TM Data

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Abstract

The study emphasizes on the ability of spectral mixture analysis (SMA) to improve the estimate of above ground biomass from spectral reflectance of satellite data. Digital number (DN) values of satellite data were converted to surface reflectance and fraction reflectance data. Linear regression analysis was performed between above ground biomass data with both total surface reflectance and SMA produced fraction reflectance values separately. The analysis revealed that the best positive correlation was observed between AGB and the fraction reflectance values of FR_TM 5/3 with R^2 = 0.865 whereas with the total reflectance data, atmospherically resistant vegetation index (ARVI) and TM5/3 resulted moderate correlation R^2= 0.452 and -0.248, respectively. Pixel level AGB ranges between 0.001t to 13.53t. The total AGB of the study area (275.85 ha) was estimated to be 14249t. Thus separation of endmembers from the mixed pixel from a course to medium resolution satellite data can play an important role in improving AGB estimation performance, especially for those sites with multiple cover features. The study demonstrates the potentiality of Landsat TM data in concatenate with SMA in improving the estimation of AGB which can be further improved by identifying all possible endmembers and highly configured methodology.

Key words: Above ground biomass (AGB), spectral unmixing, endmember, Landsat TM, Fraction reflectance value.

1. Introduction

Remotely sensed data have become the most important source for AGB estimation in recent time (Nelson *et al*., 1988; Leblon *et al*., 1993; Steininger, 2000; Lu, 2005; Wulder *et al*., 2008; Guo *et al*., 2010). The conventional method of biomass assessment is undoubtedly more reliable; however, it depends heavily on field measurements. As such this approach is time consuming, labour intensive, and difficult to implement in remote and inaccessible areas (De Gier, 2003; Lu *et al*., 2004). Remote sensing based estimates of AGB can be categorized by data source as: (i) field measurement; (ii) remotely sensed data; or (iii) ancillary data used in GIS-based modeling (Lu, 2006). Lu (2006) reviewed the methods whereby AGB can be directly estimated using remotely sensed data with different approaches, such as linear or non-linear regression analysis, K nearest-neighbor, and neural network and indirectly estimated from canopy parameters, such as crown diameter, which are first derived from remotely sensed data using multiple regression analysis or different canopy reflectance models.

A variety of remotely sensed data continue to be employed for biomass mapping such as high resolution data like QUICKBIRD (Leboeuf *et al*., 2007), IKONOS (Proisy *et al*., 2007), moderate resolution as Landsat (Sader *et al*., 1989; Roy and Ravan, 1996; Zheng *et al*., 2004; Lu, 2005; Wulder *et al*., 2008; Lu *et al*., 2012), ASTER (Muukkonen and Heiskanen, 2007) and course resolution as MODIS (Baccini *et al*., 2004; Zhang and Kondragunta, 2006; Muukkonen and Heiskanen, 2007), SPOT-VEGETATION and AVHRR (Fraser and Li, 2002; Nichol and Sarker, 2011), LIDAR (Rauste, 2005; Nelson *et al*., 2007). Among all, Landsat TM and ETM+ data are the most widely used remotely sensed data for forest biomass estimation (Roy and Ravan, 1996; Wulder *et al*., 2008; Pandey *et al*., 2010). Although research on AGB estimation using remotely sensed data has been commonly explored in the last decades, a number of earlier studies have demonstrated that biomass estimation still remains a challenging task, especially in those study areas with complex forest stand structures and environmental conditions (Lucas *et al*., 1998; Foody *et al*., 2001; Proisy *et al*., 2012). In all situations mixed pixels and data saturation are often found to be a problem in AGB estimation in those sites with complex biophysical environments (Fisher, 1997; Steininger, 2000). Data saturation problem can be minimized using narrow-wavelength images. In such cases hyper-spectral image may improve AGB estimation performance because of its large number of spectral bands with very narrow wavelengths (Mutanga and Skidmore, 2004). The other problem in AGB estimation is the "mixed pixels", i.e., containing different cover features such as different tree species and vegetation ages, soil, water in a single pixel which is often the characteristic of medium to coarse resolution sensors such as Landsat, ASTER (Fisher, 1997).

