MODELLING THE RELATIONSHIP BETWEEN TREE CANOPY PROJECTION AREA AND ABOVE GROUND CARBON STOCK USING HIGH RESOLUTION GEOEYE SATELLITE IMAGES

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ABSTRACT: Carbon stock estimation of above ground tree biomass is important for 'reducing emission from deforestation and forest degradation' (REDD) credit to mitigate climate change due to anthropogenic causes. Automatic delineation of individual tree crown (ITC) techniques results in a substantial error due to presence of intermingled canopy trees in the estimation of above ground carbon stock. The aim of this study was to establish regression models for the relationship of canopy projection area (CPA) with forest tree parameters, i.e., diameter at breast height (DBH), basal area (BA), biomass and carbon stock of standalone and intermingled canopy trees of dominant species for the prediction of above ground carbon stock. This study was carried out in subtropical broadleaf forest in Chitwan, Nepal. High resolution GeoEye satellite image was used for manual delineation of CPA of standalone and intermingled canopy trees of the dominant species. Above ground tree dry biomass was calculated from the field measured DBH using allometric equation. Above ground tree carbon stock was obtained by multiplying their dry biomass with the factor 0.47. Individual basal area of intermingled canopy trees was calculated separately and was summed up (ΣBA) along with the summation of their carbon stock (Σcarbon). Correlation analysis was carried out to assess the linear relationship between CPA, DBH, BA, biomass, and carbon stock. Four types of functions, i.e., simple linear, quadratic, logarithmic and power, were used to fit the data using least square regression method. *Shorea robusta, Schima wallichii* and *Terminalia alata* were found dominant tree species in the study area forest. The relationship of CPA with DBH of standalone trees was found linear with coefficient of determination (R^2) ranging from 0.63 for *Schima wallichii* to 0.69 for Shorea robusta and 0.74 for *Terminalia alata*. The relationship of CPA with biomass or carbon stock of standalone trees was also revealed linear with R^2 ranging from 0.53 for *Schima wallichii* to 0.62 for *Terminalia alata* and 0.65 for *Shorea robusta*. The relationship of CPA with ΣBA and Σcarbon of intermingled canopy trees of *Shorea robusta* was also found linear with R^2 of 0.29 and 0.25 respectively. Simple linear regression model resulted in the least error for the prediction of carbon stock of standalone and intermingled canopy trees.

1. INTRODUCTION

The United Nations Framework Convention on Climate Change (UNFCCC), held in June 1992, has been marked the global commitment on climate change. The objective of the Convention is to stabilize greenhouse gas (GHG) concentrations, which is the main anthropogenic cause to climate change, in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system (UNFCCC, 2010). The Kyoto protocol, a binding protocol to UNFCCC, requires party countries to limit or reduce GHG emission (Gibbs *et al.*, 2007). Forests, which occupy 31% of the total land area of the world (FAO, 2011), play a significant role in the global carbon cycle. They are the large carbon pool and acts as both carbon source and sink according to their management. Growing vegetation absorbs CO_2 from the atmosphere for the photosynthesis process and stores it in the form of carbon in their biomass. REDD stands for 'reducing emission from deforestation and forest degradation' was first introduced into the Conference of the Parties (CoP) agenda of UNFCCC at its eleventh session in Montreal in 2005 (UNFCCC, 2010). It provides financial incentives to developing countries that reduce GHG emissions from forests. Credit from reduced emissions would be quantified and sold in an emerging international carbon market (Gibbs *et al.*, 2007). Furthermore, it extends the opportunities of getting fund from developed countries. The initiative has commonly been accepted as a low cost option to deliver significant climate change mitigation benefits along with co-benefits such as biodiversity conservation and poverty alleviation that leads to win - win situation to all parties.

Nepal is a developing country with a forest cover of about 5.83 million hectares or 39.6% of the total geographical area of the country. Community forestry is the top priority programme for the forestry sector in the country.

