Improving Aboveground Carbon Stock Mapping Using Lidar and Optical Remote Sensing Data in Mountain of Nepal

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KEYWORDS

LIDAR, Segmentation, Classification, Carbon Stock

ABSTRACT

There is a demand for methods to accurately estimate above ground carbon stock in response to climate change mitigation action. The study aims to develop a method to accurately estimate and map above ground woody carbon stocks using airborne LIDAR data (0.8 point/m2) and optical images (0.45m resolution) acquired over the mountains in Central Nepal. Canopy Height Model (CHM) was generated using LIDAR first return and last return. RMSE of 2.8m was obtained for LIDAR derived height. Object based image analysis (OBIA) and nearest neighbor classification methods were used to retrieve individual tree crown area and tree species (Shorearobusta and others) information. Segmentation accuracy was 76.2% based on 1:1 correspondence andthe overall classification accuracy was 75.86%. Multiple linear regression models which showed the lowest relative RMSE36.8% (Shorearobusta) and 32.4% (others)were used to estimate carbon stocks of the study area. The total amount of carbon stocks in the study area was approximately 89.45 MgCha-1.

1. INTRODUCTION

Forests play crucial role in global carbon cycle as they act as sink as well as source of carbon (Muukkonen et al., 2007). They hold more than 60% of the carbon contained in the aboveground biomass and about 45% of the carbon contained in soils, roots and litter at a global carbon scale (Dixon et al., 1993). Reducing deforestation,afforestation, and reforestation are therefore mitigation measures for global climate change (Hunt, 2009). Reducing Emissions from Deforestation and Forest Degradation (REDD+) implementation is one of the core component of Paris Agreement (COP 21) (UNFCCC, 2016) and is a climate change mitigation action. Reliable baseline statistics on national forest carbon stocks and sources of carbon emission is required to establish a national reference scenario and to implement REDD+. Therefore, there is a need to develop a robust method which can accurately estimate forest above ground biomass (AGB) and its carbon stocks (Thapa et al, 2015). Integrating remote sensing and field measured data provide important insights on AGB estimation of forest.

Several studies have already been done on estimation of ABG using remote sensing and field measurements (Saatchi et al., 2011, Thapa et al., 2016, Flores et al., 2019). NOAA AVHRR and MODIS (Dong et al., 2003; Baccini et al., 2004) have been used for biomass estimation at global and continental scale. Coarser spatial resolution data for forest AGB estimation was found to be unsuitable due to mixed pixels and the huge difference between the support of ground reference data and pixel size of the satellite data (Muukkonen et al., 2007).AGB estimation using medium resolution satellite imagery such as Landsat TM at national and regional level showed data saturation, mixed pixels and cloudy weather problems (Lu,2005; Steininger, 2000). Very high resolution (VHR) images such as aerial photograph, satellite images such as Quickbird, IKONOS, WorldView and GeoEye images can detect individual tree crowns (Gonzalez et al., 2010). In addition, crown density and species identification had been done using high resolution data (Katoh et al., 2009) while some studies reported AGB estimation relating DBH to tree crown area delineated using VHR images (Hirata et al., 2009; Song et al., 2010). However, models based on onlycrown area (CPA) and DBH are often insufficientto estimate biomass accurately because these models missed tree height information which is crucial parameter for biomass estimation. Height varies for same DBH of trees which eventually misguides AGB estimation. Thus, height of trees should be considered for accurate estimate of biomass. In addition, intermingled trees cannot be separated even with high resolution images which cause error in individual tree crown delineation and eventually leads inaccurate AGB estimation (Hirata et al., 2009; Palace et al., 2008). If the intermingled trees are of the same species, this might have less impact on AGB as wood density remains same. However, this might not always be the case in mixed sub-tropical forest. LIDAR data can separate intermingled tree crowns based on their tree tops as it gives tree height information (Thapa et al., 2015).

Optical remote sensing data lacks height information. To overcome this, airborne LIDAR data can be used which provides tree height information. Severalstudies (Asner et al., 2012; Kronsederet al., 2012; Thapa et al., 2015) found accurate estimation of AGB using LIDAR data. Integration of LIDAR data with optical images have shown further improvement in accuracy of AGB estimation thereby improving individual tree crown delineation and forest type classification (Leckieet al., 2003; Holmgren et al., 2008; Karna et al., 2015, Wangda et al., 2019).More studies on AGB mapping are required over varying geographic areas as forest structure and associated environment varies in large geographic space. Such studies are still lacking in the unique geographic characteristics of Nepal, therefore, the study aims to develop a method to accurately estimate and map above ground woody carbon stocks using airborne LIDAR and optical images acquired overthe mountains in Central Nepal.

2. STUDY AREA AND DATA USED

Our study area is located in Ludikhola Watershed which lies in southern part of GorkhaDistrict, Nepal (Figure 1). The watershed covers 1888 ha of forest area with elevation ranging from 318 m to 1714 m (Shrestha et al., 2014; REDD, 2011) having sub-tropical forests. The watershed consists of 31 community forests (CFs). The study was carried out only in five CFs, i.e.,Ludidamgade, Birenchok, Kuwadi, Chisapani and Shikhar. These CFswere chosen as representative of sub-tropical forests of Nepal, and based on data availability and accessibility.

