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Estimating growing stock volume in a Bangladesh forest site using Landsat TM and field-measured data

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ABSTRACT

Estimation of forest Growing Stock (GS) is important in understanding the ecological dynamics and productive capacity of forests. Instead of the traditional cost-effective and time consuming ground based measurements, satellite images are being increasingly used in estimating many forest parameters including GS. This study estimates forest GS at Khadimnagar national park, Sylhet, Bangladesh using regression relationship of vegetation indices (VIs) of Landsat Thematic Mapper (TM) image with field-measured GS. Among the VIs, NDVI (Normalized Difference Vegetation Index) was found to be the best predictor of forest GS with workable accuracy (r^2= 0.77, P <0.000), while IRI (Infra-red Index) was the poorest estimator (r^2= 0.38, P < 0.001). This approach could be operationally used for wider scale estimation of GS in similar forest areas of Bangladesh.

Keywords: Growing stock, Landat TM, Vegetation Indices, NDVI, regression

1. Introduction

Forests are very important renewable natural resource of a country performing many vital functions for life. Managing and monitoring of the forest resources require information on forest capital in terms of wood resources and growing amount, which can be assessed through the volumetric measurement of the trees, commonly known as the growing stock (GS) volume (FAO 2011). In other words, forest growing stock includes the volume (usually measured in m^3) of all living trees in a given area of forest or wooded land that have more than a certain diameter at breast height includes the stem from ground level or stump height up to a given top diameter, and may also include branches above a certain diameter (FAO 2005). Forest inventory, whether in natural or plantation forests, is primarily conducted to estimate the existing GS installed in the forest (Adekunle 2007). An unbiased estimate of the GS is the key information required in forest mensuration and utilization (Singh et al. 2004) and is essential for understanding the ecological dynamics and productive capacity of a forest (FAO 2011). GS is also used to represent biomass, therefore eventually provide reliable estimate of the change in forest carbon due to deforestation (Macauley et al. 2009).

Many forest attributes such as GS, biomass, density, stand type, basal area, increment per hectare etc. are assessed by measuring individual trees in sample plots (Gunlu et al. 2008). Ground measurements of every tree in a sample plot for different variables in a forest inventory is practically incompetent, time-consuming, difficult, and not economically feasible and the accuracy of the information is often questionable (Gunlu et al. 2008, Adekunle 2007). Besides, they require higher logistic expenses (Fagan & DeFries 2009). Forest inventory can be done in a feasible nondestructive alternative way by using remotely sensed data which can provides useful information (Gunlu et al. 2008) but sometimes with lower accuracy (Fagan & DeFries 2009).

A common process of extracting information of different biophysical properties of vegetation from the satellite data is the use of vegetation indices (VIs). VIs are empirical formulae designed to highlight the contrast in spectral response in two different spectral bands of image e.g. Near-infrared and Red. A vegetation index combination of more than one image bands into one single band to facilitate extraction of useful vegetation information, for example image classification (Gibson & Power 2000). Many studies demonstrate that VIs such as spectral simple ratio (SR), normalized difference vegetation index (NDVI), vegetation index (SVI), corrected normalized difference vegetation index (NDVIc) etc. are good predictors of leaf area index (LAI), biomass, volume and productivity in grasslands and forests (Steininger 2000). Stand level biomass is frequently estimated using linear and nonlinear regression models established between VI and field measurements.

Volume and biomass are related by the equation, $B=\rho V$, where B represents biomass in tonnes (t), ρ average wood density (in t/m^3) and V volume (m^3). Therefore, when wood density is known, volume can be converted to biomass. Biomass is an important variable required to be estimated by remote sensing to measure the level of emission of carbon-di-oxide from enthropogenic changes of forest in the monitoring, reporting and verification (MRV) system of REDD+ (reducing emission from deforestation and forest degradation), a latest climate change mitigation scheme under negotiation by the United Nations. Countries willing to get monetary incentive from REDD+ scheme are required to measure, monitor and report changes in forest (deforestation and forest degradation) and biomass. Biomass can then be converted to equivalent carbon (in ton) multiplying by a conversion factor of 0.5. However, studies of remote sensing forest GS or biomass in Bangladesh are limited.

