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Estimation of above ground Forest biomass and Carbon stock by Integrating LiDAR, satellite image and field measurement in Nepal

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Abstract

For the first time in South Asia, the model-based Lidar Assisted Multisource Program (LAMP) was tested in 23500 km^2 Terai arc landscape (TAL) area of Nepal by integrating 5% airborne light detection and ranging (LiDAR) sampling, wall-to-wall Rapid Eye satellite image and a representative field inventory to estimate above ground biomass (AGB) and carbon stock. The average 1.26/m^{2}LiDAR point density recorded by the scanner was used to measure canopy height and build a model using LiDAR variables and model coefficients. The developed LAMP model successfully estimated the AGB of the study area. The research tells that the study area comprises almost 50% forest cover with an average 211.63 t/ha AGB. Standing carbon stock was converted from AGB by multiplying the 0.47 which is default carbon fraction. Average standing carbon stock is 99.47 t/ha in the study area. The LAMP method found that the standing total AGB was 214.85-208.41 t/ha at a 95% confidence level and thefield-based Forest Resource Assessment (FRA) Nepal field-plot AGB estimate is 210.09/ha. This correspondence at this level of confidence means that the LAMP estimates are as accurate as those of the field-based inventory.

Keywords: LiDAR, satellite data, field plots, LAMP, biomass, carbon, REDD+

Introduction

Tropical forests hold about 25% of the carbon in the terrestrial biosphere; emit 15-20 % of annual Greenhouse Gas (GHG) the second largest source of GHG emissions globally due to deforestation and forest degradation[1-3]. Recognizing this prospect, the United Nations Framework Convention on Climate Change (UNFCCC) has set the Reducing Emission from Deforestation and Degradation and includes the role of Conservation, Sustainable Management of Forests and Enhancement of Forest Carbon Stocks (REDD+) scheme for developing countries to reduce emissions from forested lands and invest in sustainable development by providing a financial value for the amount of carbon stored in forests[1,4]. However, a successful REDD+ mechanism requires the transparent, complete, consistent, comparable, and accurate forest Monitoring, Reporting and Verification (MRV) systems at national and sub-national scales[2,5].

Forest monitoring systems have changed in the course of time due to the continuous technological advancement[3,6,7]. In the past, intensive field-based FRA focused on timber production and applied for estimating tree volume, growing stock and growth[8]. Although traditional approach is accurate method, rigorous field measurement is time-consuming costly, and difficult to implement in unreachable extensive forest areas.

Satellite RS has become an important instrument to collect large amounts of image data over a wide geographical area with high temporal frequency and provide 2D (x, y) information on species composition and distribution. However, existing optical RS cannot provide an accurate estimate of forest biomass and sequestered carbon in the mapped area without an integrated forest inventory[5].

In current years, airborne LiDAR has become an essential part of operational forest inventory in Scandinavian countries[9]. Its high potential for REDD+ related biomass inventories has been well demonstrated[4,5,10]. Vegetation heights can be acquired with high accuracy using LiDAR height metrics. Since tree height is strongly correlated with tree volume, forest biomass can be predicted with high accuracy when regressing LiDAR metrics with data fromfield measured plots[11,12]. But wall-to-wall covering of area of interest with LiDAR is expensive. When combining Lidar from sample areas with satellite data covering the entire area of interest and in-situ measurements at sample locations, high-resolution maps of forest carbon stocks and emission can be produced in an efficient way[3]. The integrated approach is known as the LAMP – a term that was coined by the World Wildlife Fund U.S. (WWF-US) and Arbonaut Ltd. in early 2011. LAMP has been tested and proved in Peru, Laos, Madagascar, Columbia and Tanzania. In a joint effort of ArbonautLtd, FRANepal project and WWF implemented

LAMP in subtropicalmountain landscape (Terai and Siwalik) of Nepal for monitoring AGB.