LIDAR data was acquired within 16 March to 2 April 2011 with point density of 0.8 point/m^2 on average. High resolution optical camera was mounted in the same platform as LIDAR which acquired optical images at 0.45 m resolution (Arbonaut 2012).

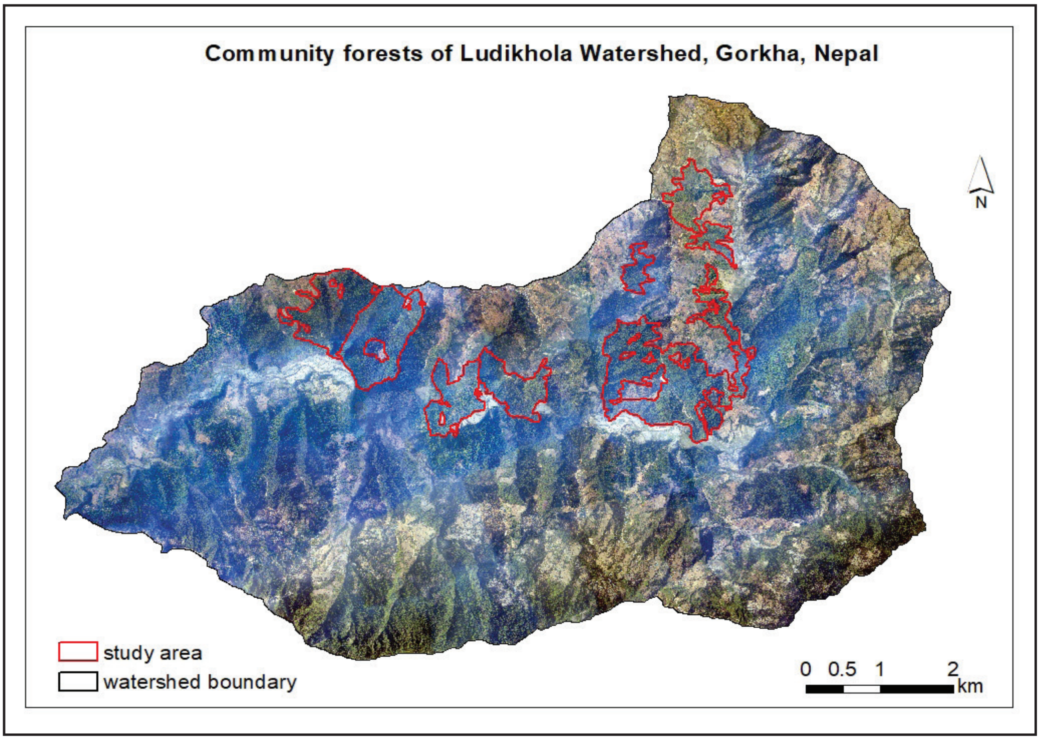


Figure 1: Location of study area

3. METHODS

3.1 Field work

Stratified random sampling, as per the Community Forest Inventory Guideline of Nepal 2004was adopted for this research as it ensures samples are being spread out over the entire study area and gives more precise estimates of forest parameters (Husch et al., 2003). The field work was carried out in September-October 2011. Circular plots with radius 12.62 m and plot area of 500 m^2 were used. Information on intermingled trees and forest parameters such as DBH, height, crown diameter, crown density and species were collected for each plot in the field.

3.2 Trees delineation

Trees identified on the field were manually delineated on 3×3 low pass filtered in the optical image. Crown diameter measured in the field was used as reference to correctly delineate the tree.Only 294 trees were recognized on the image and were manually delineated. The delineated tree crown areas were used to extract the height of the trees from the LIDAR data.

3.3 Canopy height model development and validation

Canopy height model (CHM) can be generated by subtracting Digital Terrain Model (DTM) from Digital Surface Model (DSM) which can be directly related to the height of the trees (Asner et al., 2012; Kim et al., 2010; Thapa et al., 2015). DTM represents bare ground surface whereas DSM represents ground surface including all objects on it (Heritage et al., 2009). The DTM was generated from the last returns of the LIDAR pulse which describes ground surface. Similarly,the DSM was generated from the first canopy return of the LIDAR pulse which describes the canopy surface. The available LIDAR data was in the form of point cloud which was processed using Lastoolsto develop DTM and DSM.The obtained CHM was then filtered to surpass the outliers.LIDAR derived height was validated with field measured heightinformation by computing regression coefficient of determination (R^2) and root mean squared error (RMSE).

