# MAPPING ABOVE GROUND CARBON USING WORLDVIEW SATELLITE IMAGE AND LIDAR DATA IN RELATIONSHIP WITH TREE DIVERSITY OF FORESTS

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**KEY WORDS**: Carbon stock, Canopy projection area, LiDAR derived tree height, Multi-resolution segmentation, Tree diversity

**Abstract:** Forests play a major role in global warming and climate change issues through its unique nature of carbon sinks and sources. Therefore, precise estimation of carbon stock is crucial for mitigation and adaptation of these issues through REDD+ carbon incentive program. This study aims to develop species specific regression model using canopy projection area (CPA) and LiDAR derived tree height for accurate estimation and mapping of carbon stock in tropical forests of Chitwan, Nepal. Pan-sharpened WorldView-2 image and canopy height models (CHM) were used for tree crown delineation to extract CPA and height of the individual trees. Species wise multiple regression models were developed using CPA, Lidar height and field measured carbon stock for carbon estimation of the study area. Shannon diversity index of each community forests (CF) was calculated to find out the relationship between tree species diversity and carbon stock of CF. LiDAR derived tree height was able to explain 76% of variability in field height measurement. Multi-resolution segmentation resulted with overall accuracy of 76% in 1:1 correspondence. Tree species classification resulted in overall accuracy of 58.06% and Kappa statistics 0.47 for classifying six tree species. On average correlation coefficient of CPA and carbon, height and carbon, and CPA and height was found to be 0.73, 0.76 and 0.63 respectively for five dominant tree species. Species wise multiple regression models were able to explain more than 75% of variation in carbon estimation using CPA and LiDAR height for each species. The relationship between tree diversity and carbon stock at CF level was not significant and indicated weak correlation. WorldView-2 satellite imagery and airborne LiDAR data are very promising remote-sensing sources for estimating and mapping species wise above ground carbon stock of tropical forests. Further research is suggested to explore the relationship between tree diversity and carbon stock at a broad scale of various forest types.

## 1. INTRODUCTION

The growing concentration of greenhouse gases (GHGs) in the atmosphere increases temperature of the earth and have raised concerns about global warming and climate change issues. Carbon dioxide ($CO_2$) is one of the main contributors of greenhouse effect in the atmosphere along with other gases. The global atmospheric concentration of $CO_2$ has increased from 280 ppm in pre-industrial era (1970) to 379 ppm in 2005 at an average of 1.9 ppm per year which will further contribute to increase the temperature from 1.8$^{o}$C to 4$^{o}$ C by the end of this century (IPCC, 2007). The sudden increase of $CO_2$ concentration is highly related with anthropogenic causes such as heavy use of fossil fuels, deforestation and degradation of land. Deforestation and forest degradation are responsible for about 20% of GHGs emissions, a major issue for climate change (World Bank, 2010).

Nepal is acknowledged and highly appreciated for its participatory forest management regimes. At present, approximately 39.6% of geographical area of the country is covered by forests, 25% of which are managed by local and indigenous community as a Community Forestry (DoF, 2010). The role of Community Forestry in REDD+ implementation is a central topic of discussion in Nepal's REDD+ process, and it is likely to be an important part both for environmentally effective and equitable approach. Nepal, being a UNFCCC signatory and a member of UN-REDD Program, has recently submitted the Readiness Preparation Proposal to participate in the Forest Carbon Partnership Facility. In order to further participate in the Carbon Finance Mechanism, Nepal has to show its current status of carbon stored by forests and emitted from deforestation and forest degradation (MOFSC, 2009). Therefore, it is crucial to precisely estimate the national forest carbon stocks in terms of biomass and sources of carbon emissions to determine a reference emission level (REL) and to design a robust monitoring, reporting and verification (MRV) techniques for national REDD+ strategies in Nepal.

## 1.1. Overview of techniques for above ground carbon estimation

There are different methods in practice to measure AGB and consequently the carbon stock of forests. Lu (2006) reviewed and summarized some approaches to estimate forest biomass based on field measurements, Remote Sensing (RS) and Geographic Information System (GIS). The AGB can be accurately estimated by destructive sampling (cutting and weighing) but it is not a practical approach because it is extremely costly, time consuming and labour intensive (Brown, 2002). Carbon estimation based on field measurements can be done by the measurements of diameter at breast height (DBH) alone or in combination with tree height which can be further converted to estimates of forest carbon stocks using allometric relationships (Gibbs *et al.,* 2007). Allometric equations statistically relate these measured forest attributes to destructive harvest measurements, and exist for most forests. Additionally, a sufficient number of field measurements are a prerequisite for developing AGB estimation models and for evaluating the AGB estimation results. GIS-based methods require ancillary data such as land cover type, site quality and forest age to establish an indirect relationship for biomass in an area (Lu, 2006). Such methods are difficult to implement because of problems in obtaining good quality ancillary data and the comprehensive impacts of environmental conditions on biomass accumulation (Brown, 2002; Lu, 2006). In RS based method, statistical relationship between satellite extracted tree parameters and ground based measurements is used in biomass estimation (Gibbs *et al.,* 2007).