There is no accurate information about the total forest GS in Bangladesh (Choudhury & Hossain 2011). To formulate management plans and undertake conservational policy decisions, accurate estimation of the current GS at national level using remote sensing data is needed in Bangladesh. Moreover, relationship of volume or above ground biomass with vegetation indices are often location specific (Eisfelder et al. 2011), hence it is needed to evaluate which vegetation indices are suitable in this forest environment. In this study we explore, analyze and verify the regression relationship between several VIs and field-measured GS in a tropical-wet-mixed-evergreen forest site in Bangladesh with an aim of exploring the feasibility of using mid-resolution satellite images for wider scale estimation of GS.

2. Research methodology

2.1 Study site

The study was conducted at Khadimnagar National Park (KNP) (Figure 1), a hill forest site located in Sylhet district of Bangladesh. KNP is situated in the Khadimnagar Union of Sylhet Sadar Upazilla (administrative boundary). From forestry administration viewpoint, it is known as Khadimnagar forest beat under North Sylhet Range-1 of Sylhet Forest Division. Geographically KNP is situated between 24°56′-24°58′ N and 91°55′-91°59′E. The park extends over an area of nearly 678.80 ha which is surrounded by six tea estates. For conserving the remaining invaluable natural resources of the forest from human interference, its protection status was upgraded (from a reserve forest) to a national park in 2006 under the Wildlife Preservation Amendment Act 1974.