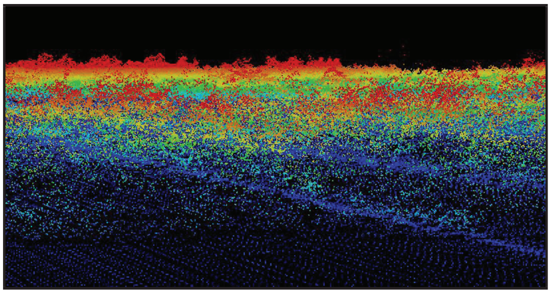


Figure 2 Point cloud (different color shows height variation of the object)

3.4 Optical image segmentation and validation

Optical image segmentation was required to obtaincrown projection area (CPA) of individual tree. Several studies (Kim et al., 2010; Leckie et al., 2003; Song et al., 2010; Karna et al., 2015) have shown individual tree crown delineation using high resolution images with segmentation techniques. We have chosen chessboard segmentation and region growing segmentation methods in eCognition Software. Grid size of two by two pixels was used for chessboard segmentation. Window size of 5×5 was given for region growing as average crown diameter measured in the field was approximately 4 m. Basic and advanced reshaping of tree crown segments were done using watershed transformation and morphology techniques to refine individual tree crown delineation. In this study, two segmentation accuracy measures were applied i.e. Relative Area Measures (Clinton et al.,2010) and 1:1 correspondence (Zhan et al., 2005). These measures wereused when manually delineated and automatic segments are available. Over segmentation, under segmentation, and segmentation goodness (D) weredefined according to Clinton et al. (2010).

3.5 Segmentation assessment for intermingled trees

Segmentation using both images (CHM and optical image) separates intermingled tree accurately. However, segmentation were visually checked with reference to field data. If there are two segments for two trees which were found to be intermingled in the field, then intermingled trees are considered separated.

3.6 Tree species classification and accuracy assessment

Nearest neighbour classification algorithm was applied for tree species classification. Though *Shorearobusta*, *Schimawallichii, Castanopsisindica*and *Rhuswallichii*tree species were found in the study area, classification was done only into two classes i.e. *Shorearobusta*and others. This is because most of the trees identified on the image were *Shorearobusta* and there were not enough samples for *Schimawallichii, Castanopsisindica*and *Rhuswallichii*on the image. About 70% of the samples were used for classification and remaining 30% were used for validation.

3.7 AGB and carbon stock calculation

Allometric equation (Eq. 1) developed for tropical moist forest by Chave et al. (2005) was used to calculate AGB as site specific allometric equations were not available.

…………(1)

Where,

AGB = above ground biomass [kg]

ρ = wood specific gravity [gm/cm^3]

D = tree diameter at breast height (DBH) [cm] and

H = tree height [m]

Wood specific gravity for *Shorearobusta* is 0.88 gm/cm^3 and for others is 0.72 gm/cm^3 (Shrestha et al., 2014). Then, carbon stock of the tree was calculated from AGB using conversion factor 0.47 (IPCC, 2003).

3.8 Regression models and validations

Models based on linear relationships between carbon and CPA, carbon and height, and carbon, CPA and height were developed. Variation Inflation Factor (VIF) was calculated to checkmulticollinearity among the variables. VIF value above 10 indicates that there will be effect of multicollinearity on the model (Obrien, 2007). Only trees which had one to one matching of the segments and correctly classified were taken for model development and validation. Outliers were removed which is the prerequisite of the regression models (Mora et al., 2010). Thus, total number of sample data becomes lesser than the trees that were initially identified on the image. Only 239 trees were used for model development and validation. Carbon calculated from the field data and carbon predicted by the model were compared to validate the models. Models performance were evaluated with coefficient of determination (R^2) and root mean squared error (RMSE).

3.9 Carbon stock mapping

Multiple linear regression models were developed for both *Shorearobusta* and other species to estimate the amount of carbon stocks in the study area. Relative RMSE for each model was reported.

4. RESULTS AND DISCUSSION

4.1 CHM preparation and accuracy assessment of LIDAR derived height

CHM showed that the tree height in the study area is upto40 m. LIDAR derived height was compared with field measured height using linear regression modelin whichcoefficient of determination (R^2) was 0.74 and RMSE was 2.8 m. LIDAR derived tree height underestimated field measured tree height by 0.98 m on average. The error could be because of low point density (0.8 point/m^2 on average) or tree height measurement errors induced by the equipment in the field. Due to the low point density, there is less probability that laser returns hit the true tree top of a tree (Suarez et al., 2005). This leads to the variation in LIDAR derived height with field measured height. Other studies also reported underestimation of ground measured tree height (Leckie et al., 2003; Saurez et al., 2005) although these studies used higher point density LIDAR data compared to the data used in this study.This could be due to coniferous forests which were their study areas in both cases. The crowns of coniferous trees have a triangular shape (Figure 3a). Compare to this, the crowns of deciduous trees found in CFs of Ludikhola Watershed are relatively flat leading to less variation in height from tree top to the edges of the crowns (Figure 3b). Due to the crown shape in coniferous trees, laser returns hitting the true tree top and those hitting the edges have a higher variation in height than in deciduous trees. Thus, in this study with low point density the underestimation is not high compared to the studies (Leckie et al., 2003; Saurez et al., 2005). In addition, the gridding process might introduce error into the CHM through the interpolation method and the grid spacing chosen (Smith et al., 2004). Canopy height underestimation might be due to the laser pulse penetration into the canopy before reflecting a signal and the signal might not be detected by the scanner as a first return (Gaveau et al., 2003).