Principally, optical remote sensing technologies face the problem of frequent cloud cover which limits the acquisition of high quality RS data. In this situation, the use of Radar (Radio Detection and Ranging)/SAR (Synthetic Aperture Radar) becomes a feasible means for acquiring RS data in a given period of time irrespective of weather or light conditions (Ahamed *et al.,* 2011). Radar systems are active remote sensors operating in the microwave portion of the electromagnetic spectrum (ca. 1cm to 10m VHF). It generates their own source of electromagnetic radiation allowing capturing images independently of solar energy (Patenaude *et al.,* 2005). The Radar backscatter returned from the ground and tops of the trees are used to estimate tree height, which are then converted to forest carbon stock estimates using allometry (Gibbs *et al.*, 2007; Toan *et al.*, 2004). Although Radar backscatter has the capability to penetrate the clouds, it poses a saturation problem in tropical forest environments where AGB level generally exceed 200-250 Mg/ha (Ustin, 2004) and sometimes mountainous and hilly conditions also increase the errors (Toan *et al.*, 2004). To overcome this problem, active remote sensing sensor (*e.g.* airborne laser scanning or airborne Lidar) is a promising mapping technique for estimating forest biomass, as no saturation is observed at high biomass levels (Patenaude *et al.,* 2005). Airborne LiDAR also offers the unique capability of measuring the three-dimensional vertical structure of vegetation in great detail which in itself is an advantage over high resolution satellite imagery (Song *et al.,* 2010). Moreover, forest structural characteristics such as canopy heights, stand volume, basal area and aboveground biomass can be accurately estimated directly by Lidar data.

## 1.2. Problem statement and justification

DBH and tree height are crucial forest inventory attributes for calculating timber volume, above ground biomass, site quality and silvicultural treatment scheduling. Measuring of stand height or tree height by current manual photogrammetric or field survey techniques is time consuming and rather expensive (Popescu & Wynne, 2004). DBH cannot be directly retrieved either from very high resolution (VHR) satellite imagery or from low point density Lidar data. Therefore, relationship between DBH, crown diameter/crown projection area (CPA) and tree height should be established from regression analysis so that AGB can be estimated from remote sensing techniques (Popescu & Wynne, 2004). However, crown diameter or CPA can be obtained from VHR satellite imagery whereas tree height can be easily obtained from CHM developed from Lidar data. The combination of VHR optical imagery and Lidar systems permit individual tree and canopy height information to be extracted along with the species, health, and other biophysical tree attributes (Leckie *et al.,* 2003). Besides, the integration of both spectral and Lidar data will be resulted in more accurate forest classification than using either of the data sources independently. Several studies (Andersen *et al.*, 2005; Hudak *et al.*, 2002; Lu, 2006) also showed that the integration of VHR satellite images and airborne Lidar data provides an accurate and efficient measurement of AGB in a variety of forest types and extensively larger areas. Furthermore, Tsendbazar (2011) and Shah (2011), who already done their research in the same geographical location, highly recommended the integration of VHR images such as GeoEye-1 and WorldView-2 with Lidar data for accurate estimation of AGB in the mountainous topography.

The UNFCCC and Convention on Biological Diversity (CBD) aim at addressing the global agenda of climate change and loss of biodiversity. The existence of potential synergies between the two conventions offers opportunities for implementing practices that aim at achieving the objectives of both conventions simultaneously (Caparros & Jacquemont, 2003). The relationship between tree species diversity and above ground carbon stock is of great concern among forest managers interested in estimation and mapping of carbon stock over a short time period and at a local level. But a few studies have been conducted to analyze this relationship. Therefore, it is essential to assess the relationship between carbon stock and tree diversity of the tropical forests since local communities rely on a wide range of tree species for meeting their sustenance needs. Such relationship needs to be better understood while the country is in the process of formulating the National REDD+ Strategy which needs to take cognizance of the issues pertaining to forest management so that the rights of local and indigenous populations can be safeguarded. In other words, a synergistic relationship between REDD+ and biodiversity conservation program should be considered for integrating social and environmental safeguards in REDD+. Thus, this paper aims to develop an approach for accurate estimation of carbon stock using WorldView-2 satellite image and airborne Lidar data and its relationship with tree diversity of tropical forests.

## 2. MATERIALS AND METHODS

### 2.1. Study Area

The study was conducted in Kayerkhola watershed of Chitwan district, Nepal as shown in Figure 1. Geographically, Chitwan district is located in lowland and Siwalik regions of the country which is situated between $27^0$30'51"N - $27^0$52'01 N latitude and $83^0$55'27"E - $84^0$48'43"E longitude in central development region of Nepal. The district is around 70 kilometres south east ($133^0$) of the approximate centre of Nepal and 80 kilometres south west ($260^0$) of the capital Kathmandu. The altitude varies from 300m to 1200m above sea level and is characterized by many steep gorges and slope varies from 30% to 100%. Basically, the study area has three dominant types of forest. They are Sal (*Shorea robusta*) forest, mixed hardwood forest and Riverine Khair-Sissoo forest. Sal is pre-dominant tree species found in the study area and occupies nearly 70% of forest composition. It is commercial woody species of Nepal and mainly found as Terai and hill Sal. Mixed hardwood forest is composed by Sal and other hardwood species. The watershed is inhabited by socially and ethnically diverse forest-dependent indigenous communities such as Chepang and Tamang (ICIMOD, 2011).