Mixed pixel problem can be minimized using data fusion technology through the use of higher spatial-resolution data, such as the SPOT panchromatic band. An alternative is to apply the spectral mixture analysis (SMA) approach to unmix the multispectral image into fraction images (Lu, 2006). Peddle *et al*. (1999) also stated that SMA could be used to potentially increase the improvement in AGB estimation.

SMA is a technique used to measure the percentage of spectra for each land-cover type in a single pixel. SMA has been successfully used to classify successional forest types and forest types of varying carbon-sink strengths (Settle and Drake, 1993). Various methods of SMA have been developed to improve the classification of mixed pixels and to detect and identify subpixel components and their proportions. Most of the techniques have employed a linear mixing approach (Huguenin *et al*., 1997). SMA approach and its applications have been discussed by several workers (Smith *et al*., 1990; Settle and Drake 1993; Lu *et al*., 2003; Pu *et al*., 2003, 2008; Palaniswami *et al*., 2006; Obata and Yoshioka, 2010; Obata *et al*., 2012).

The objective of present study was to test the stability of spectral mixture modeling method in improving the estimation of sub-pixel biomass of *Albizia lebbeck* in the study area. This study further aims to see the correlation between the ground biomass data with mixed pixel reflectance data and also with SMA produced fraction percentage reflectance data and validation of hypothesis that SMA results better biomass estimation.

2. Materials and Methods

The study was conducted in Silonibari Tea Estate (275.85 ha) of Lakhimpur district of Assam. The area has been selected because the whole tea garden was planted with *Albizia lebbeck*, which acts as the shadow plant for the growth of the tea plant. The area experiences a subtropical and humid climate characterized by high rainfall. The average annual rainfall is around 2830 mm as against 2300 mm of the state. Forests of the district are mainly tropical semi-evergreen forest and the soil of the district is alluvial type. LANDSAT TM data of 29th November 2009 covering the Silonibari Tea Estate was downloaded from Global Visualization Viewer (GLOVIS), (www.glovis.usgs.gov). The data comprised of all the 7 bands and were used in this study except band 6. Secondary data such as climatic data, soil data, information about the Tea Estate, and its area were also collected and used.

Geometric rectification and atmospheric calibration are two important aspects in any remote sensing analysis. TM image was geometrically rectified into a Universal Transverse Mercator (UTM) projection using ground control points taken from field data and SOI topographic maps of 1:50000 scale. A nearest neighbor re-sampling technique was used with rms. error of 0.02 pixels was obtained for the TM image during the image rectification. In radiometric correction the DN of the data was first converted to Top of Atmospheric Radiance (TOA) after that the TOA was converted to Surface Reflectance following Chavez (1996). Proper subset of the study area was then prepared to reduce the extra data and also the computation time.

Before modeling the linear mixture for unmixing, endmembers for the given study area has to be extracted. Pure features in a mixed pixel are referred to as endmembers. The selection of appropriate endmembers to input into a linear spectral model is important. Spectral profile of any object can be achieved in two ways (Van der Meer, 1999): (i) From a spectral (field or laboratory) library; and (ii) From the purest pixels in the image. In our study we used the second method i.e. extracting the pure pixel from the image itself together with known GPS locations. In this analysis pure pixel has been selected for four endmembers (*Albizia lebbeck*, tea, soil and grass). SMA was done using the reflectance value. SMA generates mixture maps constraining the individual material fractions in percentage on to the range of 0.0 to 1.0 (i.e. 0 means absent and 1.0 means 100 percentage). SMA is an iterative process, based on the model and r.m.s error images, four endmember images have been developed (Fig. 1).