Community forest management forms an integral part of the rural subsistence economy in many parts of Nepal (Karky & Skutsch, 2010). More than 1 million hectares of forestland or about one quarter of the country's forest are being managed by local communities (DoF, 2010). However, according to Ministry of Forests and Soil Conservation (2009), deforestation rate is 1.7 %. Deforestation and forest degradation have been a great concern for Nepal as well for biodiversity conservation, livelihood of people and to address global commitment of mitigating impacts of climate change. Moreover, Nepal is a party country for UNFCCC and the Kyoto Protocol that requires reporting carbon balance of the country. The carbon pools in forest ecosystem are comprised of above ground biomass, below ground biomass, deadwood, litter and peat soil (IPCC, 2006). Of them, above ground biomass (hereafter above ground biomass is referred to as biomass) of trees contains the largest carbon pool and is the most directly impacted by deforestation and forest degradation. Biomass estimation is the primary step in quantifying carbon stock of a forest as dry biomass contains about 47 % carbon (IPCC, 2006). Biomass of trees can be derived directly by measuring sample tree attributes in the field or indirectly by transforming available volume data from forest inventory (IPCC, 2006). Although the direct way to quantify biomass is accurate for a particular location, it is too time consuming, expensive, destructive and impractical for country level analysis. There is no methodology to measure biomass of trees across a large area directly. Remote sensing (RS) provides alternatives to conventional forest inventory to estimate biomass and carbon stock across a large area (Gibbs *et al.*, 2007).

The identification of relationship between DBH and CPA (derived from satellite image) allow predicting above ground tree biomass at a larger scale. Allometric equations can be used to estimate biomass that relate with the tree parameter, i.e., DBH (Basuki *et al.*, 2009; Chave *et al.*, 2005). Allometry means the relative growth. Tree allometry describes the relationship between its different diamentions. Allometric equations are developed on the basis of destructive sampling (Basuki *et al.*, 2009). Individual tree crown (ITC) or CPA has been extracted from very high resolution (VHR) satellite image using ITC software and object oriented image analysis for forest stand information (Culvenor, 2003; Katoh *et al.*, 2009; Leckie *et al.*, 2005). Object oriented image analysis can make full use of image information which combine spatial as well as spectral information and extract objects at multiple scales. Whereas conventional pixel based image analysis, mainly focus on spectral information, is irrelevant using VHR satellite data as the target object size, for instance, tree crown is larger than a pixel (Greenberg *et al.*, 2005). Individual tree crown delineation using high resolution imagery and ITC software technique is appropriate and consistent for conifer forests with abundant shade between trees that provides a crown outline (Katoh *et al.*, 2009; Leckie *et al.*, 2005). Indistinct or absence of valley of shade between trees in broadleaf forest stand makes it difficult to delineate individual tree crown using ITC software (Chubey *et al.*, 2006). Automatic delineation of individual tree crown techniques such as valley following and pattern matching has wide variation in their accuracy. Their accuracy varies from 50 to 80 % (Bunting & Lucas, 2006). They all have poor accuracy attributed largely to overtopping of smaller crowns and presence of intermingled crowns or overlapped canopy in complex forest (Bunting & Lucas, 2006). Tree crown identification algorithm (TIDA) cannot separate overlapping or adjacent intermingled tree crowns, which is common in natural forest, and computation is very intensive that cannot be applied over a large area (Asner *et al.*, 2002; Palace *et al.*, 2008; Song *et al.*, 1997).