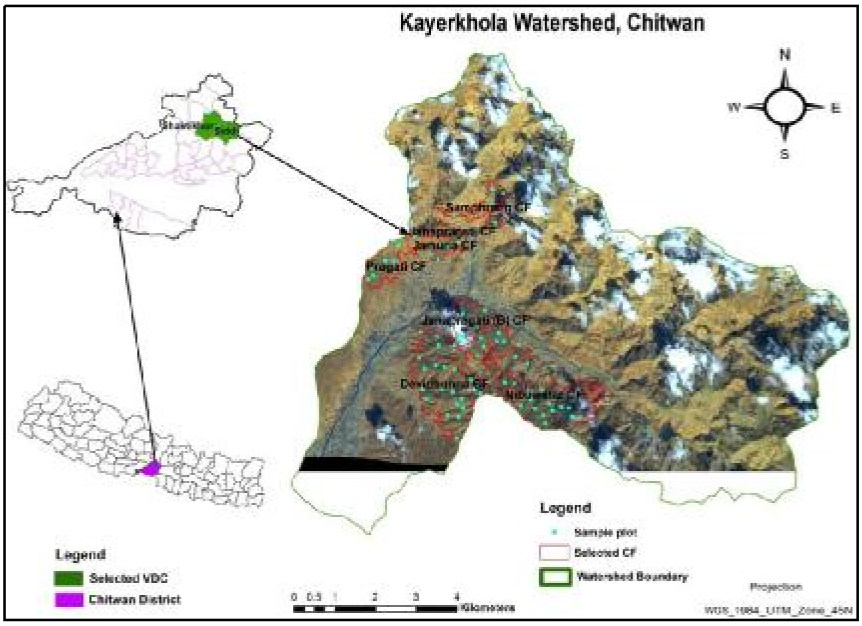


*Figure 1: Location map of the study area.*

### 2.2. Materials

Worldview-2 VHR satellite imagery obtained on 25th October 2010 was used for this study. The 8-bands multispectral of 1.84 cm spatial resolution have been resampled to 2 m, while panchromatic of 46 cm is resampled to 0.5 m for its use. Lidar data were originally acquired for the purpose of national forest inventory of Nepal by Forest Resource Assessment (FRA) project under the Ministry of Forests and Soil Conservation. The data was collected by Arbonaut Oy Ltd., Finland from 16 March to 2 April 2011 (leaf-off season) with Helicopter (9NAIW) at a flight altitude of 2200 m above ground level using Leica ALS50-II Laser scanner with footprint size of 50 cm, average laser beam density 0.8 points $m^{-2}$ and scan frequency of 52.9 kHz. The field work was carried out during September - October, 2012 using standard inventory guidelines developed by Department of Forests. DBH, tree height, crown diameter, canopy density and regeneration were recorded in each concentric circular plot with a radius of 12.62 m, 5.64 m and 2.78 m. Diameter tape is used for DBH measurements while crown diameter and radius of the plot was measured by linear tape. TruPulse 360 B was used to measure the tree height of at least 10 trees reside in the plot.

### 2.3. Methods

The method of this research mainly comprises of three parts: field work for data collection, satellite image and Lidar data processing, object based image analysis (OBIA) and model development. Panchromatic and MSS image of Worldview-2 were co-registered to intensity image obtained from Lidar point cloud. Co-registered panchromatic and multispectral images of WorldView-2 were fused to create pan-sharpened VHR image which was further smoothened to remove the noise. The Lidar data was further processed to obtain the CHM by subtracting the digital terrain model (DTM) from the digital surface model (DSM). Both the pan-sharpened image and CHM layers were used for tree crown delineation and later the canopy projection area (CPA) and height of the individual tree can be extracted. Accuracy assessment of segmentation was performed and later used for species classification. After that, multiple regression models were developed using CPA and height as explanatory variables for carbon estimation/mapping. Field measured tree parameters were used to analyze tree species diversity and to estimate carbon stock of each tree and also for accuracy assessment of CPA, Lidar derived tree height and regression models. Species wise carbon stock of the study area was calculated and mapped using regression models developed for each major species. The relationship between tree diversity and carbon stock was assessed from Pearson's correlation analysis. A flow diagram showing the research methodology is illustrated in Figure 2.

