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Estimation of Forest Carbon Using LiDAR-Assisted Multi-source Programme (LAMP) in Nepal

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Abstract

LiDAR (Light Detection and Ranging) is an active remote sensing technology which provides precise 3D information of the terrain and vegetation. LiDAR pulse density from 0.5 to 2 returns per square meter is sufficient for forest inventory applications in general cases. It is also possible to assess vegetation height and density directly from LiDAR data. Accurate and high-resolution mapping of biomass and carbon density requires tree level field sample data and biomass models to calibrate statistical models based on LiDAR pulse data properties. LiDAR-Assisted Multi-source Programme (LAMP) is the forest inventory methodology that integrates LiDAR data with satellite imagery, and field data for estimating forest characteristics, such as biomass and carbon stocks. Therefore, it complies with the Tier 3 requirements of REDD+ in measuring, reporting and verification (MRV) of forest resources.

A landscape-level forest carbon inventory in Terai Arc Landscape (TAL) of Nepal has been carried out. Aboveground forest carbon was estimated using a novel LAMP approach. A Sparse-Bayesian method was used to calibrate data from well-measured 738 ground-truth plots with airborne discrete-return LiDAR data in selected sample areas from the same season. In the second step, the LiDAR estimates were used as simulated ground-truth and regressed with variables derived from satellite imagery to cover the whole study area with continuous AGB values. The resulting carbon/biomass map was validated against highly accurate LiDAR-based carbon estimates. The accuracy of the LiDAR model was verified against 46 independent field plots. The LAMP combines LiDAR information with field plots and satellite data to develop a forest carbon map of one hectare resolution that will be useful for the Nepalese REDD+ process, in particular to derive subnational reference levels and to support future forest monitoring activities in the country.

INTRODUCTION

Tropical deforestation and forest degradation account for about 20% of annual greenhouse gas (GHG) emissions, thus being the second largest source of global GHG emissions (IPCC 2007). The Reducing Emissions from Deforestation and forest Degradation (REDD+) scheme may provide sustained incentives for developing countries in the future to reduce emissions from forested lands and invest in sustainable development by providing a financial value for the amount of carbon stored in forests (Angelsen et al. 2009). REDD+ also recognizes the role of forest conservation, sustainable management of forests, and enhancement of forest carbon stocks (Angelsen *et al.* 2011). A successful REDD+ mechanism will require the design and implementation of operational forest monitoring, reporting and verification systems that are transparent, complete, consistent, comparable, and accurate at national and sub-national scales (Walker *et al.* 2010, IPCC 2003).

An integrated system of unbiased geospatial and statistical estimators of sequestered carbon amounts across specific forest land is highly important for REDD+. Combining remotely sensed data with a forest resource inventory provides practical means to generate such information. Remote sensing collects and interprets information about features from a distant location and obtains continuous data over large areas in the forms of continuous thematic maps (e.g., forest biomass). There is tremendous diversity in the number and properties of the sensors and imagery available today ranging from space-borne to airborne to ground-based systems. Each system has different properties with spatial resolution, number of spectral bands, temporal frequency and the cost of acquiring the imagery. Despite this diversity of sensors, no current remote sensing system directly measures forest biomass and sequestered carbon. Thus, remote sensing is effective at indicating where specific features are and how they are distributed but cannot provide an accurate estimate of how much of that feature is in the mapped area without an integrated field reference data. Hence, in a joint effort, Arbonaut, the Forest Resource Assessment Nepal project and WWF are carrying out landscape-level LiDAR-assisted forest biomass inventory in the Terai and Siwaliks region of Nepal. This will hopefully help Nepal's REDD+ readiness process as Nepal is a member of World Bank's Forest Carbon Partnership Facility and has observer status within the UN-REDD programme.

In recent years, airborne LiDAR has become an integral part of operational forest inventory in Scandinavian countries (Næsset 2007). Its high potential for REDD-related biomass inventories in tropical countries has been well demonstrated (Asner *et al.* 2009, Gautam *et al.* 2010, Asner *et al.* 2012, Asner *et al.* 2013). Wall-to-wall LiDAR data acquisition tends to be expensive, thus a more feasible approach is to apply the two-phase estimation that only requires LiDAR sample data from the area of interest (Sah et al. 2012, Gautam et al. 2010). The LiDAR-Assisted Multi-source Programme (LAMP) combines LiDAR sample data with field plots and satellite data to develop aboveground carbon density map down to one-hectare resolution. The accurate, precise and high-resolution forest carbon baseline together with activity data helps to derive reference levels/reference emissions levels, and supports forest carbon monitoring activities (Meridian Institute 2011).