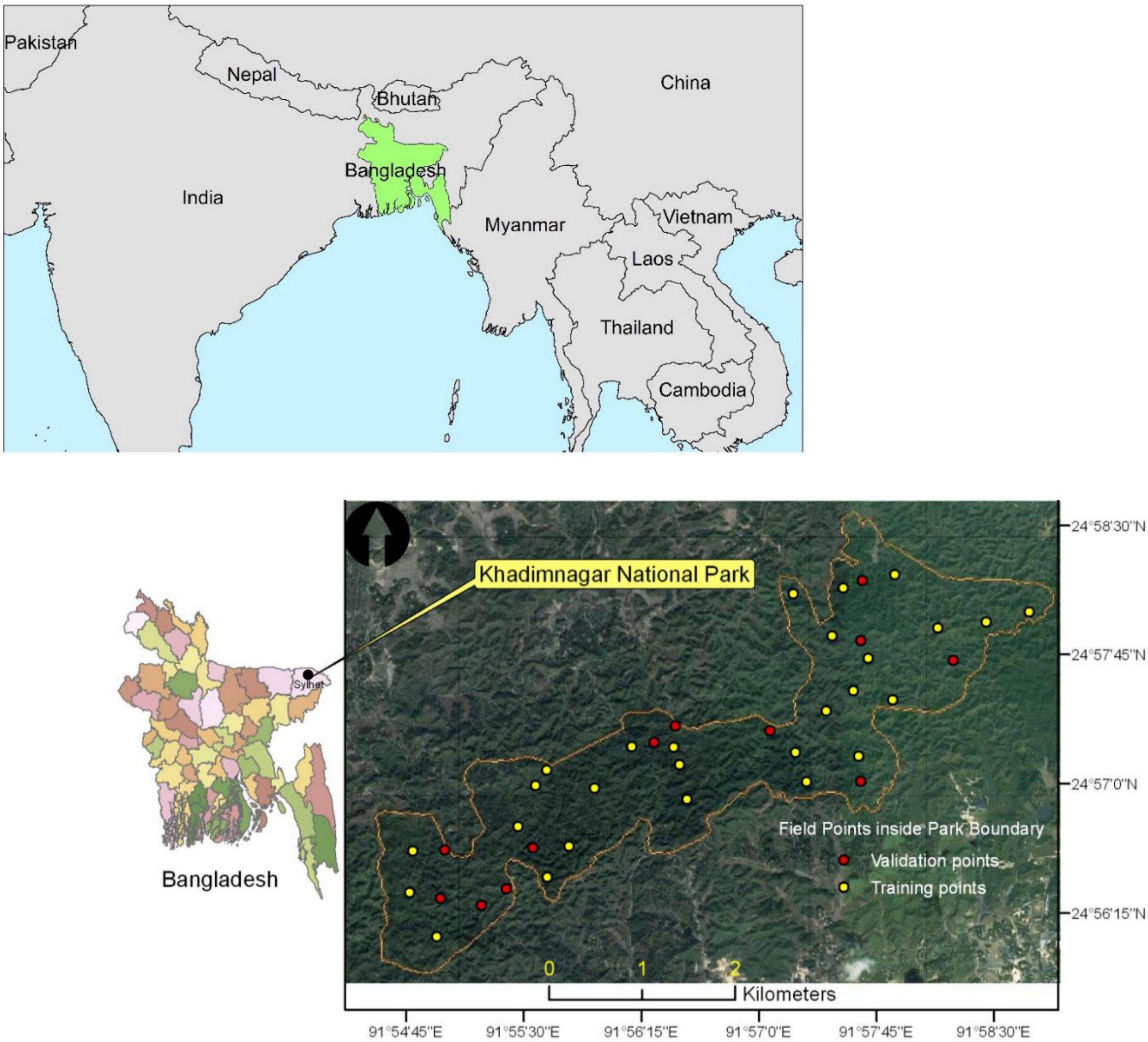

Figure 1: Location of Bangladesh in world map and field samples in Khandimnagar National Park, Sylhet, Bangladesh on a Google Earth background image

The topography of this forest is undulating with small hillocks (10 to 50-meter height) and vallies drained by several small, sandy-bedded streams locally known as chora. Soil ranges from clay loams to pale brown (acidic) clay loams (Anon 2006). Climate is warm and humid. Temperature ranges from 18.9˚-30.7˚C with an average annual rainfall of 3931 mm, most of which falls between June and September (BBS/UNDP 2005). Humidity remains high at 70% to 85% throughout the year with minor variations (FMP 1998).

Ecologically forest type of KNP is tropical-wet-mixed-evergreen. KNP is a natural forest with enrichment plantations. At KNP, evergreen vegetation communities are mixed with deciduous dominant tree communities along with various herbs, shrubs and bamboo species. Forest Department started plantation activities at KNP in 1951. During 1980-1990 plantation raising with long rotation species mainly Teak (Tectona grandis) and short-rotation monoculture mostly with exotic, rapid growing species such as Akashmoni

(Acaciaauriculiformis), Champa (Michelia champaca), Mangium (Acacia mangium) etc. were intensified. Various species of bamboos and canes was also planted in this forest.

Species composition at KNP in the upper canopy includes Garjan (Dipterocapus spp), Chandul (Tetrameles nudiflora), Simul (Salmalia spp), Sal (Shoria robusta), Koroi (Albizia spp), Jam (Syzygium cumini), Chapalish (Artocarpus chaplasha), Sutrong (Lophopetalum fumbriatum) and Ramdala (Duabanga sonneratioides). Bamboo species in this canopy are Mitinga (Bambusa tulda), Kali (Oxytenanthera nigrociliata), Dolu (Neohouzeaua longispathus), Borua (Dendrocalanus longispathus), Parua (Bambusa polymorpha) and Muli (Melocanna baccifera). Species in the middle and lower canopy include Chikrassi (Chikrassia tabularis), Tilsundi (Taluama phellocarpa), Pitraj (Amoora spp), Toon (Toona ciliata), Darchini (Cinnamonum spp), Chaitan (Alstonia scholaris), Nageswar (Mesua ferrea), Gamar (Gmelina arborea) and Bohera (Terminalia bellirica).

KNP is the habitat of a number of faunal species. 20 species of amphibians, 9 species of reptiles, 28 species of birds and 26 species of mammals are found in the park (IPAC 2009). Cobra, rock python, jungle fowl, Jungle cat, resus macaque, jackal, capped languor, fishing cat, asian giant tortoise, hill moyna, oriental pied hornbill are some important faunal species found in the park. Wildlives like pythons, porcupines, monkeys etc. captured by humans at different locations of Sylhet in different times are also released to this forest by Forest Department personnel.

KNP was purposively selected for this study for its closeness to Sylhet city and availability of necessary logistic support for navigation and fieldwork. A natural forest with heterogeneous species composition made this site ideal for such study in Bangladesh.