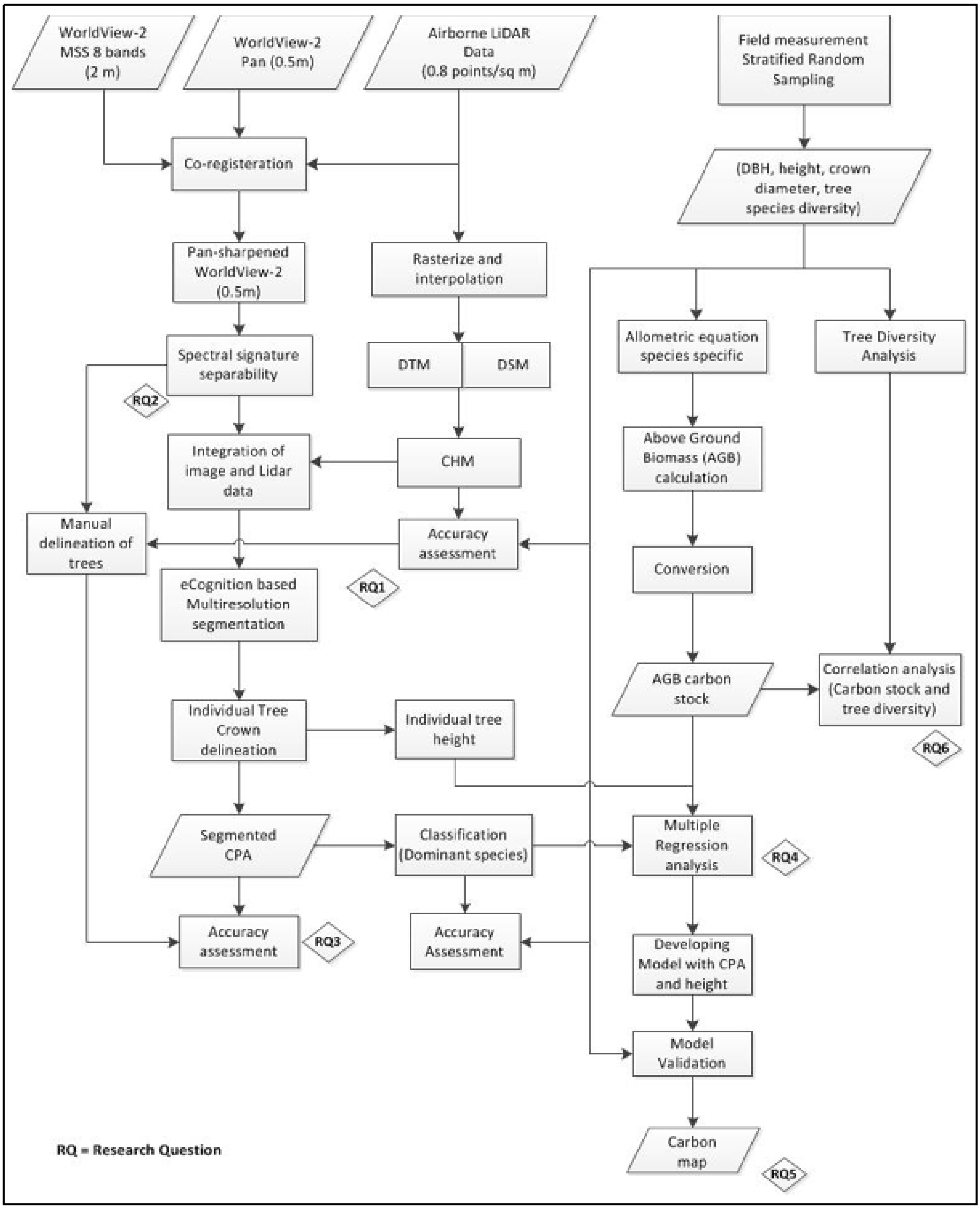


*Figure 2: Flow diagram of research methods*

## 3. RESULTS

### 3.1. CHM generation from Lidar data

Lidar data was processed to obtain the CHM as shown in Figure 3. The extracted ground points were interpolated for generating a DTM, while DSM was created by interpolating the first return points which are often located on top of the trees (Figure 3 (a) & (b)). Figure 3 (c) shows the CHM which was obtained from subtraction of DTM from DSM. The actual tree height in 3D view is shown in Figure 3 (d).

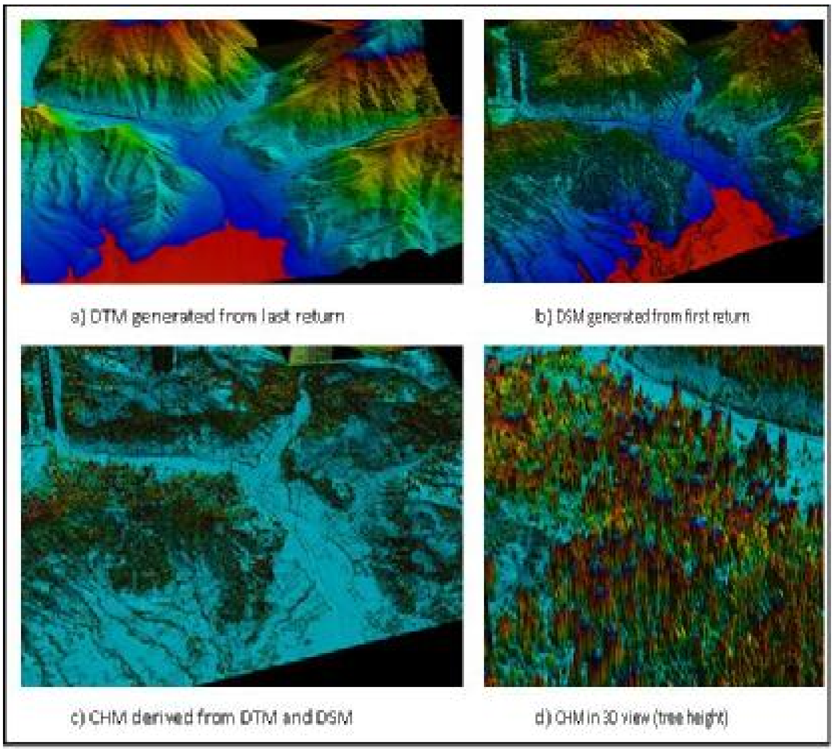


*Figure 3: Lidar-derived images a) DTM, b) DSM), c) CHM, d) CHM visualized in 3D*

### 3.2. Accuracy assessment of Lidar derived tree height

Tree height collected from the field and the one derived from Lidar was evaluated using Pearson's correlation coefficient and one way ANOVA. A total of 205 tree height measured in field and corresponding Lidar height extracted from the manual delineation of tree crown were used as a sample dataset. On average mean value of Lidar derived height was 0.14 m greater than the field height, which was explained by 111 trees overestimated and 94 trees underestimated. Best of fit between field and Lidar-derived tree height was analyzed in R stat. Summary of regression equation was depicted in Figure 4. Field height was considered as independent variable, whereas Lidar derived height as dependent variable for linear regression. R square and adjusted R square showed that Lidar derived height was best predicted at 76 % with 3.84 m RMSE. Pearson's Correlation test and one way ANOVA was applied to test the hypothesis and conclusion made that there is no significant difference between height measured from field and derived from Lidar.