Methodology

Study area: Covering an area of 23500 sq.km TAL Nepal area issituated along the foothills of the Himalayas in the southernmost part of Nepal, ranging from the lowlands of Terai region up to the southern slopes of the Himalayas in Siwalik region (figure 1).

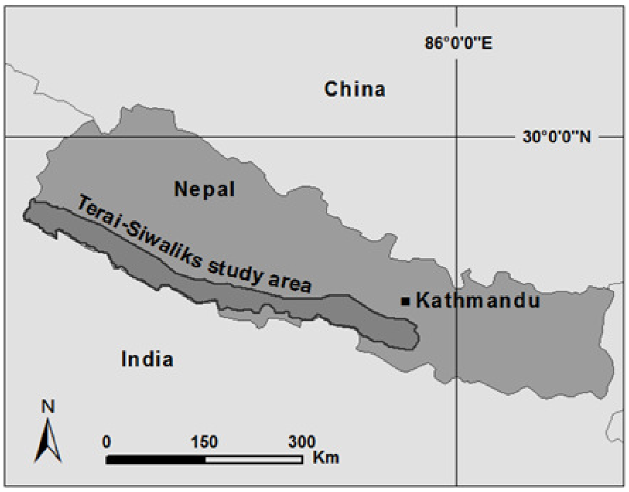

Figure-1
Map showing the study area in the Terai Arc Landscape

Altitude varies from 300 m in the South to 1500 meters in the northern hills from above mean sea level. The area is a spatial mosaic of tropical and subtropical forest types, and covers 75% of the remaining forests of Terai and foot hills of Siwalik[13]. The dominating forest type is Sal (*Shorearobusta*) with smaller proportions of moist evergreen forest, dry deciduous forest, Khair-Sisoo (*Acacia catechu/Dalbergiasissoo*) and subtropical Pine (*Pinusroxburghii*).

LAMP method: The LAMP integrates LiDAR sampling, full coverage of satellite image and in-situ measurement to calibrate LiDAR data. The data set includes: a set of ground-truth sample plots (field plots) with tree-level measurements, LiDAR data for sample areas, and satellite data for the entire study area. In addition, a set of large random field plots were collected from two LiDAR blocks for independent validation of the results. All input datasets and their pre-processing are introduced in the following sections.

LiDARdata acquisition and processing: Wall to wall LiDAR scanning was done in 5% representative forest area of the study area. LiDAR samples were designed by creating weighted vegetation map to represent the regional variation and vegetation types. Probability proportional-to-size sampling was used to select the areas for LiDAR data collection. Total twenty blocks of each 5 km x 10 km size were considered over the area and scanned by using the Leica ALS50-II- airborne LIDAR scanner from 2200 m average height during March and April 2011.

LiDAR raw data were classified into three categories: ground returns, vegetation returns, and errors. This classification was visually verified. Further pre-processing included the calculation of a Digital Terrain Model (DTM) from the ground returns, the removal of overlaps from the raw data, and the conversion of height coordinates for vegetation returns from absolute elevation into distance-to-ground using the DTM. Average recorded point density was 1.26 pulses/m^2.

LiDAR data were processed by calculating LiDAR features following Junttila et al. (2010)[14]. These features are an extended and modified version of those published by Næsset (2002)[15]. The features included different height percentiles for the first-pulse and last-pulse returns, mean height of first-pulse returns above 5 meters (high-vegetation returns), standard deviation for first-pulse returns, ratio between first-pulse returns from below 1 meter and all first-pulse returns, ratio between last-pulse returns from below 1 meter and all last-pulse returns, and several intensity-related features.