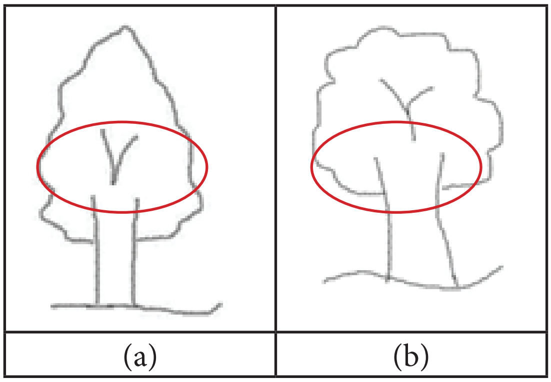


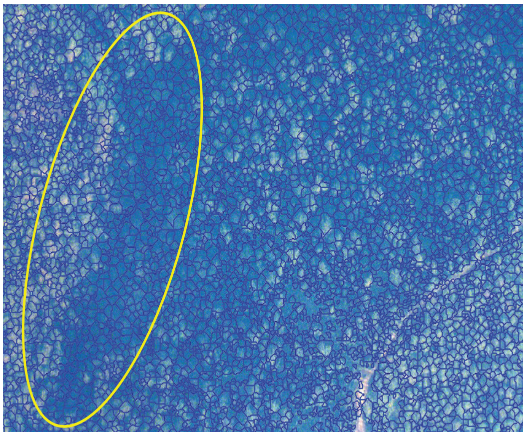
Figure 3: Crowns shape (a) coniferous tree (b) deciduous tree

4.2 Tree crown delineation and accuracy assessment

For the all delineated tree crowns of the study area, over segmentation was 0.29, under segmentation was 0.33 andD value was 0.31. For the accuracy measures of 1:1 correspondence, manually delineated tree crowns and automated segments from segmentation were assessed by matching on one to one basis. On the basis of this accuracy measures, overall segmentation accuracy was 76.2%.

Both images (CHM and optical image) were used in order to assign the classes trees and others (shadow, bare land). The use of CHM in this step helped to extract trees in shadow area (Figure 4) which would be missed if only reflectance values were used. The use of height information helped to separate trees from other vegetation (shrubs and herbs). In this regard, the use of height information for tree crown delineation helped to eliminate most of the commission errors (delineating shrubs or other ground vegetation as trees) that often occur in open forest area with optical imagery. Lopped trees were filtered using height information.

a. Shadow area



b. Segments on shadow area

Figure 4: Digital camera image showing shadow area and segments on the shadow area

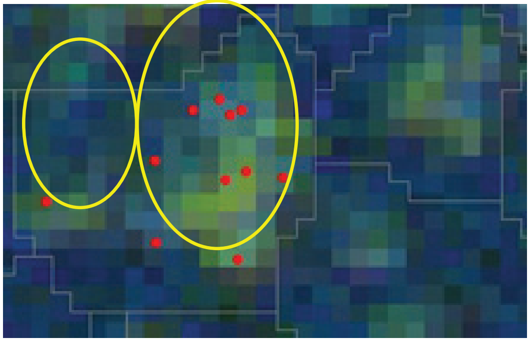
Both commission and omission errors were found in the segmentation. Omission errors occurred due to intermingled trees whereas commission errors were due to irregular shape of the tree crowns where an individual branch may create falsetree tops, so there seems to be two trees instead of one. Segmentation accuracy in this study was improved as compared to Shah (2011).The improvement could be due to the addition of height information in the segmentation as similar to Kim et al. (2010).

4.3 Image classification and accuracy assessment

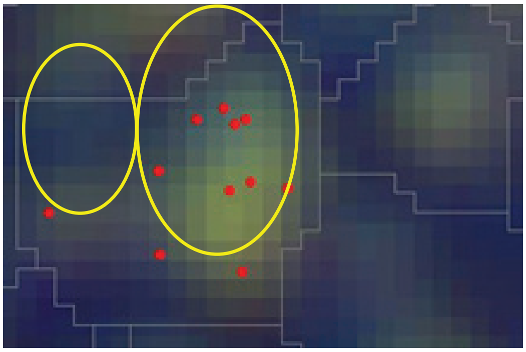
Trees were classified into two groups i.e. Shorea robusta and others. Overall classification accuracy was 75.86%. The accuracy might be affected by quality of crown delineation (Ke et al., 2010), the spectral information being used (ITC, 2010) and shadow due to high hills. Shadow was prominent due to the topography of the study area which led to variation in brightness values of trees even for same species. Eventually, this has affected in crown delineation and classification. The accuracy is lower than Ali et al. (2008) which achieved 86% overall classification accuracy for two species using different multi-spectral imagery (4 bands) and higher resolution LIDAR data (16 points/m2).