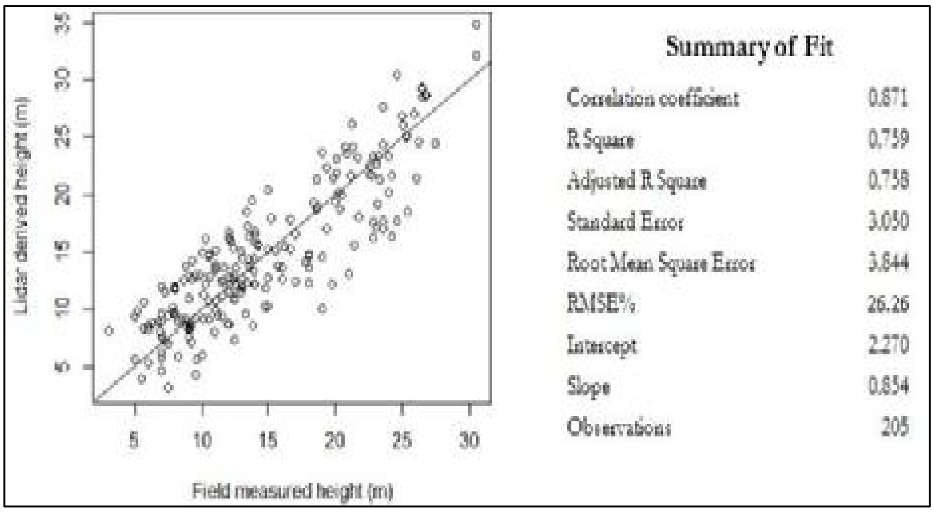


*Figure 4: Scatterplot and summary of fit for tree height measurements*

### 3.3. Image segmentaion

Image segmentation was done in two steps. Firstly, multi-resolution segmentation was performed in panchromatic image by using the best multi-resolution segmentation parameter combinations (scale, shape and compactness) for each subset area of forest. The best segmentation parameter combination for panchromatic image, after an iterative process, was found at scale 21, shape 0.8 and compactness 0.6. Secondly, the output of panchromatic segmentation was used as a thematic layer to segment the pan-sharpened image and CHM in order to get the same size and shape of crown. Convolution filter of 5*5 was used to filter pan-sharpened image as well as CHM. Shadow, cloud and non-tree cover was masked out from the image before segmentation process so that the overestimation of the crown projection area can be avoided. The CHM and pan-sharpened images were used as a different layer for segmentation. The different weights were given to the NIR1, NIR2, Red-Edge and CHM layers. The filtered image was segmented using the same scale, shape and compactness as used in the panchromatic band. Rule set for segmentation was applied according to the brightness of near-infrared band and height threshold of CHM. After watershed transformation, morphology and refining the shape of tree crown, the final output of segmentation was obtained as shown in Figure 5.

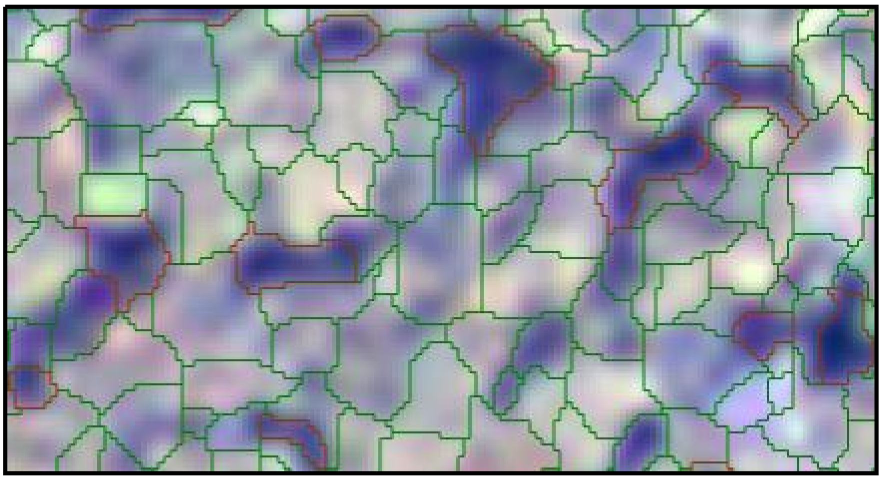

*Figure 5: Segmentation of pan-sharpened image and CHM*

### 3.4. Validation of segmentation

Validation of tree crown segmentation was obtained using accuracy measures of D and 1:1 spatial correspondence for 344 manually delineated reference tree crowns. Figure 6 shows accuracy measures of D of segmented crowns for each CF. Overall, the over-segmentation, under-segmentation, and D value were 0.29, 0.34, and 0.33, respectively. Total accuracy of tree crowns delineation was about 67% which means 33% of segmentation error. In Jamuna CF, D value was the lowest (0.29), as it implied a lower over segmentation error, whereas Janpragati and Pragati CF have a higher D value of 0.40 and 0.39 respectively.

