Exploring multi-scale forest above ground biomass estimation with optical remote sensing imageries

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Abstract. Forest shares 80% of total exchange of carbon between the atmosphere and the terrestrial ecosystem. Due to this monitoring of forest above ground biomass (as carbon can be calculated as 0.47 part of total biomass) has become very important. Forest above ground biomass being the major portion of total forest biomass should be given a very careful consideration in its estimation. It is hoped to be useful in addressing the ongoing problems of deforestation and degradation and to gain carbon mitigation benefits through mechanisms like Reducing Emissions from Deforestation and Forest Degradation (REDD+). Many methods of above ground biomass estimation are in used ranging from use of optical remote sensing imageries of very high to very low resolution to SAR data and LIDAR. This paper describes a multi-scale approach for assessing forest above ground biomass, and ultimately carbon stocks, using very high imageries, open source medium resolution and medium resolution satellite datasets with a very limited number of field plots. We found this method is one of the most promising method for forest above ground biomass estimation with higher accuracy and low cost budget. Pilot study was conducted in Chitwan district of Nepal on the estimation of biomass using this technique. The GeoEye-1 (0.5m), Landsat (30m) and Google Earth (GE) images were used remote sensing imageries. Object-based image analysis (OBIA) classification technique was done on Geo-eye imagery for the tree crown delineation at the watershed level. After then, crown projection area (CPA) vs. biomass model was developed and validated at the watershed level. Open source GE imageries were used to calculate the CPA and biomass from virtual plots at district level. Using data mining technique, different parameters from Landsat imageries along with the virtual sample biomass were used for upscaling biomass estimation at district level. We found, this approach can considerably reduce field data requirements for estimation of biomass and carbon in comparison with inventory methods based on enumeration of all trees in a plot. The proposed methodology is very cost effective and can be replicated with limited resources and time.

1. Introduction

Since long there has been a viable debate on GHG (Green House Gas) emission especially the carbon as the prime cause behind the perceptible global warming (Angelsen, 2008; Herold et al., 2011). Forest account for about 80% of the exchange of carbon between terrestrial ecosystems and the atmosphere(Uddin et al., 2015). It is estimated that deforestation and degradation of forest ecosystems
It is also reported that carbon sequestration by afforestation and avoiding deforestation could be effective in countering global warming at a low cost than the massive energy conservation and innovation adjustments we will need to minimize the use of fuel energy guzzling world economies (Smil, 2010). Due to this monitoring of forest above ground biomass (as carbon can be calculated as 0.47 part of total biomass) has become very important. Forest above ground biomass is the major portion of total forest biomass, hence a very careful consideration should be taken in its estimation. It is hoped to be useful in addressing the ongoing problems of deforestation and degradation and to gain carbon mitigation benefits through mechanisms like Reducing Emissions from Deforestation and Forest Degradation (Kim et al., 2010; Lu, 2006; YousifAli & Hammad, 2011).

Nepal is a rich country in forest resources occupying 40% (5.83 million hectares) of its total area by forest (DOF 2012). (FAO, 2010) estimated the level of forest living biomass in Nepal in 2010 at 484 million tons (t) (359 million tons above ground biomass [AGB] and 126 million tons below ground biomass [BGB]), but these values are aggregated at the national level, and not detailed enough to use for planning purposes. Also, the proposed introduction of a mechanism for REDD+ (Reducing Emissions from Deforestation and Forest Degradation) and associated requirements for monitoring, reporting, and verification (MRV) requires detailed information on forest biomass and changes in carbon stocks.

Remote sensing techniques, using different sensors and methods, offers as a better tool for estimating Forest Above ground Biomass. Remote sensing data has the advantage of being capable of obtaining spatial distribution of forest biomass at reasonable cost with acceptable (DeFries et al., 2007). Many efforts have been made to estimate forest biomass and carbon stock using different platforms (air-borne and space-borne) and sensors (optical, radar, and Lidar) (Gibbs, Brown, Niles, & Foley, 2007). Also, several methods have been proposed for estimating forest biomass using remote sensing techniques that make use of a combination of regression models, vegetation indices, and canopy reflectance models (Baccini et al., 2012; Bastin et al., 2014; Cutler et al, 2012; Frazier et al, 2014; Hussin et al., 2014; Kim et al., 2010; Ploton et al., 2012).

Medium and coarse spatial resolution imageries has always been a potential AGB estimator at National and regional scale, but in the sites with complex biophysical environment, it possess problems like mixed pixel and data saturation (Goetz et al., 2009). On the other hand, the High spatial resolution data provide more accurate results than medium resolution but they are expensive and have less area coverage per tiles and demands high processing, thus they are not appropriate for use in developing countries. (Lu, 2006) has suggested that combining remotely sensed data derived at different scales (coarse to fine resolution) could improve the accuracy of biomass estimation at national and global scales.