2.2 Satellite image acquisition and preparation

A geometrically corrected 30m x 30m spatial resolution Landsat TM 5 scene of path 136 and raw 43 acquired on 08 February 2010 was obtained from the Center for Environmental and Geographic Information Services (CEGIS), Bangladesh. The image was projected to Universal Transverse Mercator (UTM) zone 46N coordinate system with datum WGS84. Image of KNP was subset from a 185 km ×185 km scene in ERDAS IMAGE 9.2, using the boundary shape file of KNP obtained from the Integrated Protected Area Co-management (IPAC) project of Bangladesh Forest Department. The subset image was cloud and defect free. Of the seven available bands of TM, all bands except band six were used in calculating VIs. Band six is a thermal band and generally not used in vegetation remote sensing. To reduce the atmospheric noise, radiometric correction (transformation of image digital number (DN) values of each pixel to top-of-atmosphere radiance values) of the image was done following dark object method in Erdas Imagine. Densest part of the vegetation was regarded as dark object of the image in this case as reflectance of dense vegetation is very low in the visible spectrum.

2.3 Field sampling

Field data was collected during the months of September and October in 2011. A total of 50 sample points were randomly generated on a thematic map of KNP, prepared by unsupervised classification of TM image with 5 classes using Hawth's tool extension of ArcGIS. All together 40 sample points could be accessed in the field. 10 sample points could not be reached due to accessibility constraints (e.g. dense and thorny undergrowth) and unsuitability as sample points (e.g. outside forest boundary). In each accessed sample points, sample plot of 30×30 m (900 m^2) size, which is standard for such work (Gunawardena et al. 2008, Oladi 2005), was laid using measuring tape. In each sample plot, height and sectional diameter at the base, breast height (dbh, 1.3 meter above ground), middle and top of the stem of each tree were recorded using diameter tape and Spiegel Relaskope. Trees with dbh less than 10 cm were not considered for measurement. Of the 40 sample plots, GS information of two-third plots (28) were used for establishing regression model and one-third plots (12) were used for validation of the model (Figure 1).

Table 1: Equipment used for various purposes in the field data collection

Parameters	Equipment used
Field navigation, recording the geographic position of field sample plots	GPS (GARMIN, 12 channel), Topographic Map
Delineating each sample plot in the field	Linear Measuring Tape
Diameter at the base and breast height (dbh) of the trees in each sample plot	Diameter Tape
Diameter at the middle and top of the stem (for calculating tree form factor)	Spiegel Relaskop
Tree height	Sunto Clinometer

2.4 Calculation of GS volume of field plots

Tree volume is commonly calculated using equation based on tree parameters e.g. diameter and height (Akindele & Lemay, 2006). The volume of individual trees in each plot was calculated using the following formula:

$$V = \pi \times \frac{d^2}{4} \times h \times ff \qquad \text{(FAO 2011)}$$

Where, V = tree volume (m^3), d = tree diameter (cm) at breast height, h = tree height (m), π = 3.1415 and ff = form factor. Volume of trees of each plot was then estimated by summing all individual tree volume of that particular plot.

2.5 Extraction of spectral values from the image

The DNs (digital number) of the image were converted to reflectance for each band and pixel in raster calculator option of ArcGIS using the following standard formula:

$$\text{Reflectance} = gain \times DN + bias$$

Where, DN is the digital number value of the cell. Gain and bias for specific bands were obtained from the header information of the image. GPS (Global Positioning System) location of 28 training and 12 validation plots were converted to shape files in ArcGIS. The point shape files were overlapped with the image to extract spectral values of the pixels corresponding to field plots using 'extract points to values' option of ArcGIS. Extracted spectral values were then exported to MS Excel for calculating VIs.

2.6 Calculation of VIs

A number of VIs (20-50) are cited in literature for remote sensing vegetation, however, no particular VI was reported appropriate to provide concrete and accurate information of vegetation parameters in all environmental settings without being saturated, as values of these VIs are affected by soil-substrate, atmosphere, plant leaf structure and viewing angle of sensors (Campbell 1996). However, VIs which are commonly used in vegetation remote sensing have been used in this study to relate spectral response of the image with the field-measured GS. Using the spectral values of each band of the image, the following VIs were calculated in raster calculator option of ArcGIS.