4.4 LIDAR data in separating intermingled tree crowns

In this study, intermingled trees were not separated even using LIDAR data with point density of 0.8 point/m^2. In region growing segmentation, a region grows from the tree top until it reaches to local minima. In intermingles trees, there are two trees but there are not enough points with brightness values that are sufficiently different due to which the algorithm cannot separate two intermingled trees (Figure 5). In addition, the points are irregularly shaped. However, this logic is applicable for low degree of intermingling, as trees can be intermingled in different degrees in nature (Figure 6).



a. Multipoint on the image



b. Multipoint on the smoothen image

Figure 5: Showing multipoint (from point cloud) (yellow oval shapes show 2 trees that are intermingled)

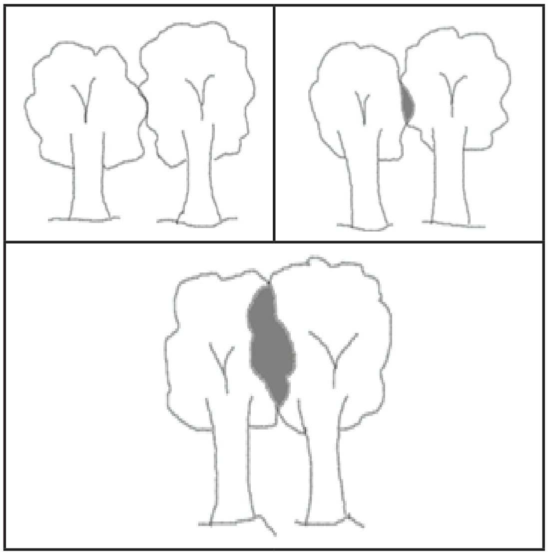


Figure 6: Different degree of two intermingled canopy trees

In this study, data on the degree of intermingled trees were not collected. If crowns have a high degree of intermingling there would be no local minima or valleys between tree tops and the crowns are considered to be one. There were more omission errors observed in deciduous trees due to densely growing trees with homogenous height distribution resulting in inability to separate neighboring trees.

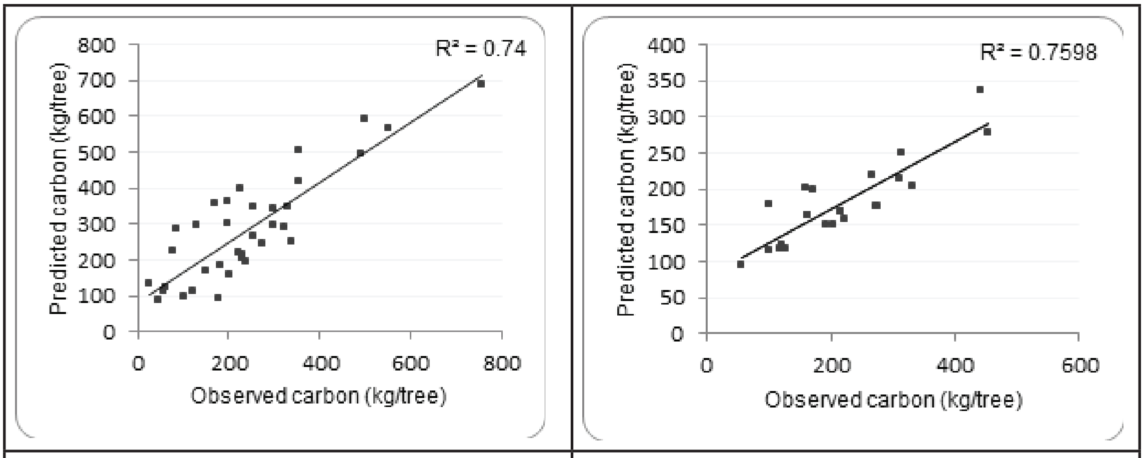
4.5 Regression models and validations

Relationships of field measured carbon with CPA and CHMfor both *Shorearobusta* and other species were obtained using multiple linear regression model (Eq. 1 and 2).132 measurements were used for model development for *Shorearobusta*and 47 measurements were used in case of the other species. In general, all models were explaining well the relationship of carbon with CPA and CHM. In this relationship, the VIF was less than 1. The multiple linear regression models had relative RMSEs,i.e. 36.8% and 32.4% for both *Shorearobusta* and other species, respectively.

$$Carbon\ stock\ (Shorea\ robusta) = -163.07 + 10.58 \times CPA + 11.58 \times CHM \quad \ldots\ldots. (2)$$

$$Carbon\ stock\ (Others) = -102.2 + 6.2 \times CPA + 9.48 \times CHM \quad \ldots\ldots. (3)$$

Result showed that there were improvements in the models using two explanatory variables (CPA and the canopy height). Height and CPA are important biophysical parameters to estimate biomass of a tree using remote sensing. Moreover, biomass depends on volume and volume can be calculated from height and DBH. Since there is relation between CPA and DBH (Hirata et al., 2009; Shimano, 1997), it is expected that CPA and height will give a good estimate of biomass. Consequently, these two variables i.e. height and CPA can explain more about variability of biomass than using either of variables alone. Coefficient of determination (R^2) were 0.74 and 0.76 for *Shorearobusta* and others, respectively (Figure 7).



a. *Shorearobusta*	b. Others

Figure 7: Scatterplots of predicted versus observed carbon

4.6 Carbon stock mapping

The carbon stock models (Eq. 1 and 2) were used for both *Shorearobusta* and other species to extrapolate the amount of carbon stock spatially and mapping the carbon stock in the study area (Figure 8). The study area has approximately 89.45 $MgCha^{-1}$.