Multi scale biomass estimation with multiple resolution optical imageries can hence be one of the best option for forest above ground biomass estimation for the developing and REDD+ participant countries. This paper describes a methodology of using multi-resolution imageries i.e. the very high and medium resolution satellite datasets together with a very limited number of field plots. A crown projection area (CPA) vs. biomass model was developed and validated at the watershed level. Open source google imagery was used to derive CPA and Biomass of virtual plots for scaling up at district level. Using data mining technique, different parameters from Landsat imageries along with the virtual sample biomass were used for upsampling biomass estimation at district level. This approach could considerably reduce the requirement for field level data for estimation of biomass and carbon in comparison with inventory methods based on enumeration of all trees in an area. The proposed methodology is very cost effective and can be replicated with limited resources and time. It is relatively straightforward to obtain meaningful estimates of biomass in their forest areas.

The specific objectives of the study were:

- to develop and validate a CPA (delineated and extracted from VHRI satellite imageries) vs. Biomass (based on the field data) model
- to design virtual plots using open-source Google Earth imagery
to develop a multi-regression model through the data mining technique for scaling up based on the virtual plot data and parameters extracted from remotely-sensed datasets

2. Materials and Method

2.1. Study Area

The overall study area is Chitwan District of Nepal and within this the Kayerkhola watershed was selected for detailed development of the model (Figure 1.). The whole district has area of 2,218 km² with forest area of 1308 km² whereas the watershed occupies area of 80 km² and with forest area of 59 km². The study area was selected on the basis of accessibility, data availability, variation in terrain, and ongoing implementation of a REDD+ pilot project.

The study area has mixed forests with the dominant species *Shorea robusta* (sal) found on most areas. Other major species are *Schima wallichii* (chilaune) and a few associated species.

![Figure 1. Study area](image)

2.2. Data and Software

At the watershed level cloud and haze free GeoEye-1 images captured on 15 December 2012 were used. Landsat-8 Operational Land Imager (OLI) images from 9 and 18 November (winter), on row/path 142/041 and 141/41 were used for scaling up at district level. The GE very high resolution Digital globe imageries from 2013 were used as the virtual plots for upscaling. A digital elevation model (DEM) was extracted from topographic sheets with a horizontal resolution of 30 m with extracted products like slope, aspect, and hill shade, to understand the topography of the area. An ordinary global positioning system (GPS) receiver was used for location identification in the field study, tree height was measured with a TruPulse 360B and DBH was measured with a measuring tape.

eCognition developer was used for the delineation of the tree crown from the very high resolution GeoEye imageries. The pre-and post-processing of the Geo-Eye and Landsat imageries were done with the use of Erdas Imagine and ENVI software. General spatial analysis processing were done with the use of Arcmap. Other statistical analysis were done using the R.

2.3. Research Method
The overall methodology of this work is summarized in the form of a flow chart in Figure 2. The method followed for has been described briefly in the sub sections below.

The research method followed in this work can be broadly divided into 3 distinct parts i.e. Field work, Geospatial analysis (Remote Sensing and GIS) and statistical modeling.

Field work was performed to obtain the in-situ data of DBH and other measurements. The geospatial operations were carried out to delineate the tree crown from the VHRI and GE virtual plots and to obtain the forest biomass at the watershed and the district level. The statistical analysis was done to develop the relation between the CPA delineated in the VHRI imageries with biomass from the field plots and the biomass generated from the filed plots with that to the Landsat imagery reflectance variables.

![Figure 2. Methodological flow chart](image)

2.3.1. Field data collection. A total of 58 stratified randomly selected inventory sample plots of 500m² each were collected within the watershed area for the field based biomass estimation. Out of it 38 plots were used to develop the regression model; and a further 20 plots with the same area were used for validation. The position, height, and DBH of every tree with DBH > 5 cm in each plot were recorded.

2.3.2. Pre-processing of remotely sensed data. Individual band-wise GeoEye-1 images were ortho-rectified using rational polynomial coefficient (RPC) files along a horizontal 20 m topographic DEM by applying a cubic convolution method in zone 44 of the Universal Transverse Mercator (UTM) coordinate system, with datum and spheroid from the World Geodetic System (WGS) 84. The spectral information at lower resolution (2 m) was pan-sharpened with the high spatial resolution information (0.5 m) from the panchromatic image. The two GeoEye-1 images were independently ortho-rectified and fused with their respective multi and panchromatic spectral bands, but positional differences were observed when they were overlaid. To overcome this, their rectification was done taking 26 points were taken as ground control points (GCPs) in both datasets. This resulted in an overall root mean square error (RMSE) of 1.2 m for the panchromatic image and 1.5 m for the multispectral image. Prior to segmentation, low pass median filters was applied to avoid over-segmentation and smooth the appearance (Platt and Schoennagel 2009). In this study, convolution $3 \times 3$ low-pass filters were used to reduce local variation, remove noise, enhance tree features, and improve the quality of the analyzed satellite images.
The Landsat TM images were downloaded and a layer stack prepared to make multi-spectral images for visualization. The Normalized Difference Vegetation Index (NDVI) was extracted using the NIR and RED bands.