Simple Ratio (SR) Index

$$SR = \frac{R_{NIR}}{R_R}$$

Normalized Difference Vegetation Index (NDVI)

$$NDVI = \frac{R_{NIR} - R_R}{R_{NIR} + R_R}$$

Enhanced Vegetation Index (EVI)

$$EVI = \frac{G(NIR - RED)}{NIR + (C_1.RED) - (C_2.BLUE) + L}$$

Where, G= Gain Factor

C_1= Atmospheric Resistance Red Correction Coefficient

C_2= Atmospheric Resistance Blue Correction Coefficient

L= Canopy Background Brightness Correction Factor

L is the canopy background adjustment term and C_1 and C_2 are the coefficients of the aerosol resistance term, which uses the blue band to correct for aerosol influences in the red band. The coefficients used in the EVI algorithm commonly adopt values as L = 1, C_1 = 6, C_2 =7.5 and G = 2.5. The value of this index ranges from -1 to 1. The common range for green vegetation is 0.2 to 0.8.

Infrared Index (IRI)

$$IRI = \frac{NIR-MIR}{NIR+MIR}$$

Transformed Normalized Difference Vegetation Index (TNDVI)

$$TNDVI = \sqrt[2]{\frac{NIR - R}{NIR + R} + 5)}$$

2.7 Regression of GS and VIs and validation

GS volume of field plots were put in regression with vegetation indices calculated using the spectral responses of Landsat TM 5 image. Both linear and non-linear (such as logarithmic, inverse, quadratic, cubic, compound, power and exponential) regression options were tested. GS volume of 28 field plots were used for building regression models and 12 field plots were used for validating the models. The goodness of fit of the obtained regression equations were assessed by comparing the significance of regression, F-ratio, and R^2 values. Accuracy of the best-fit equation was assessed by examining the standard error (% deviation) between observed (field validation data) and predicted (obtained using the best-fit equation) GS volume.

3. Results

The equations and graphs resulted from the linear and non-linear regressions between GS volume and vegetation indices have been presented in Table 2 and Figure 2, and at a glance in Figure 3.

Table 2: Relationship between GS volume and vegetation indices. Y= volume, X= respective VI

Vegetation Indices	Predictive relations	r^2	F	sig.
NDVI	Y=2172.545X3.780	0.768	85.875	.000
SR	Y=1.629X4.362	0.749	77.421	.000
TNDVI	Y=577.924X3.863	0.639	46.045	.000
EVI	Y=19118.965X2.480	0.636	45.400	.000
IRI	Y=36.237X1.999	0.377	15.759	.001

The regression analysis indicates that all the vegetation indices except IRI show fairly good relation with GS. NDVI is the best estimator of GS volume (r^2= 0.77, P <0.000) while IRI is the poorest estimator (r^2= 0.38, P < 0.001). The ranking of the VIs from best to worst can be considered as NDVI>SR>EVI>TNDVI>IRI. Thus the best-fit equation to estimate forest GS using VI is, Y (GS) =2172.545*NDVI image$^{3.780}$. Accuracy assessment shows the predicted volume is underestimated (by nearly 7%) than the observed volume (Figure 4 and 5).

4. Discussion

Five vegetation indices (independent variables) were regressed with forest GS volume (dependent variable) to ascertain the best fit model for forest GS estimation in a Bangladesh hill forest site. There was a workably high relationship between GS volume and vegetation indices except IRI which showed the lowest coefficient of determination. NDVI, a popular vegetation index comparing with other vegetation indices, has proved to be the best remote sensing independent variable for estimating GS volume in the study site. The highest accuracy of the obtained regression model using NDVI was workable. In fact, remote sensing of various biophysical traits of forest vegetation including GS showed best result mainly in the species-poor sites with monotonous and distinct canopies. Present study area is a tropical semi-deciduous/monsoon forest with heterogeneous canopy. In such a forest site, the accuracy obtained is workable in comparison to the results of other similar studies. Gunawardena (2008) reported r^2=0.72 while estimating merchantable timber volume of *Pinus caribea* plantations using multi-spectral satellite images. Gong et al. (2003) reported r^2=0.55 between the Hyperion data NDVI and LAI (leaf area index) of coniferous plantation in southern Argentina.

The suitability of NDVI for assessing GS volume goes down for natural forest with wide variation of tree species. For example, Huong (2003) found a low coefficient of determination (r^2=0.31) between NDVI and GS volume in a species-rich tropical evergreen broad-leaved forest in China. Sritakae (2006) observed a very weak relationship (r^2=0.002-0.276) in the coniferous forest of Bedford, UK. Lee et al. (2004) also observed a weak relationship between NDVI of airborne hyper-spectral data and LAI of evergreen needle-leaf boreal forest (r^2=0.01). Some studies used active remote sensor data. For example, 53-83% accuracy was reported using SAR data and 46-97% using LiDAR data in coniferous temperate and boreal forests for stem volume estimation (as reviewed by Patenaude et al. 2005 and referred in Fagan & DeFries 2009).