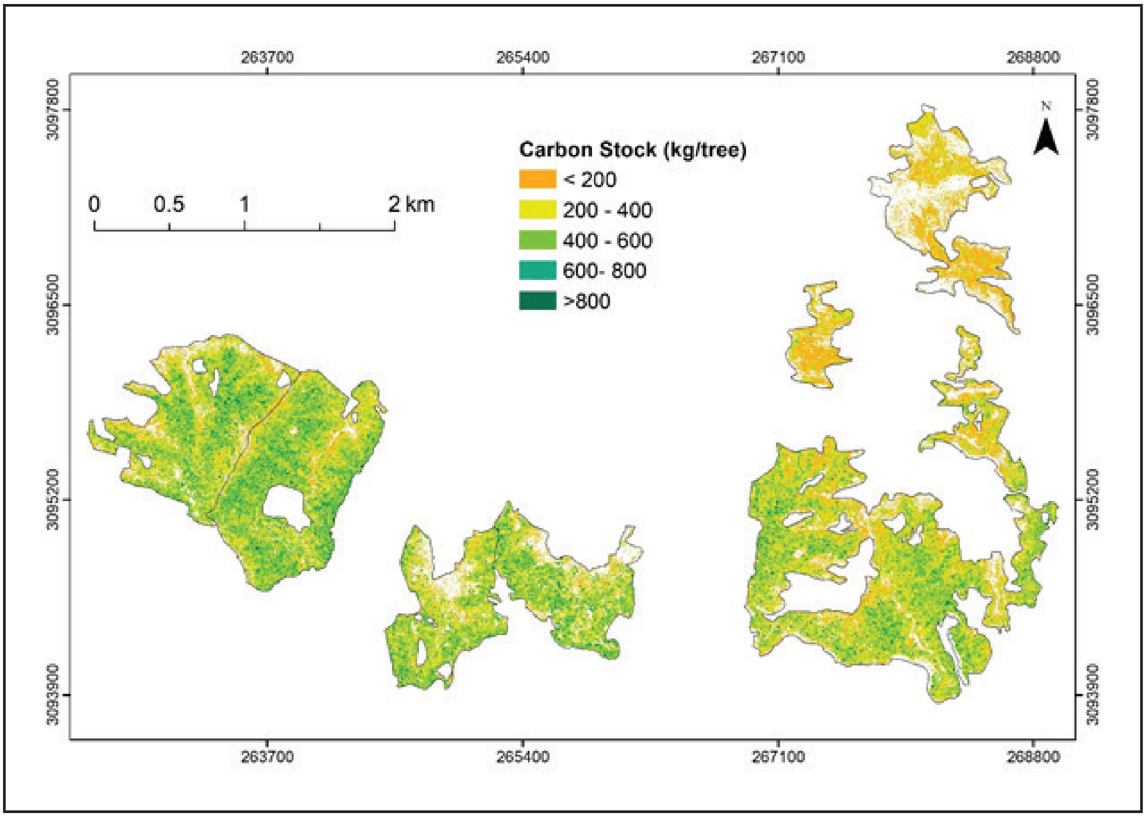


Figure 8: Carbon Stock Map of the Study Area

5. CONCLUSIONS

Although, numerous studies to estimate forest carbon stocks from LIDAR were documented, there are limited examples in the literature that address the combination of the LIDAR pulse returns and the very high resolution optical imagery in such varied topography. This study has demonstrated the development forest carbon stock estimation model using LIDAR and the optical imagery at species level accurately. Employing field and airborne LIDAR measurements, forest-specific models were developed, capturing major variety of forest species. Because of the structural differences and associated carbon content between the forest types, the forest specific models provided improved results with reduced uncertainty.The modeling outcomes has provided more options for forest carbon assessment in the Nepal where topography matters.Using height information in mountain region is crucial as the information not only help to improve the model but also extract trees information even in shadow area which would be missed if only reflectance values were used. The methodology for measuring carbon stock in sub-tropical forests will contributein response to climate change mitigation action.

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REFERENCES:

Ali, S. S., Dare, P., & Jones, S. D. (2008). Fusion of remotely sensed multispectral imagery and lidar data for forest structure assessment at the tree level. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XXXVII*(Part B7).

Arbonaut. (2012). *LAMP Processing Materials and Methods*. Kathmandu.