2.3.3. Delineation of CPA. In eConition developer, Object based image analysis (OBIA) with a region growing technique was used for CPA delineation at the watershed level. In this method, tree tops are identified as maxima and the shadows between trees as minima. The segments are ‘grown’ from these maxima and the valleys act as boundaries. The first step in region growing was to create minimum size homogeneous objects through ‘chessboard segmentation’; the brightest pixels were then identified as seed pixels (tree tops). Regions were ‘grown’ from the seed pixels up to the local minima, resulting in homogeneous objects based on predefined homogeneity criteria (Hussain et al., 2014; Ke & Quackenbush, 2008; Kim et al., 2010; Shih & Cheng, 2005). Validation of the delineation was done using manually delineated tree crowns (visual interpretation of the images in a 1 ha grid).

2.3.4. Modeling field based Biomass with delineated CPA. Using the allometric equation developed by (Sharma, 1990) the DBH (in centimetres) of each tree recorded in the field was converted into Biomass (tons). CPA was derived from the GeoEye-1 image of 2012 for the same plot areas using the region growing technique. After that the regression relation between the CPA and biomass was modelled.

2.3.5. Development of GE virtual Plots and biomass estimation at district level. Thirty-five virtual plots of 1 ha (10,000 m2) randomly distributed on a Google Earth were generated for scaling up across the entire district. The number of crowns and the crown area were observed in each plot by visual analysis and digitizing. Their biomass value were then calculated using the regression equation, derived in the watershed before thus taking the diversity and different sizes of tree crowns into account. The forest biomass value for the district level was derived using the CART, and MARS data mining techniques which used the biomass values for the virtual plots calculated from the CPA using the regression equation, together with additional parameters extracted for each of the three seasons from the virtual plots in the Landsat images. The parameters used were blue, green, red, and near infrared reflectance, elevation and NDVI values.

3. Result and Discussion

3.1. CPA delineation and development of CPA vs Biomass regression model for watershed.

The CPA delineated through OBIA was compared with the CPA extracted manually within a 100 x 100 m grid for accuracy assessment. The results is shown in Figure 3; there was an 83% match (coefficient of determination R² = 0.83) between the values.

After then, the CPA extracted from the satellite image of 2009 was regressed with the Biomass derived from the DBH measured on the ground in the field plots. Out of the 58 field sample plots collected 38 samples were used for deriving the relation. The two values showed a linear relationship with the coefficient of determination R² = 0.76 (Figure 4.).

The extrapolated map had an accuracy of 85% based on observed and predicted Biomass values.
3.1.1. Forest Biomass estimation at district level. The Classification and Regression Trees (CART) mapping model was used to map forest biomass at the district level. CART is a non-parametric decision tree learning technique that produces either classification or regression of trees, depending on whether the dependent variable is categorical or numeric, respectively.

At first a total of 18 parameters were fed into the CART system to see out which parameters will define the forest biomass in a best way. Out of these 18 parameters 15 parameters were that from the Landsat imageries the bands. Red, Green, Blue, Near Infra-Red and NDVI of the summer, winter and rainy season respectively. The other three parameters taken were the Dem, slope and aspect.

CART find out the 5 parameters as the finest one which define the forest biomass in the best fit way (see Figure 6.) with coefficient of determination 0.76. These five parameters are Rainy season NIR, rainy season Blue band, DEM, Rainy season Green band and Rainy NDVI in the respective order based on their higher influence (Figure 7.).

After that all these five major parameters along its biomass value for the plots were fed into MARS (Multivariate Adaptive Regression Splines) to generate the Multivariate model that will help to interpolate Biomass at district level.
4. Conclusion
The methodology for Above Ground Biomass mapping at both watershed and district level is convenient and easy to replicate. The use of the google earth virtual plots is very much cost effective and efficient. This approach could considerably reduce the requirements for field data for estimation of biomass and carbon in comparison with inventory methods based on enumeration of all trees in an area. Many researchers (Hussin et al., 2014; Karna et al., 2015) have explored different forms of allometric equations and found that the allometric equation from (Sharma & Pukkala, 1990) is one of the preferable one for the field biomass estimation in Nepal.

The next step in this research will be to expand the methodology to entire country and also to the HKH level with the use of other lower resolution imageries as MODIS. Instead of using commercial very high resolution satellite imagery, we are proposing to use less expensive imagery such as CARTOSAT-2 which will minimize the cost of estimation without compromising the quality. The proposed methodology is very cost effective and can be replicated with limited resources and time. The virtual plotting techniques will be tested to confirm that the method can be used by general foresters to obtain meaningful estimates of crown cover and biomass in their forest areas for reporting purposes.

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