Passive sensor data independently and in combination with active sensor data have also been used to estimate forest GS volume and basal area. For example, use of Landsat and forest inventory data resulted with 50% accuracy (Franco-Lopez et al. (2001), Landsat data with 66% accuracy (McRoberts et al. 2008), and mid-resolution and forest inventory data with 69% accuracy (Hall et al. 2006) in estimating forest volume and basal area in different study sites. High-resolution image has also been used to estimate forest GS volume and basal area with a range of accuracies, e.g. optical sensor data with 55-58% accuracy (Hyyppa et al. 2000), SPOT image with 71% accuracy in an open temperate forest (Wolter et al. 2009), 1m-resolution IKONOS-2 image with 35% accuracy in a mixed coniferous deciduous forest (Kayitakire et al. 2006), and Quickbird image with 87-92 percent accuracy in a poplar plantation (Wang et al. 2007) among others. However, in practice, the comparison of results with other studies was difficult due to differences in study sites and respective stand characteristics, criteria used for model evaluation (r^2, standard error), procedures of validation (how testing was done), and number of predictors used in the model. All these accounted for large variation in accuracies among the studies.

The number of training (28) and validation (12) plots used for collecting necessary field measurements was relatively small for model build up (though can be considered sufficient to capture the total variation of this small study site of 678 ha area), hence very high coefficient of determination (r^2) could not be achieved. Moreover, the 'selective availability (SA)' error of the GPS machine (+/- 15 m) and larger pixel size of the image (30 meter) could have introduced inaccuracy in positioning and linking the field data with satellite image.

This might be responsible for error propagation in linking ground points with image. Further, no topographic normalization was considered for this study though the area has hilly topography. Landsat TM data was acquired in February 2010 but the field work was carried out in September 2011. This might be a cause for not getting very high regression accuracy in the result. A few other factors including forest canopy cover, canopy architecture, undergrowth vegetation, atmospheric scattering, soil moisture condition, slope and sun angle might have bearing on the reflected energy recorded by the sensor at the top of the atmosphere.

Data from optical sensors such as Landsat TM, in fact, are sensitive to the green biomass of forests i.e. LAI (Kayitakire et al. 2006, Flores 2006) which is obviously related to growing stock. As a result, VIs, especially NDVI as a measure of vegetation greenness has shown good positive relation with GS.

In each plot in the ground, data were collected for only the tree component; herbs and shrubs were not considered. Therefore, the GS estimated here is the GS volume of the trees only. Major species of the GS at KNP include Garjan (Dipterocarpus turbinatus), Teak (Tectona grandis), Champa (Michelia champaca), Dhakijam (Syzygium grande), Chapalish (Artocarpus chaplasha), Chickrassi (Chickrassia tabularis), Mangium (Acacia mangium) and Akashmoni (Acacia auriculiformis). The GS that resulted from the developed regression equation varies from as low as 8 m3 ha-1 to as high as 190 m3 ha-1, which is conformant to the GS volume reported in the management plan of KNP prepared for the period of 2009-2018 (FMP 2009).