Automatic ITC delineation techniques have been unable to separate canopies seen as one canopy in the image but in fact intermingled of two or more canopies, which causes substantial error for biomass estimation (Browning *et al.*, 2009; Hirata *et al.*, 2009 ; Palace *et al.*, 2008). Study has not yet explained the relationship between canopy delineated from the image, which are seen as one canopy in the image but in reality formed from two or three or sometimes more crowns of trees, and their corresponding DBH, BA, biomass and carbon. In this context, CPA of standalone as well as intermingled canopy trees was manually delineated from GeoEye satellite image. The relationship between CPA, DBH, BA, biomass and carbon of standalone and intermingled canopy trees was investigated using correlation and regression analysis. The main objective of this work is to establish regression models for the relationship of CPA delineated from the high resolution GeoEye satellite image with forest tree parameters, i.e., DBH, BA, biomass and carbon stock, of standalone and intermingled canopy trees of the dominant species for the prediction of above ground tree carbon stock.

2. MATERIALS AND METHODS

2.1 Study Area

The study area, covering 2374.67 ha, is located in Chitwan district of the Central Development Region of Nepal (Figure 1). There are forty village development committees in the district. Of them, study area is limited to four village development committees, namely, Shiddi, Shaktikhor, Chainpur and Pithuwa. The natural subtropical forest with broadleaf species is dominating the study area. *Shorea robusta* is the dominant tree species (Figure 2-2). The main associated tree species are *Terminalia alata, Terminalia bellirica, Lagerstromia parviflora, Schima wallichii, Semicarpus anacardium, Mallotus phillippensis, Cassia fistula, Cleistocalyx operculatus, Careya arborea,* *Holarrhena pubescens, Adina cordifolia, Syzygium cumini, Aesandra butyracea, Terminalia bellirica.* The area lies in the central climatic zone of the Himalayas. The subtropical monsoon climate exists in the area. Usually monsoon rain starts in mid-June and last till late September. During the period, most of the annual precipitation falls in the form of rain. Annual average precipitation is 1830mm that varies from 1584 to 2287mm. Annual mean temperature is 24^{o}C that ranges from 36^{o}C to 18^{o}C (Panta *et al.*, 2008). The area is mountainous with highly undulating terrain. The altitude varies from 300m to 1200m above sea level. The land is characterized by many steep gorges and slope varies from 30% to more than 100%. The area is drained by Khayarkhola stream having many small tributaries feeding into it**.**

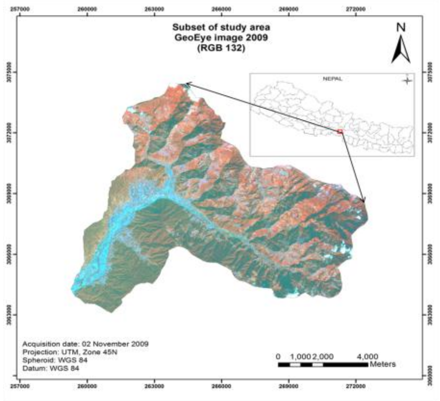

Figure 1: Location of the study area

2.2 Research Methods

General flow diagram of research methods is presented in Figure 2. It mainly consists of image processing (violet colour block), field data collection especially DBH of trees (blue colour block) and data analysis, i.e., correlation and regression analysis (green colour block). RQ 1, RQ 2 and RQ 3 in the diagram refer to research question 1, 2 and 3 respectively.