Field data collection: The location of sample plots was designed using a systematic cluster sampling within blocks that were designed for LiDAR sample acquisition. Each designed LiDAR block contained six clusters of eight sample plots each (figure 2). The distance between cluster center was 3333m in West-East and 2500m in North-South direction. Within the clusters, the sample plots were aligned in two parallel columns in North-South direction, with 4 plots per column (figure 2). The distance between plots was 300m in West-East direction, and 300 and 150m in North-South direction in Terai and Siwaliks, respectively. The smaller North-South distance for Siwaliks was chosen because of the large variations in altitude in the mountainous region. The plots were of fixed circular shape with a radius of 12.62 meters (500 sq.m).

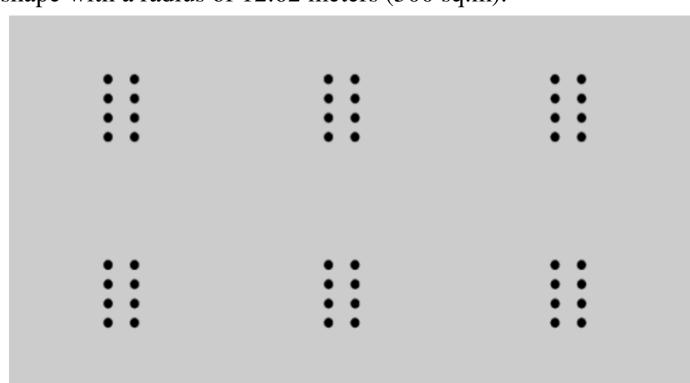

Figure-2
Sampling design: LiDAR block with six clusters of 8 field plots each

Highly accurate field sample plots were located with sub-meter accuracy using a differential GPS with ProMark 3 and Mobile

Mapper devices, and corrected in post-processing mode (GNSS Solutions software and Mobile Mapper Office software). Total 792 forest located circular plots were measured in the field and characteristics of 738 included for AGB estimation. The measurements at tree-level included all living trees and shrubs above 5cm diameter within the plot area. Plot volume and biomass were calculated using species-group specific volume and biomass equations prepared by Sharma and Pukkala (1990)[16].

For each field sample plot the following attributes were derived from the tree-level measurements, by species group and totals: stem count (1/ha), mean diameter at breast height weighted by basal area (cm), basal area (m^2/ha), mean tree height weighted by basal area (m), stem volume (m^3/ha), and above-ground biomass (tons/ha). Mixed-effects models are an appropriate tool for modeling the relationship between tree height and field-measured tree diameter because the explanatory variables are clustered and spatially correlated[17]. Stem volume was converted to stem biomass by applying wood density coefficients. Above-ground tree biomass was calculated by summing up the biomass of stem, foliage and branches. After computing the volume and Above Ground Biomass (AGB) for each tree, plot-level results were computed as aggregates of the tree-level results. Height and diameter were calculated as basal area weighted mean. Volume, basal area and AGB were calculated by summing the tree-level results and scaling them to hectare level by multiplying the sum by 1 ha/plot area. Finally, the field plot data were screened for outliers.

Satellite Image: High -resolution RapidEye satellite imagery of March-April 2010 and 2011 was used for wall-to-wall mapping and biomass and carbon stock modeling. These images have five spectral bands ranging from blue to near -infrared (NI). The image has the ability to discriminate vegetation types and map forest conditions. Google Earth images such as Geo-eye, Worldview and Quick Bird were utilised for visual interpretation. The images used were acquired in two different years. To accommodate these differences, relative calibrations were made. More specifically, a local radiometric calibration was done using the ArboLiDAR tool.

AGB estimation: The LAMP method follows a two-phase estimation approach. In the first phase, forest variables related to biomass are estimated with high accuracy for LiDAR sample area by using LiDAR and field inventory data. The field plots were used as training data set for the first-phase biomass estimation. In the second phase, AGB estimates of the LiDAR blocks through first phase approach were used as a simulated ground-truth (surrogate plots) in the interpretation of high-resolution satellite scenes for the entire study area[3,5].