For accuracy measure of 1:1 spatial correspondence, matching of reference and segmented polygons was observed on one to one basis. Out of 344 reference polygons obtained from manual delineation, only 261 automatic polygons obtained from segmentation had one to one relationship. Put differently, only 76% of the total reference crowns were matching to the segmented tree crown thus the reported accuracy of segmentation was 76%.

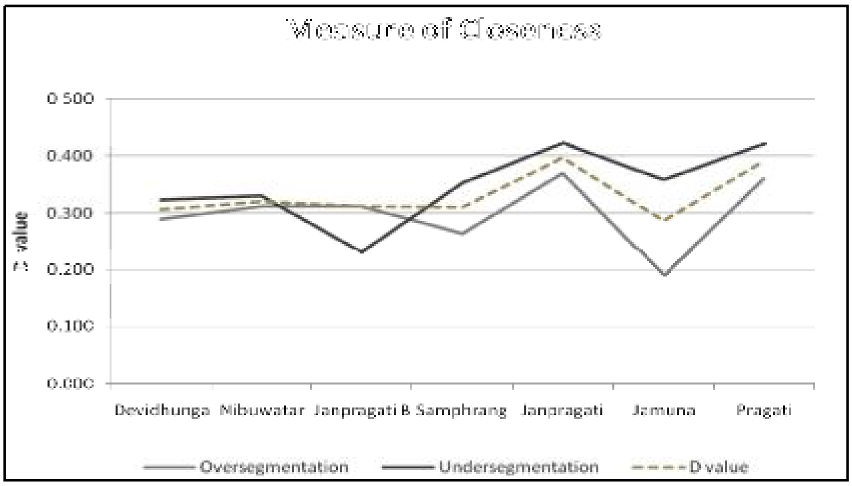


*Figure 6: Measure of closeness (D value) for accuracy assessment of segmentation*

### 3.5. Image classification and accuracy assessment

Segmented tree crowns were classified into six major dominant species *i.e. Shorea robusta, Lagerstroemia parvifloa, Terminalia tomentosa, Schima wallichii, Mallotus philippinensis* and one general class so called others. Classification was performed on the pan-sharpened image using nearest neighbourhood classifier in eCognition Developer 8.7. All seven CFs were segmented in 4 clusters *viz.* Devidhunga, Nibuwatar, Janpragati B and Samphrang, Jamuna, Janpragati and Pragati because all above mentioned species were not common in each CF and eCognition could not process large dataset at one run. Therefore, the output segmented image was classified for each of four clusters with different number of species. A total of 228 observations were used to train the image and 101 observations (Table 1) to assess the accuracy of the classified image. Table 1 shows the number of species classified, an overall classification accuracy and Kappa statistic for each cluster.

*Table 1: Summary of classification accuracy assessment*

| Name of CFs | Number of species classified | Reference/ classified Totals | Correctly classified | Overall Accuracy (%) | Kappa statistic |
|---|---|---|---|---|---|
| Devidhunga | 6 | 31 | 18 | 58.06 | 0.47 |
| Nibuwatar | 5 | 27 | 15 | 55.56 | 0.43 |
| Janpragati B | 3 | 11 | 8 | 72.73 | 0.62 |
| Samphrang, Janpragati, Jamuna and Pragati | 5 | 32 | 20 | 62.50 | 0.48 |

The classification of CFs resulted as Janpragati B CF with the highest overall accuracy and Kappa statistic with three species whereas Nibuwatar CF implied a lowest rank based on an overall accuracy and Kappa statistics with 5 numbers of species classified. 18 out of 31 reference polygons of Devidhunga CF were correctly classified with overall accuracy of 58.06% and 0.47 Kappa statistics and six species could be classified. A moderate overall accuracy (62.50%) and Kappa statistics (0.48) was obtained from group of four CFs with five classified species.

### 3.6. Model calibration and validation

Multiple regression models were developed for five tree species in such a way that the carbon stock can be properly estimated. CPA and height were used as explanatory variables to estimate the carbon stock of individual trees. Linear regression model in Log form as shown in Equation 1 was developed for each species because it can describes the relationship between CPA, height and carbon stock. The relationship between these variables was also significant at 95% confidence level. Besides, in order to avoid multi-collinearity amongst the explanatory variables (*i.e.* CPA and height), collinearity test was done using a variance inflation factor (VIF) and it was less than 10 for all five species. Summary statistics and regression coefficient of variables is given in Table 2.