Since the endmember image represents the percentage coverage of each feature within a pixel, this percentage value for each feature has been further used to extract the total reflectance value shared by each feature within a pixel, using equation 1.

$$FR = \text{percentage fraction of the endmember}/100 * \text{total reflectance} \quad (1)$$

Where: FR = fraction reflectance value of any feature in a pixel.

Calculation of vegetation indices and band ratios was done using different bands of Landsat data. The following vegetation indices and band ratio have been calculated in order to find out the correlation between the ground biomass with total reflectance value and fraction reflectance value (Table 1). Indices and ratio has been calculated using bands having total reflectance value and also using the bands having fraction reflectance value (for *Albizia lebbeck*). The study area was converted into grids of size 30m x 30m pixel. The grids were carefully created and finally the centroid points of the grids were created for selecting the study site. Random selection of sampling was done in order to collect the ground biomass data. Sampling points were considered using the centroids points in each grid. Coordinate location of each of the centroids for the selected points were noted and GPS device was used to track the location in the field. Sampling was done at each of the given locations using the standard sampling methodology.

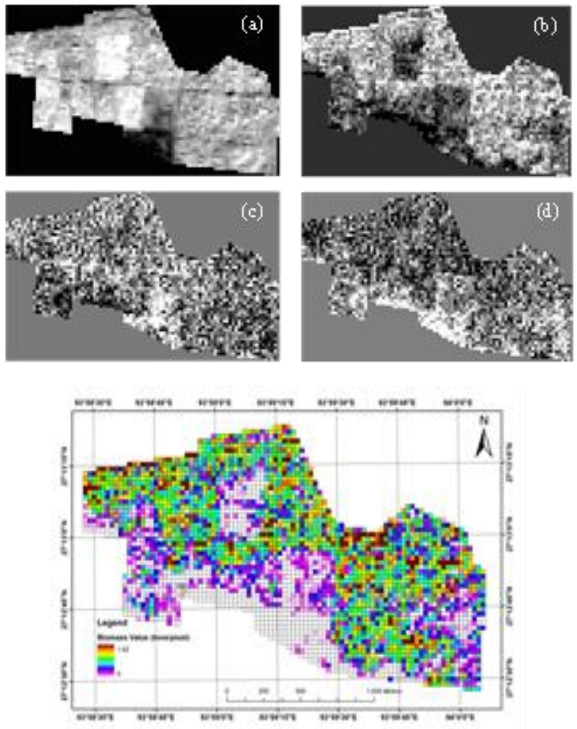

Fig. 1: Fraction images for (a) tea (b) *Albizia lebbeck* (c) soil (d) grass and (e) final biomass map

Table 1: Vegetation indices and band ratio used in the study

Vegetation index	Formulae	Reference
NDVI	(NIR-R)/(NIR+R)	Rouse *et al.*, 1974
RVI	NIR/R	Rouse et at., 1974
ARVI	(NIR-2RED+BLUE)/ (NIR+2RED-BLUE)	Kaufman and Tanre, 1992
MRVI	NIR/R+G+B+NIR	-
TM 5/7	BAND 5/7	-
TM 5/3	BAND 5/3	-
TM 4/2	BAND 4/2	-
TM 5/3	BAND 4/3	-

Field survey was conducted during the month of February and March 2011. A total of 8 sample points were selected based on the density of *Albizia lebbeck*. For data collection, 30x30 m quadrats were laid in accordance to the centroid points and the GBH (girth at breast height) and height of all the individual trees inside the quadrat was recorded. From the recorded GBH, DBH (diameter at breast height) was calculated. Finally, volume of *Albizia lebbeck* was calculated using volumetric equations (2) based on measured DBH (FSI 1996). If volume is negative, then Quarter Girth formula has been applied (eq. 3).

$$\sqrt{V} = -0.07109 + 2.99732\,D - 0.26953\,\sqrt{D} \quad (2)$$

Quarter Girth formula: $V = (G/4)^2 * H$ (3)

Where, V = Volume (m^3); D = Diameter at Breast Height (m); G = Girth at breast Height (m); H = Height (m)

The estimated volume of each individual tree using the volumetric equations was then converted into dry biomass by using specific gravity or wood density as the product of specific gravity and volume (Rajput *et al*., 1996).