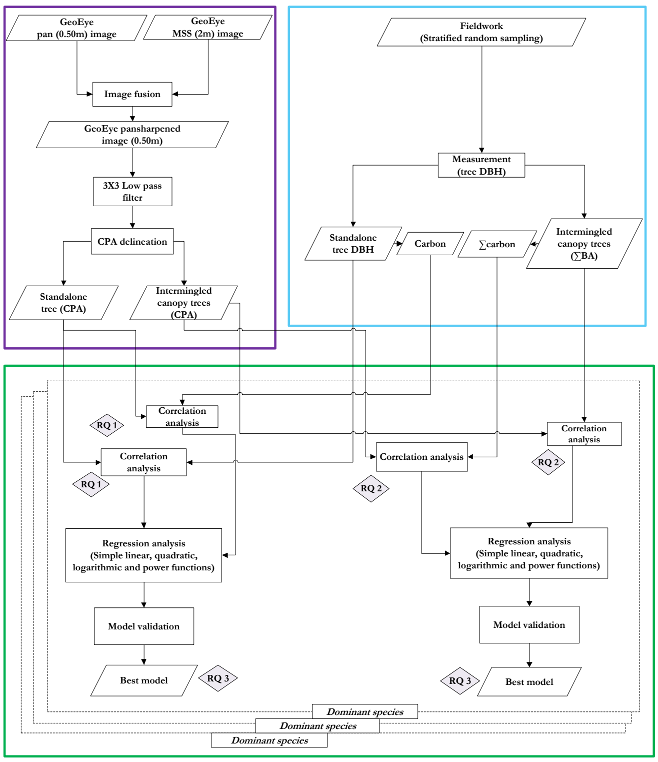

Figure 2: Research Method.

GeoEye – 1 images acquired on 02 November 2009 were used for this study. Orthorectified images were provided by ICIMOD. They were geo-registered in the Universal Transverse Mercator (UTM) coordinate system (WGS 84, Zone 45 N).

3. RESULTS

Regression equations with coefficients of determination are shown in scatter plots in Figure 3 for the selected simple linear models. The strength of relationship of CPA with DBH was the highest, with intercept more than zero. This suggested that the equation is suitable to predict outside the range of delineated CPA (Anderson *et al.*, 2000). However, the intercept terms in the regression equations of CPA with biomass and carbon were found less than zero and unsuitable to predict outside the range of delineated CPA

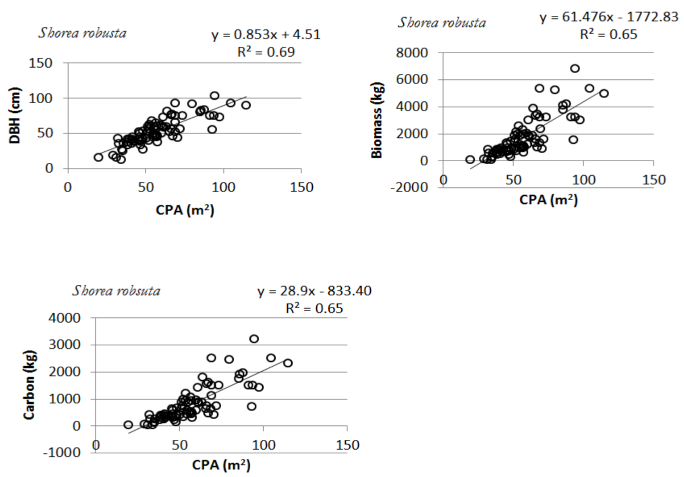

Figure 0: Linear regressions of DBH, biomass and carbon on CPA of standalone trees of *Shorea robusta*

Regression equations with coefficients of determination are shown in scatter plots (Figure 4) for the selected simple linear models. The strength of relationship of CPA with DBH was found the highest. The y- intercepts in all cases were found less than zero. It implied that the equations are not suitable to predict outside the range of delineated CPA (Anderson *et al.*, 2000).

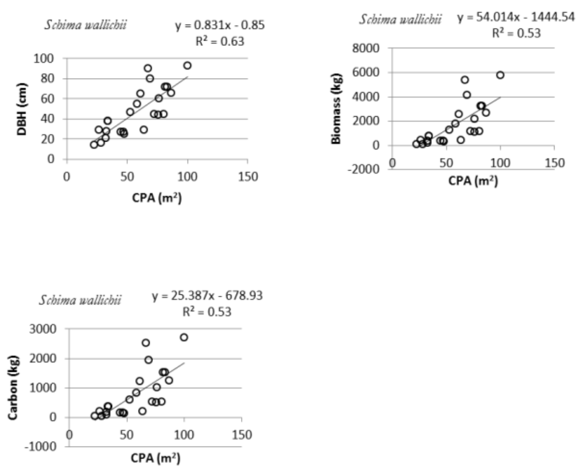

Figure 4: Linear regressions of DBH, biomass and carbon on CPA of standalone trees of *Schima wallichii*

Regression equations with coefficients of determination are shown in scatter plots (Figure 5) for the selected simple linear models. The scatter plots reveal that relationships between the parameters were weak. These plots do not show any distinct nonlinear pattern.