In the first phase of the LAMP approach, a regression model was generated based on the relationship between LiDAR height metrics and field measurements. It has been shown that Sparse Bayesian methods offer a flexible and robust tool for regressing LiDAR pulse histograms with forest parameters. While performing comparably to traditional regression methods, they are computationally more efficient and allow better flexibility than step-wise regression[12,18]. Sparse-Bayesian regression is a non-parametric procedure where the set of suitable explanatory variables is selected from the given input data in order to reduce the complexity of the model and prevent over-fitting. The regression model was applied to predict forest characteristics for a set of 10,000 circular-shaped “surrogate plots” (simulated field plots) of 1-hectare size within the forested area of the LiDAR blocks. The locations of the surrogate plots were selected through weighted random sampling using the inverse of the block weights applied in LiDAR block sampling.

In the second phase, the forest characteristics estimated for the “surrogate plots” from LiDAR height data were applied as simulated ground-truth to generate a regression model between bio-physical forest parameters and features derived from satellite imagery. Again, Sparse-Bayesian method was used to regress satellite-derived variables with forest characteristics for the locations of the surrogate plots. The satellite-based variables were derived from the previously calculated textural variables and vegetation indices as zonal mean values for the area within each surrogate plot. Some particularly valuable satellite image features have been identified from the analysis of Normalized Difference Fraction Index (NDFI).

The final output includes stem count (1/ha), mean diameter at breast height weighted by basal area (cm), basal area (m^2/ha), mean tree height weighted by basal area (m), stem volume (m^3/ha), above-ground biomass (tons/ha), and above-ground carbon (tons/ha).The above-ground carbon was calculated by using carbon fraction 0.47 of above-ground biomass[2].

Assessing the Accuracy of LAM biomass estimates: In the study area FRA Nepal applied a stratified two-phase systematic cluster sampling in 2011 to generate forest statistics. The field based FRA estimates were compared with LAMP estimates to validate the accuracy of LAMP. Confidence limits of 95% were set for the biomass and volume estimates. Assessment of the accuracy of the LiDAR model at the plot level was carried out by calculating the error statistics of AGB estimates of LAMP.

Results and Discussion

AGB in TAL-Nepal: The AGB was calculated by using the LAMP model prepared for the study area. The result reveals that there is 1,154,279ha forest area which comprises about 51% of the total study area. The result also divulges that there is 235,706,921 t total AGB in the forest area. The quantity of biomass estimated was categorized under five classes (table 1).

Amount of standing volume depends upon area of forest, density of standing trees and their sizes. The highest amount (59%) of standing biomass is under the third biomass class (200.01-300 t/ha) which class covers about 50% forest area.

The small amount of AGB (84,232.78 t) is under the last biomass class (400.01-478 t/ha) which comprises only 204.51 ha forest area. The trend shows that average AGB is gradually increasing with increasing the biomass classes. The average weighted standing total AGB (living and dead) is 211.63 t/ha. Figure 3 presents the extent of AGB map under five biomass classes.

Assessing and validating the accuracy of LAMP model biomass estimates: Total biomass results at a 95% confidence level: Table 2 presents the LAMP model-estimated mean values of several variables, including biomass at a 95% confidence level. Data collected using field-based FRA processes were utilized to compare and validate these results.

Table-1
Total AGB in TA-Nepal

Biomass classes t/ha)	Area (ha)	Total standing biomass (t)	Carbon sock (t)	Average (t/ha)	Average carbon stock (t/ha)
0.01-100	80,412.97	4,904,430.77	23,05,082.46	61	28.67
100.01-200	427,720.82	69,313,179.97	3,25,77,194.49	162	76.14
200.01-300	579,131.83	139,854,357.49	6,57,31,548.21	241.5	113.5
300.01-400	66,809.36	21,550,720.03	1,01,28,838.3	322.5	151.56
400.01-478	204.51	84,232.78	39,589.41	412	193.64
Total	1,154,279	235,706,921	11,07,82,252.87	211.63 weighted	99.47weighted