$\text{Ln Carbon} = \beta_0 + \beta_1 * \text{Ln (CPA)} + \beta_2 * \text{Ln (Height)}$........Equation 1: Multiple regression model

Where,

Ln is natural logarithm to the base 2.71828
Carbon is above ground carbon stock per tree in Kg
$\beta_0$ is intercept
$\beta_1$ is coefficient of CPA
$\beta_2$ is coefficient of Lidar derived tree height

*Table 2: Regression coefficients and summary statistics of model*

| Species | $\beta_0$ | $\beta_1$ | $\beta_2$ | R Square | Adjusted R square | Standard error | Observations |
|---|---|---|---|---|---|---|---|
| *Shorea robusta* | -0.877 | 0.597 | 1.873 | 0.66 | 0.65 | 0.90 | 62 |
| *Lagerstroemia parviflora* | 0.205 | 0.370 | 1.494 | 0.60 | 0.57 | 0.58 | 31 |
| *Terminalia tomentosa* | -0.126 | 0.458 | 1.848 | 0.82 | 0.80 | 0.37 | 18 |
| *Schima wallichii* | -0.144 | 1.124 | 0.883 | 0.75 | 0.73 | 0.61 | 25 |
| Others | 0.044 | 0.616 | 1.396 | 0.64 | 0.63 | 0.57 | 51 |

Model for each species and regression coefficient was tested using F-test and t-test respectively. All the models and regression coefficients showed statistically significant at 95% confidence level.

Multiple regression models were validated using randomly selected 30% of independent datasets (total 77) in case of each species as described in Table 3. Observed and predicted carbon stocks from regression models were plotted against each other and co-efficient of determination ($R^2$) was calculated to see the goodness of fit. A root mean square error (RMSE) and RMSE percentage (average field measured carbon divided by RMSE) were calculated. *Shorea robusta* described the best fit of model with 94% of variation explanation and 24.85% of RMSE. For all species $R^2$ values was greater than 75% which means carbon stock of individual trees estimated by the regression model were able to explain up to 75% the carbon stock measured from the field. However, model error RMSE and RMSE% varies from 22.48 to 289.68 kg/tree and 24.85 to 49.75% respectively depending on the species and calculated mean carbon stock of individual tree.

*Table 3: Summary of model validation and RMSE (kg/tree)*

| | Coefficient of determination | Calculated mean carbon | RMSE | RMSE % | Observations |
|---|---|---|---|---|---|
| *Shorea robusta* | 0.94 | 849.39 | 211.12 | 24.85 | 25 |
| *Lagerstroemia parviflora* | 0.78 | 80.98 | 22.48 | 27.77 | 11 |
| *Terminalia tomentosa* | 0.76 | 865.93 | 289.68 | 33.80 | 10 |
| *Schima wallichii* | 0.84 | 198.21 | 75.24 | 37.96 | 11 |
| Others | 0.78 | 163.36 | 81.27 | 49.75 | 20 |

### 3.7. Comparison of RS based and Field inventory carbon stock estimation

This paper attempts to compare above ground carbon stock estimated by RS/GIS method with field based inventory. Six CFUGs were chosen for the comparison which showed relatively higher carbon stock estimation from RS/GIS method than the field based inventory. Devidhunga, Nibuwatar and Pragati CFs have higher carbon stock while Janpragati and Jamuna CFs have slightly lower stock than field inventory method as shown in Figure 7. In case of Samphrang CF, it showed almost same amount of carbon stock estimated from RS and field inventory. However, mean difference between two measurements was 37.55 $MgCha^{-1}$ for the selected community forests.

There might be several reasons for difference in carbon stock estimation from RS/GIS and field inventory method. The selection of allometric equation could be one of the reason for variation of carbon estimation from field and RS method because in field inventory method above ground carbon was estimated from general allometric equation developed by Chave *et.al.,* (2005) using DBH and height whereas multiple linear regression using CPA and height of the tree were used for AGB estimation by this study. RS/GIS based estimation was carried out for species wise carbon stock whereas field based inventory was only for trees as general. Moreover, tree crown segmentation error, overestimation of individual tree height and GPS error were the main sources of variation in carbon stock estimated from RS/GIS methods while personnel and instrumental error might be the sources of error in case of field based inventory.