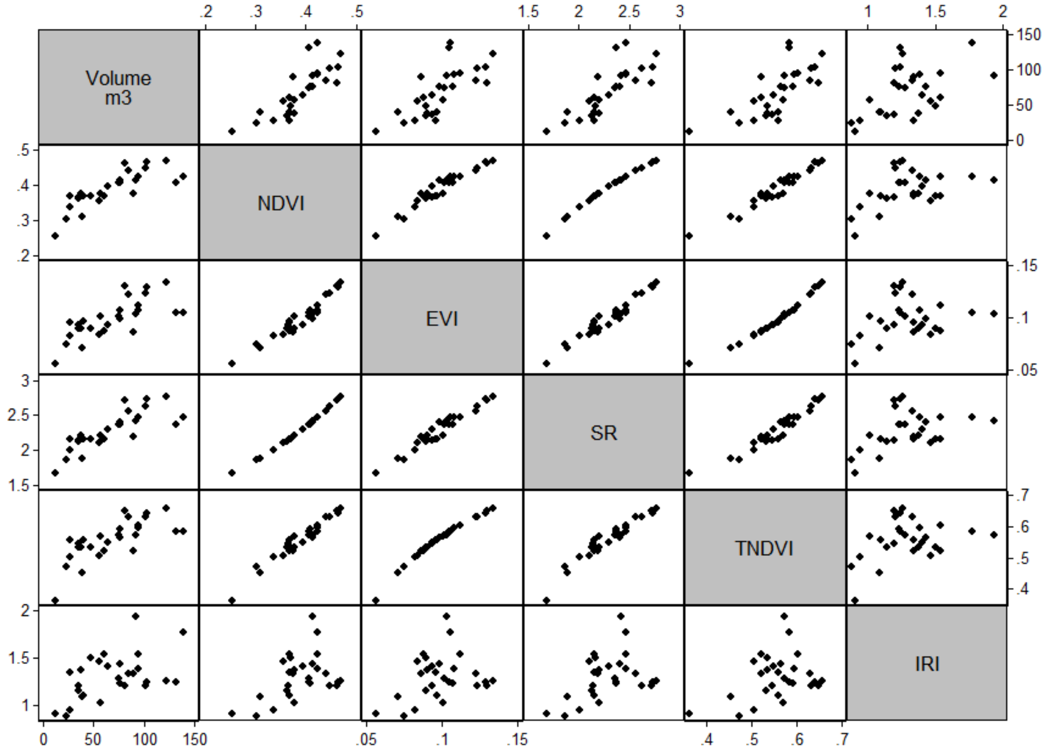

Figure 3: Scatter plot matrix of GS volume and VIs

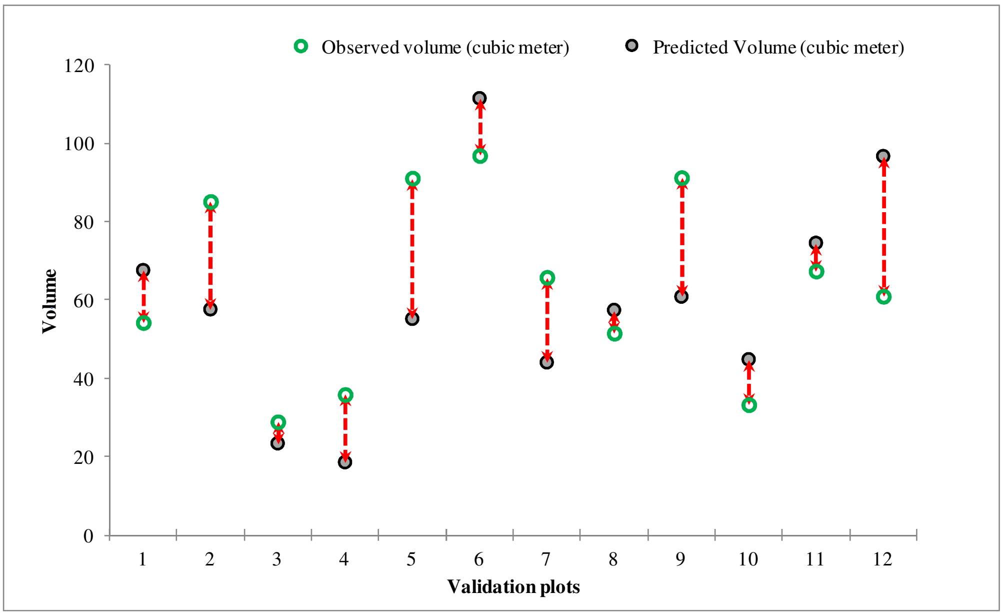

Figure 4: Distribution of observed and predicted volumes of the validation plots in the study area. The red dotted arrow line indicates the relative difference between the corresponding values of each validation plots.