Biomass (tonnes) = Volume (m^3) x Specific Gravity

Specific Gravity of *Albizia lebbeck* was considered as 0.534 (Rajput *et al*., 1985).

The AGB of the selected sample points on the field were statistically analysed with the selected indices to find the best linear relation. Linear regression analysis was performed between vegetation indices and band ratio for both total reflectance value and the fraction reflectance value with the ground data to monitor the maximum possible correlation. The most suitable and highly correlated equation was then opted to prepare the final biomass map.

3. Results and Discussion

AGB of the individual trees were calculated using the volumetric equation and quarter girth formula within a quadrat (pixel) and AGB of all the individuals present in a pixel were added for the total biomass within a pixel. The observed AGB of the sampled plot varied from 2.42t to 5.83t per pixel. The variation in the estimated AGB of each plot across the study area was mainly because of variation in tree density and basal area as was reported from other study area (Slik *et al*., 2010; Kumar *et al*., 2011).

The basic purpose of study is to find the correlation between observed AGB with the total reflectance value and also with the fraction reflectance value extracted from Landsat TM data. As such, linear regression analysis was done between all the calculated indices (ARVI, MRVI, NDVI, RVI, TM 4/2, TM 4/3, TM 5/3 and TM 5/7) and observed AGB for both total and fraction reflectance values. Scattered plot of vegetation indices versus total AGB of each sampling point were effectively plotted to measure the linear relation (Fig. 2). It shows linear relationship between total AGB and spectral responses of various indices. The linear regression relation between AGB and various indices are given in Table 2. From the above analysis it has been observed that poor correlation exists between the AGB and spectral responses of various indices of total reflectance. Roy and Ravan (1996) also reported a low correlation between the observed biomass and DN values.

Table 2: Linear regression relation between AGB and various indices

Indices	**Linear Regression Equation**	**R^2**	**SE**
ARVI	y = -11.483+17.193x	0.452^{ns}	0.364
MRVI	y = 3.615+1.705x	0.026^{ns}	0.408
NDVI	y = -1.597+9.193x	0.189^{ns}	0.401
RVI	y = 1.955+0.512x	0.185^{ns}	0.401
TM 4/2	y = 5.172-0.188x	-0.036^{ns}	0.408
TM 4/3	y = 1.955+0.512x	0.185^{ns}	0.401
TM 5/3	y = 9.616-2.124x	-0.248^{ns}	0.395
TM 5/7	y = 3.660+0.341x	0.069^{ns}	0.407
Indices	**Linear Regression Equation**	**R^2**	**SE**
FR_ARVI	y = 0.132+1906.288x	0.823*	0.172
FR_MRVI	y = 0.376+3119.784x	0.748*	0.205
FR_NDVI	y = 0.251+2592.577x	0.783*	0.190
FR_RVI	y = 0.395+332.121x	0.779*	0.192
FR_TM 4/2	y = 0.779+445.979x	0.683*	0.230
FR_TM 4/3	y = 0.395+332.121x	0.779*	0.192
FR_TM 5/3	y = -0.766+901.149x	0.865**	0.150
FR_TM 5/7	y = 1.575+463.211x	0.565*	0.269

The statistical analyses are significant at 95% confidence interval. **p < 0.001; *p < 0.05; and non-significant, ^{ns}p > 0.05

Correlations between the spectral indices and above-ground biomass were generally modest; as such log transform of the data can yield slightly better results (De Jong *et al*., 2005). However a good correlation was observed between the observed AGB with that of the fraction reflectance values derived by estimation of percentage contribution of each endmember within a pixel through spectral mixture analysis. FR_TM 5/3 shows the most significant correlation (R^2 = 0.865, p<0.001) followed by FR_ARVI (R^2 = 0.823, p <0.05) in case of the fraction reflectance values. FR_NDVI, FR_RVI and FR_TM4/3 also shows a signification relationship (about R^2 = 0.78, p<0.05). In case of the total reflectance values, it has been observed that vegetation index ARVI shows a fair correlation but not significant (R^2 = 0.452) whereas TM 5/3 show a negative correlation (R^2 = -0.248). Lu *et al*. (2005) stated that regression model using the fraction image can improve the biomass estimation performance compared to that of using TM spectral bands.