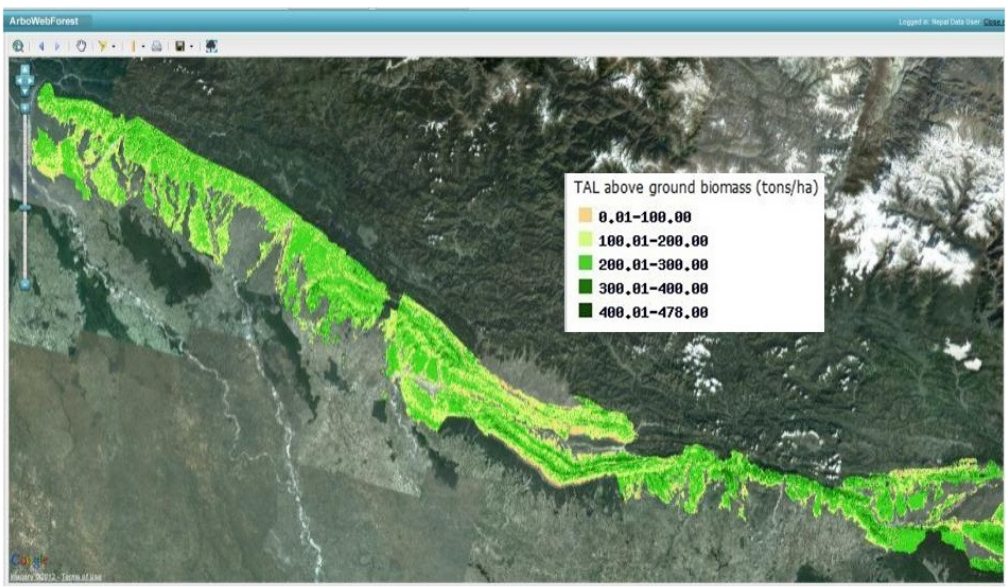

Figure-3
Map of TAL-Nepal showing extent of AGB under five categories

Table-2
LAMP results at a 95% confidence level and comparison with FRA results

Variable (mean/ha)	LAMP (mean/ha)	LAMP (range)	field-based FRA (mean/ha)
Standing total basal area (m^2/ha)	18.51 ± 0.24	18.75-18.27	18.96
Basal area (m^2/ha) of living trees	18.30± 0.23	18.53-18.07	18.16
Standing total volume (m^3/ha)	167.89 ± 2.57	170.46- 165.32	172.60
Volume (m^3/ha) living trees	164.76 ± 2.54	167.30-162.22	170.2
Standing total AGB (t/ha)	211.63 ± 3.22	214.85-208.41	210.09
Living AGB (t/ha), living trees	208.38± 3.17	211.55-205.21	209.5

The intention behind calculating the confidence levels of LAMP results and comparing them with field-based FRA results is to test the reliability and validity of those results. The LAMP method found that the standing total AGB was 214.85-208.41 t/ha at a 95% confidence level and the field-based FRA field-plot estimate of 210.09/ha (Table 2). The LAMP mean living AGB estimates lies between 211.55 to 205.21t/ha at a 95% confidence level which is validated by the FRA field-plot estimate. The FRA field plot mean Living AGB estimate is 209.5 t/ha which is accurate enough to the value (208.38 t/ha) of LAM estimate. This correspondence at this level of confidence means that the LAMP estimates are as accurate as those of the field-based inventory.

Error statistics of the AGB estimates of LAMP: Sampling or estimation error is the degree of inaccuracy in estimating values of inventoried variables that is caused by measuring only a portion of a population (i.e. a sample) rather than the whole population. In this case, the sampling error is caused by inaccuracies in the estimations of volume and biomass.