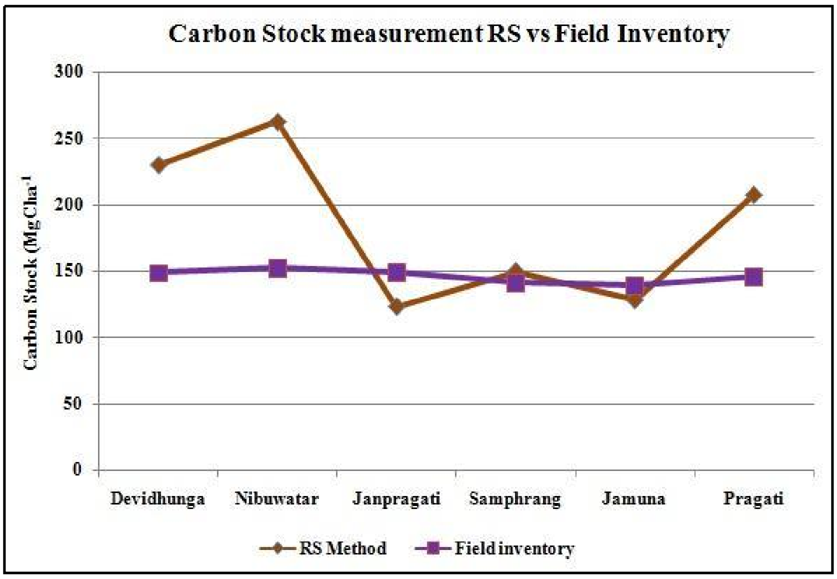


*Figure 7: Comparison between RS based and field based carbon stock estimation*

## 4. DISCUSSION

The research showed that 54% field measured tree height was overestimated and 46% was underestimated by Lidar derived tree height. The percentage difference of overestimation and underestimation of tree height is very small and there is a tendency for the heights of smaller trees to be overestimated and those of tall trees to be underestimated. Different types of error can be attributed due to the following reasons: interpolation of the point cloud data into a grid-based canopy height model, precision of laser height measuring instruments (TruPulse 360 B) and random errors introduced by the field personnel during height measurements. Complexity of the landscapes (undulating, rugged, steep slope) and uneven forest age may contribute to the error propagation found in this study. Noise could be one of the prominent reasons for overestimation of tree height because maximum height of the tree on the ground was up to 37 m but Lidar height showed beyond this range. This may have occurred due to the low quality (unfiltered) raw Lidar data. Since, this study area is natural broadleaved forest type with several age gradation and different species composition, multi-resolution segmentation technique was performed to fully explore the information content of VHR satellite images. However, relatively lower accuracy was obtained when assessed from measure of closeness “D value”. Overall D value (segmentation error) in this research was higher mainly due to under segmentation (0.34) of big trees and large number of clumped trees. This might be due to improper splitting up of bigger crowns into actual trees using the multi-resolution segmentation and also images still affected by the cloud, huge light shadow and distortion.

In terms of values of $R^2$, it indicated that on average carbon stock can be predicted with 82% variability and 35% RMSE from the model developed for each species. Thus, it can be highlighted that carbon stock can be predicted more accurately from regression models of this study which composed of both CPA and height than the use of CPA or tree height alone. Result of this study is comparable to the study done by ICIMOD, (2011) in the same study area *i.e.* Kayerkhola watershed. They reported a mean above ground carbon stock of 153.10 Mg C per ha which is lower estimate than our study of 216.38 Mg C per ha. However, in two studies undertaken by Baral *et al.,* (2009) -70 $MgCha^{-1}$ and Baral (2011) - 96.6 $MgCha^{-1}$ in the same forest types of Nepal were also found to be much lower than this study. Estimation of carbon stock of several tree species using species specific allometric equation can be one of the reasons for higher estimation than the previous studies because they have used different allometric equation for different studies. Nevertheless, higher RMSE and RMSE percentage calculated for each species showed error in model which could also be attributed for higher estimation.

Understanding the relationships between biodiversity and carbon sequestration owing to international interest is important aspect both in preserving terrestrial carbon pool and conserving biodiversity. Although this study showed a weak relationship between tree diversity and carbon stock at local level, attention should be given to the conservation of tree species diversity along with the carbon stock enhancement of natural forest. Focusing only to afforestation or reforestation program for forest carbon could be counterproductive to biodiversity conservation, because forests are managed as “carbon farms” with the application of intensive silvicultural management that could homogenize diverse forests of the country. Conservation of forests having large amount of carbon stocks is also a valuable way to reduce $CO_2$ emission as it may be more beneficial than afforestation in the short term. In this context, REDD+ provides unique financing opportunity for conservation of natural forests along with biodiversity conservation. Hence, attention should be given not only for the carbon stock measurement but also for the conservation of tree species diversity which will further preserve our forests and reduce carbon emissions.

## 5. CONCLUSIONS & RECOMMENDATIONS

WorldView-2 satellite imagery and airborne Lidar data are very promising remote-sensing sources for estimating and mapping the above ground carbon stock of tropical broadleaved forest in Nepal. The species specific regression models developed from CPA and height of the tree using OBIA is the main technique to estimate the carbon stock of study area. With respect to this approach, following conclusions were made to address the research questions (RQ) as indicated in Figure 2 of methods subsection.

*How accurately the height of individual trees can be estimated from the Lidar derived CHM?*

The result showed that Lidar derived tree height was able to explain 76% of field measured tree height with RMSE of 3.84 m.

*How accurately WorldView-2 image can differentiate tree species on the basis of spectral separability?*

Transformed divergence among six major dominant tree species showed the best average separability of 1970.99 which indicated a good separation among the species. NIR1, NIR2 and Red-Edge of WorldView-2 image were found to be the best bands for spectral separabilty of different tree species in comparison to other visible bands of the image.

*How accurate is the segmentation of CPA from WorldView-2 image in combination with Lidar data?*

Two types of accuracy assessment for segmentation of image were applied in this study *i.e.* measure of closeness (D value) and 1:1 spatial correspondence. Overall D value for the study area was found to be 0.33 with 0.29 over segmentation and 0.34 under segmentation that means there was 33% error (67% accuracy) in segmentation whereas 76% accuracy of segmentation was obtained from 1:1 spatial correspondence.

*What is the relationship between CPA, height and carbon stock of dominant tree species?*

Pearson’s correlation analysis indicated that there is a strong positive correlation ($r>0.70$) between height and carbon stock for all five tree species. However, on average correlation coefficient of CPA and carbon, height and carbon, and CPA and height was found to be 0.73, 0.76 and 0.63 respectively.

*How much carbon is stored by each major type of tree species in the study area?*

A total of 188485 Mg C carbon was estimated in the study area with an average of 216 Mg C per ha. Approximately 60% of carbon stock (112637 Mg C) was stored by *Shorea robusta* with 129 Mg C per ha.

*What is the relationship between tree diversity and carbon stock of each community forests (CF)?*

There is no significant relationship between tree diversity and carbon stock of each CF of the study area. Pearson’s correlation test and F-test did not indicate any statistically significant relationship between tree diversity and carbon stock of forest at 95% confidence level.

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