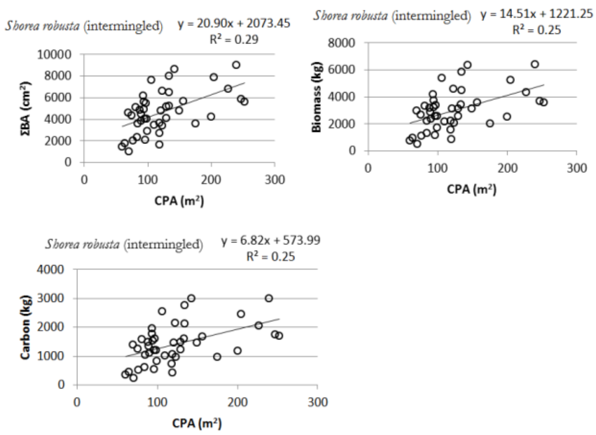

Figure 5: Linear regressions of ΣBA, Σbiomass and Σcarbon on CPA of intermingled canopy trees of *Shorea robusta*

4. CONCLUSIONS

Manually delineated CPA from GeoEye satellite image which is intended to be used to predict above ground tree carbon stock of subtropical broadleaf forest is not having high R^2 to the level that the CPA can be utilized to model or predict carbon stock on an operational base. The identified simple linear regression models having the least error are not applicable for the prediction of above ground tree carbon stock of broadleaf forest in hilly terrain. The vertical projection area of tree canopy is subject to error because of low sun angle and shadow in the scene. This is further exacerbated by the mountain topography of the study area. In addition, manual delineation of CPA has been affected by the fuzziness tree crown boundary in the image.

- **Nevertheless, all the research questions are well answered as follows:**

Is there any relationship between CPA, DBH, biomass and carbon of standalone trees of the dominant species?
There is a linear relationship between CPA, DBH, biomass and carbon of standalone trees of the dominant species. The Pearson's correlation between CPA and DBH was 0.83, 0.80, and 0.86 for *Shorea robusta, Schima wallichii and Terminalia alata* respectively. The correlation between CPA and biomass was 0.80, 0.73 and 0.79 for *Shorea robusta, Schima wallichii and Terminalia alata* respectively. The correlation between CPA and carbon was also 0.80, 0.73 and 0.79 for *Shorea robusta, Schima wallichii and Terminalia alata* respectively. The correlation between them were highly significant ($P<0.001$).

Is there any relationship between CPA, ΣBA, Σbiomass and Σcarbon of intermingled canopy trees of the dominant species?
There is a linear relationship between CPA, ΣBA, Σbiomass and Σcarbon of intermingled canopy trees of *Shorea robusta.* The Pearson's correlation of CPA with ΣBA, Σbiomass and Σcarbon was 0.54, 0.50 and 0.50 respectively. The correlation between them were highly significant ($P<0.001$).

Which regression models best explain the relationship between CPA, DBH, BA, biomass and carbon of standalone and intermingled canopy trees of the dominant species?
Simple linear regression models best explain the relationship between CPA, DBH, biomass and carbon in standalone trees of *Shorea robusta, Schima wallichii,* and *Terminalia alata*. Similarly, simple linear regression models best explain the relationship between CPA, ΣBA, Σbiomass and Σcarbon of intermingled canopy trees of *Shorea robusta*. The precision and predictive accuracy of the selected simple linear models were not high enough to predict carbon.

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