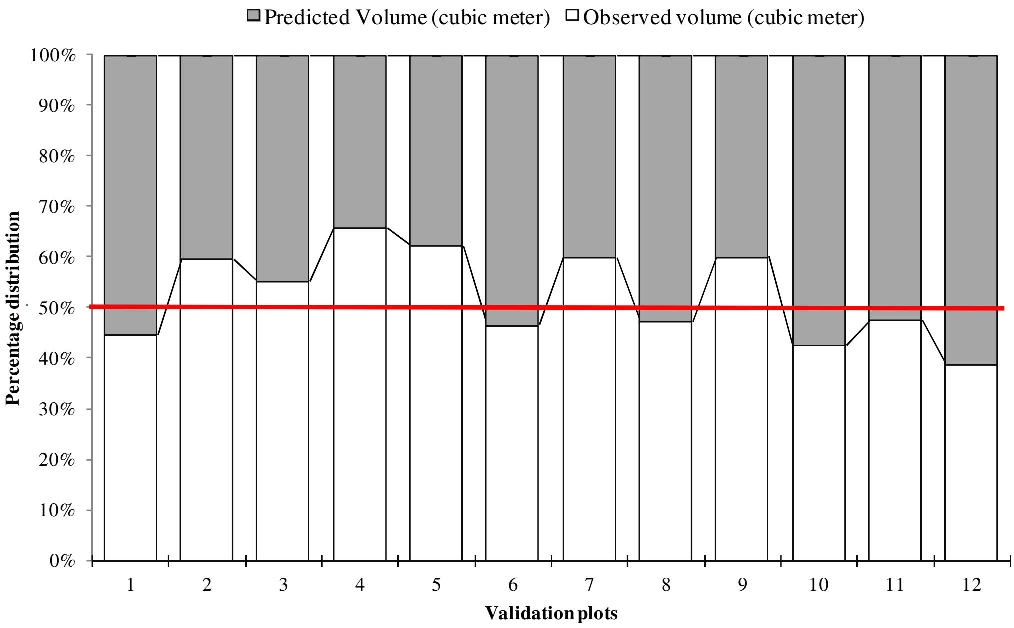

Figure 5: Percentage distribution of observed and predicted GS volumes of validation plots. Ideally, there will be no difference between observed and predicted values, meaning that both should coincide at the benchmark point at 50% level (horizontal red line). Observed GS values in most cases are higher than the predicted values.

Areas showing very less amount of GS per hectare are the bare lands of the park with few sparse standing trees, while areas with high GS are representative of the denser areas with closed canopies. It can be considered that the GS at KNP belongs to the higher-medium level in comparison to the national level. ADB (1993) reported the government forest carries a growing stock of about 30 m^3 ha^{-1} in Bangladesh. In 1980, there was about 71 million m^3 of growing stock volume in government forests which declined by two thirds by the year 1990 (ADB 1993). The National Forest Inventory conducted by FAO during 2006 reported the total GS volume in Bangladesh is about 212 million m^3 including homestead forests (as mentioned in Choudhury and Hossain 2011). Managing authorities of the forests and protected areas of Bangladesh should undertake forest management operations like enrichment planting and gap filling to the natural and plantation forests, and plantation programs to the bare lands of the forests under their jurisdiction.

5. Conclusion

Present study revealed good regression relationship of several vegetation indices, calculated out of Landsat TM image with the field sampled forest growing stock in a hilly tropical-wet-mixed-evergreen forest site in Bangladesh. Among the vegetation indices, NDVI was found to be the best predictor of forest GS. NDVI calculated from the Landsat TM image can be related with GS in regression analysis as shown here to estimate GS as a continuous map. More sample and validation plots might increase the accuracy of estimates and reliability of model. Finer spatial resolution could also enhance the quality and prevision of estimates. The operational method of integrating image spectral response with field-measured data for estimating GS, as investigated in this study, can be extrapolated and operationalized over larger forest areas. Thus, regular monitoring of the GS of the forests of the country is very effectively possible at reasonable cost, time and effort using mid-resolution satellite data like Landsat TM. Remote sensing technology has been proved to be powerful research and management tool for inventory and assessment of the forest resources of the world. Free availability, larger area and repeated coverage of the Landsat TM data opens new horizons of opportunities for continuous monitoring of the forest GS at minimal cost, especially for the developing countries like Bangladesh, where a large number of natural resource managers/organizations are practically not in a position to buy and use high resolution airborne or satellite data. However, precision should be maintained in all stages of the field work and image processing operations as the ultimate accuracy of the regression model for GS estimation largely depends on that. Precision is an important issue to be ensured especially during taking measurement of tree parameters in the field plots, recording geographic position of the field plots and pre-processing and processing of the image. Use of differential GPS might reduce the SA error to nearly zero, therefore recommended to be used.

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