Table 3 shows the per-hectare level error statistics of the AGB estimates of LAMP. The Root Mean Square Error (RMSE) is a measure of the difference between values predicted by a model or an estimator and the values actually observed. The smaller a RMSE is the higher is the accuracy of the model in question. RMSE depends on what is achievable given the data that is being modelled. In this case, the RMSE of LAMP model estimate was 53.42. The LAMP result was also validated by comparing it to the field-based FRA estimates; in fact, the Standard Deviation (SD) of the LAMP estimate (25.06 t/ha) is less than that of the FRA estimate (60.64t/ha). It means that LAMP method is accurate enough to estimate AGB.

Table-3
Error statistics of the AGB estimates of LAMP

Parameter	Value
Mean living AGB of LAMP estimate (t/ha)	207.23
SD of LAMP estimate (t/ha)	25.06
Mean of FRA reference plots estimates (t/ha)	209.93
SD of FRA reference plots estimate (t/ha)	60.64
RMSE	53.42
Relative RMSE (%)	24.5
Bias	-2.69
Relative bias (%)	-0.013
Statistical significance of bias (P)	0.83

Correlation between AGB estimates using field data and LAMP model estimates: Figure 4 reveals the square of the correlation between the total AGB calculated using actual data measured in the field (x-axis) and the LAMP model estimate (y-axis). The result shows that R2 = 0.616, which means the association is sufficiently high between model-estimated AGB and the primary field data-based AGB.

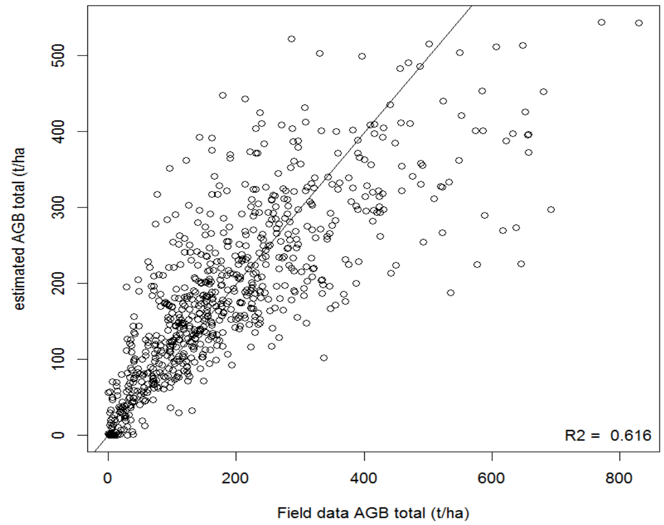

Figure-4
Correlation between estimated AGB and field data AGB

The squared correlation gives the variance of the predicted responses as the fraction of the variance of the actual responses[19]. In this case LAMP model estimated AGB is the predicted value and AGB calculated by field data is the actual response.

Conclusion

This research was carried out to estimate and map of AGB in TAL-Nepal by using model based LiDAR assisted forest inventory approach, and assess and validate the accuracy of LAMP model biomass estimates.

The average 1.26/m2LiDAR point density recorded by the scanner was used to measure canopy height and build a LAMP model using LiDAR variables and model coefficients. This model successfully estimated the AGB of the study area. The research reveals that the study area comprises almost 50% forest cover with an average 211.63 t/ha AGB. Standing carbon stock was converted from AGB by multiplying 0.47 which is the default carbon fraction. Average standing carbon stock is 99.47 t/ha in the study area.

The LAMP-estimated AGB was validated with the FRA mean values of AGB from the same area, which lie within the 95% confidence interval of LAMP estimates. Thus, it can be said that LAMP estimates are as precise as those of a design-based field inventory. The square of the correlation between the total AGB was calculated using actual data measured in the field (x-axis) and the LAMP model estimate (y-axis). The result shows that R2 = 0.616, which means the association is sufficiently high between model-estimated AGB and the primary field data-based AGB. This study concludes that the LAMP approach is reliable and accurate to estimate AGB and carbon stock.

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