Asner,G.,Mascaro,J.,Muller-Landau,H.,Vieilledent,G.,Vaudry,R.,Rasamoelina, M.,Hall,J.,Breugel,M.,2012. A universal airborne LiDAR approach for tropical forest carbon mapping. Oecologia168,1147–1160.

Baccini, A., Friedl, M. A., Woodcock, C. E., & Warbington, R. (2004). Forest biomass estimation over regional scales using multisource data. *Geophysical Research Letters, 31*(10).

Chave, J., Andalo, C., Brown, S., Cairns, M., Chambers, J., Eamus, D., et al. (2005). Tree allometry and improved estimation of carbon stocks and balance in tropical forests. *Oecologia, 145*(1), 87-99.

Chen, Q., Baldocchi, D., Gong, P., & Kelly, M. (2006). Isolating individual trees in a savanna woodland using small footprint lidar data. *Photogrammetric engineering and remote sensing, 72*(8), 923-932.

Clinton, N., Holt, A., Scarborough, J., Yan, L., & Gong, P. (2010). Accuracy assessment measures for object-based image segmentation goodness. *Photogrammetric engineering and remote sensing, 76*(3), 289-299.

Dixon, R. K., Winjum, J. K., & Schroeder, P. E. (1993). Conservation and sequestration of carbon : The potential of forest and agroforest management practices. *Global Environmental Change, 3*(2), 159-173.

Dong, J., Kaufmann, R. K., Myneni, R. B., Tucker, C. J., Kauppi, P. E., Liski, J., et al. (2003). Remote sensing estimates of boreal and temperate forest woody biomass: carbon pools, sources, and sinks. *Remote Sensing of Environment, 84*(3), 393-410.

Flores-Anderson, A. I., Herndon, K. E., Thapa, R. B., &Cherrington, E. (2019). The SAR Handbook: Comprehensive Methodologies for Forest Monitoring and Biomass Estimation. Huntsville, AL: NASA.

Gaveau, D. L. A., & Hill, R. A. (2003). Quantifying canopy height underestimation by laser pulse penetration in small-footprint airborne laser scanning data. *Canadian Journal of Remote Sensing, 29*(5), 650-657.

Gibbs, H. K., Brown, S., Niles, J. O., & Foley, J. A. (2007). Monitoring and estimating tropical forest carbon stocks: making REDD a reality. *Environmental Research Letters, 2*(4).

Gonzalez, P., Asner, G. P., Battles, J. J., Lefsky, M. A., Waring, K. M., & Palace, M. (2010). Forest carbon densities and uncertainties from Lidar, QuickBird, and field measurements in California. *Remote Sensing of Environment, 114*(7), 1561-1575.

Heinzel, J. N., Weinacker, H., & Koch, B. (2008). *Full automatic detection of tree species based on delineated single tree crowns-a data fusion appproach for airborne laser scanning data and aerial photographs*. Paper presented at the SilviLaser.

Heritage, G. L., & Large, A. R. G. (2009). *Laser Scanning for the Environmental Sciences*. Chichester,UK: Wiley-Blackwell Publishing Ltd.

Hirata, Y., Tsubota, Y., & Sakai, A. (2009). Allometric models of DBH and crown area derived from QuickBird panchromatic data in Cryptomeria japonica and Chamaecyparis obtusa stands. *International Journal of Remote Sensing, 30*(19), 5071-5088.

Holmgren, J., Persson, Å., & Söderman, U. (2008). Species identification of individual trees by combining high resolution LiDAR data with multi-spectral images. *International Journal of Remote Sensing, 29*(5), 1537-1552.

Hunt, C. A. G. (2009). *Carbon sinks and climate change: forests in the fight against global warming*. Cheltenham,United Kingdom: Edward Elgar Publishing Limited.

Husch, B., Beers, T. W., & Kershaw, J. A. (2003). *Forest mensuration*. Hoboken, New Jersy: John Wiley & Sons, Inc.

IPCC. (2003). *Good Practice Guidance for Land Use, Land Use Change and Forestry*. Hayama, Kanagawa, Japan.

ITC. (2010). *GIScience and Earth Observation: a process-based approach*. Enschede, The Netherlands: ITC.

Karna, Y. K., Hussin, Y. A., Gilani, H., Bronsveld, M. C., Murthy, M. S. R., Qamer, F. M., ... &Baniya, C. B. (2015). Integration of WorldView-2 and airborne LiDAR data for tree species level carbon stock mapping in KayarKhola watershed, Nepal. *International Journal of Applied Earth Observation and Geoinformation*, *38*, 280-291.

Katoh, M., Gougeon, F., & Leckie, D. (2009). Application of high-resolution airborne data using individual tree crowns in Japanese conifer plantations. *Journal of Forest Research, 14*(1), 10-19.

Ke, Y., Quackenbush, L. J., & Im, J. (2010). Synergistic use of QuickBird multispectral imagery and LIDAR data for object-based forest species classification. *Remote Sensing of Environment, 114*(6), 1141-1154.