Spectral mixture analysis is applied to decompose the mixed spectral components of Landsat-7 ETM+ imagery into fractional images and it can improve the accuracy of biomass estimation (Basuki *et al*., 2012). Ji and Feng (2011) argued that AGB determination should be conducted at sub-pixel level using spectral mixture analysis, i.e., the recorded radiance of individual pixels must be decomposed so that the spectral portion of individual endmember can be detected and quantified. Hence, improvement in estimating ABG using fraction reflectance value developed using spectral unmixing of Landsat TM data is a very crucial process.

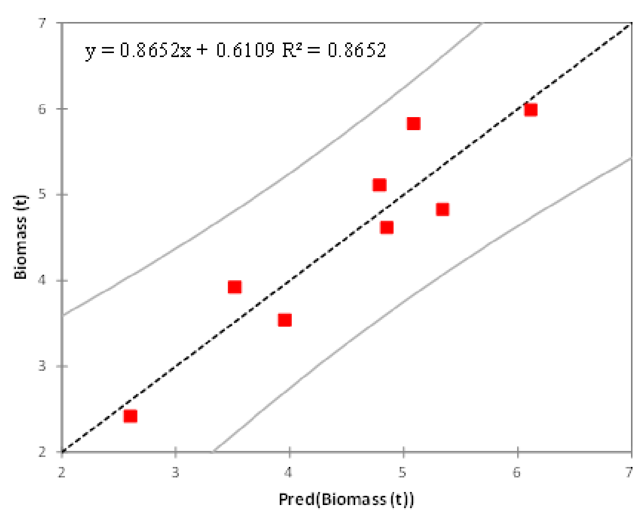

Fig. 2: Linear regression scatterplot between field biomass sampling data and corresponding vegetation indexes