Kim, S. R., Kwak, D. A., oLee, W. K., Son, Y., Bae, S. W., Kim, C., et al. (2010). Estimation of carbon storage based on individual tree detection in Pinus densiflora stands using a fusion of aerial photography and LiDAR data. *Science China-Life Sciences, 53*(7), 885-897.

Kronseder, K.,Ballhorn, U.,Böhm, V.,Siegert, F., 2012. Above ground biomass estimation across forest types at different degradation levels in Central Kalimantan using LiDAR data. *International Journal of Applied Earth Observation and Geoinformation,* 18,37–48.

Leckie, D. G., Gougeon, F. A., Tinis, S., Nelson, T., Burnett, C. N., & Paradine, D. (2005). Automated tree recognition in old growth conifer stands with high resolution digital imagery. *Remote Sensing of Environment, 94*(3), 311-326.

Leckie, D., Gougeon, F., Hill, D., Quinn, R., Armstrong, L., & Shreenan, R. (2003). Combined high-density lidar and multispectral imagery for individual tree crown analysis. *Canadian Journal of Remote Sensing, 29*(5), 633-649.

Lu, D., 2005. Above ground biomassestimation using Landsat TM data in the Brazilian Amazon. *International Journal of Remote Sensing*26,2509–2525.

Mora, B., Wulder, M. A., & White, J. C. (2010). Segment-constrained regression tree estimation of forest stand height from very high spatial resolution panchromatic imagery over a boreal environment. *Remote Sensing of Environment, 114*(11), 2474-2484.

Muukkonen, P., & Heiskanen, J. (2007). Biomass estimation over a large area based on standwise forest inventory data and ASTER and MODIS satellite data: A possibility to verify carbon inventories. *Remote Sensing of Environment, 107*(4), 617-624.

Obrien, R. (2007). A Caution Regarding Rules of Thumb for Variance Inflation Factors. *Quality & Quantity, 41*(5), 673-690.

Palace, M., Keller, M., Asner, G. P., Hagen, S., & Braswell, B. (2008). Amazon forest structure from IKONOS satellite data and the automated characterization of forest canopy properties. *Biotropica, 40*(2), 141-150.

Popescu, S. C. (2007). Estimating biomass of individual pine trees using airborne lidar. *Biomass and Bioenergy, 31*(9), 646-655.

REDD. (2011). Community REDD working area. Retrieved 15 november, 2011, from http://communityredd.net/

Saatchi, S. S., Harris, N. L., Brown, S., Lefsky, M., Mitchard, E. T., Salas, W., Zutta, B. R., &Petrova, S. (2011). Benchmark map of forest carbon stocks in tropical regions across three continents. *Proceedings of the national academy of sciences*, *108*(24), 9899-9904.

Shah, R. (2011). *Comparison of individual tree crown delineation method for carbon stock estimation using very high resolution satellite images.* MSc thesis, University of Twente Faculty of Geo-Information and Earth Observation ITC, Enschede.

Sharma, E. R. and Pukkala, T. 1990. Volume Equations and Biomass Prediction of Forest Trees of Nepal. Forest Survey and Statistics Division. Publication No. 47, Kathmandu, Nepal

Shimano, K. (1997). Analysis of the relationship between DBH and crown projection area using a new model. *Journal of Forest Research, 2*(4), 237-242.

Shrestha, S., Karky, B. S., &Karki, S. (2014). Case study report: REDD+ pilot project in community forests in three watersheds of Nepal. *Forests*, *5*(10), 2425-2439.

Smith, S., Holland, D., & Longley, P. (2004). *The importance of understanding error in lidar digital elevation models*.

Song, C., Dickinson, M. B., Su, L., Zhang, S., & Yaussey, D. (2010). Estimating average tree crown size using spatial information from Ikonos and QuickBird images: Across-sensor and across-site comparisons. *Remote Sensing of Environment, 114*(5), 1099-1107.

Steininger, M. K. (2000). Satellite estimation of tropical secondary forest above-ground biomass: data from Brazil and Bolivia. *International Journal of Remote Sensing, 21*(6-7), 1139-1157.

Suárez, J. C., Ontiveros, C., Smith, S., & Snape, S. (2005). Use of airborne LiDAR and aerial photography in the estimation of individual tree heights in forestry. *Computers & Geosciences, 31*(2), 253-262.

Thapa, R. B., Watanabe, M., Motohka, T., Shiraishi, T., & Shimada, M. (2015). Calibration of aboveground forest carbon stock models for major tropical forests in central Sumatra using airborne LiDAR and field measurement data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *8*(2), 661-673.

Thapa, R. B., Watanabe, M., Shimada, M., &Motohka, T. (2016). Examining high-resolution PiSAR-L2 textures for estimating tropical forest carbon stocks. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *9*(7), 3202-3209.

UNFCCC (2016). *Report of the conference of the parties on its twenty-first session, held in Paris from 30 November to 13 December 2015*. Paris.

Zhan, Q., Molenaar, M., Tempfli, K., & Shi, W. (2005). Quality assessment for geospatial objects derived from remotely sensed data. *International Journal of Remote Sensing, 26*(14), 2953-2974.

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