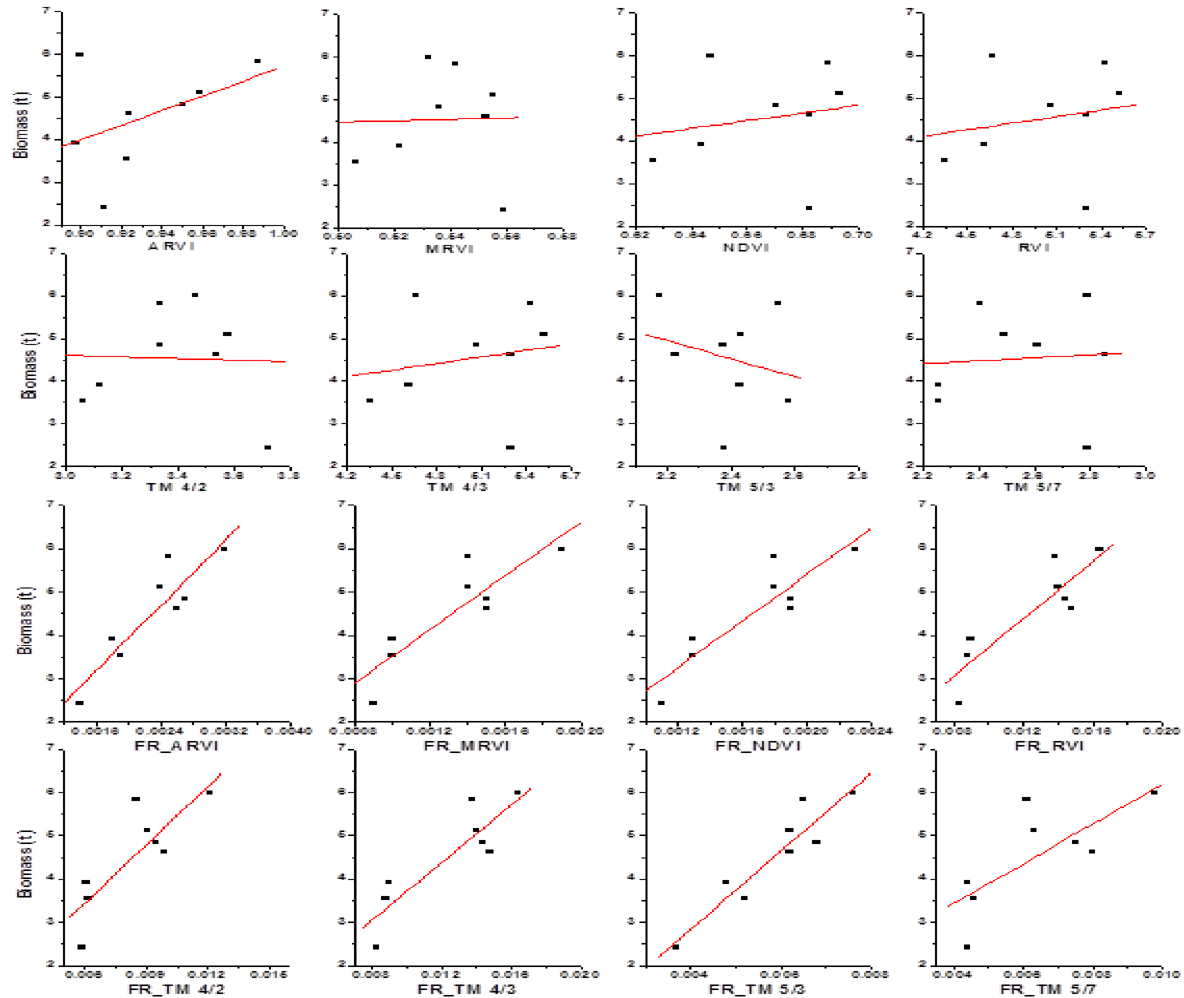

Fig. 3: Scatter plot of estimated AGB and predicted AGB

Results showed that the best positive correlation was found between AGB and fraction reflectance values of FR_TM 5/3. Hence, linear regression model established between the observed data and FR_5/3 data was used to estimate the ABG of *Albizia lebbeck* pixel by pixel. The AGB per single plot/pixel ranged between 0.001t to 13.53t. The total AGB of the study area was 14249t.

Further an assessment has been made to findout the relationship between the observed AGB and the predicted AGB obtained through linear regression model established between the sampling data and FR_5/3 data. Scatter plot was drawn between the observed and predicted AGB values (Fig. 3). The predicted AGB was found significantly related to that of the observed value ($R^2 = 0.86$, $p < 0.001$), explaining 86% variability at 95% confidence level. The difference in the observed AGB values and the predicted AGB could be attributed due to the difference in tree density within each plot and sensitivity of the remote sensing sensor and time of data acquisition (Zheng *et al*., 2008; Kumar *et al*., 2011).

4. Conclusions

The study demonstrates the improvement in estimating AGB using fraction reflectance value developed using spectral unmixing of Landsat TM data which is otherwise very often a complex process. Separation of endmembers from the mixed pixel plays an important role in improving AGB estimation performance, especially for those sites with multiple cover features. It was observed that the result of biomass estimation improved many-fold using the linear regression between the ground biomass and the endmembers percentage derived fraction reflectance value than with the total reflectance value of mixed pixel. Thus it can be concluded that extraction of all possible endmembers from the mixed pixel could further improve the result in biomass estimations, which can be achieved by using correct SMA of the studied area.

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