2. STUDY AREA

The study area (Figure 1) spreads across 23,300 km^2 in the Terai Arc Landscape (TAL). TAL is situated 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 Churia hills. The average altitude in the study area varies from less than 100 to 2,200 metres. The area is influenced by tropical and subtropical climate. About half of the study area is covered by subtropical, mainly deciduous forests. The dominating forest types are sal (*Shorea robusta*) terai mixed hardwood, khair-sisau (*Acacia catechu/Dalbergia sissoo*) and chir pine (*Pinus roxburghii*).

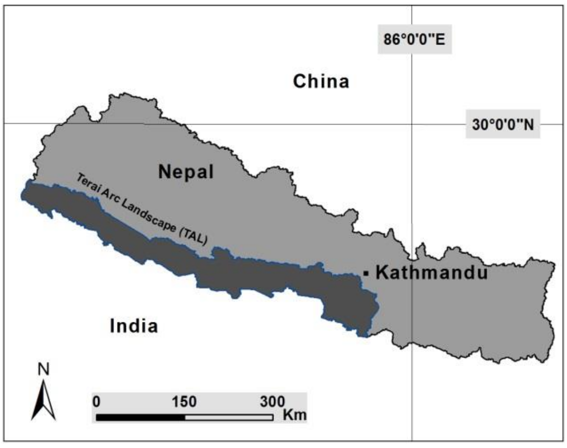

Figure 1: Study area (TAL).

The Terai Arc Landscape is linked with eleven trans-boundary protected areas across Nepal and India. TAL is home to flagship species like tigers, rhinos, Asiatic wild elephants, and many other endangered species. This landscape has the second largest population of rhinos and one of the highest densities of tiger populations in the world.

3. MATERIALS AND METHODS

3.1 Materials

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 bigger size 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.

3.1.1 Ground-truth plots for modelling and validation

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 centres was 3333 meters in west-east and 2500 meters 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 300 meters in west-east direction, and 300 and 150 meters in north-south direction in Terai and Siwaliks, respectively. The smaller north-south distance for Siwaliks was chosen because of the large variation of altitude in this undulating and dissected hilly region. The plots are of fixed circular shape with a radius of 12.62 meters (500 sq.m). The radius of the independent random validation plots is 30 meters (2826 sq.m.).

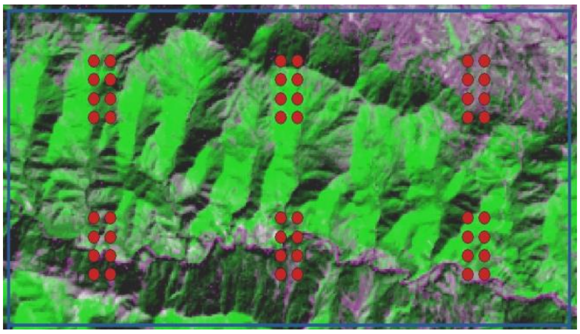

Figure 2: LiDAR block with six clusters of eight field plots each

Highly accurate field sample plots were collected with sub-meter accuracy using a differential L1 GPS with Ashtech Magellan ProMark 3 and MobileMapper CX devices, and corrected in post-processing mode (GNSS Solutions software and MobileMapper Office software). For each field sample plot by using mixed-effects models (Eerikäinen 2003, Mehtätalo 2004, Nothdurft *et al.* 2006, Sharma & Parton 2007) 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 aboveground biomass (tons/ha). Stem volume was converted to stem biomass by applying wood density coefficients (Paladinic *et al.* 2009, Zhou & Hemstrom 2009, Sharma & Pukkala 1990). Aboveground tree biomass was calculated by summing up the biomass of stem, foliage and branches. After computing the volume and aboveground 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.

3.1.2 LiDAR Data

LiDAR data were acquired from about 5 per cent coverage of the study area. The sampling method for selecting the blocks is described in the section 3.2. All blocks were scanned in full coverage from 2200 meters average height above ground. Airborne LiDAR raw data had been classified by the vendor into three categories: ground, vegetation and error returns. Further pre-processing included calculation of a Digital Terrain Model (DTM) from the ground returns, removal of the overlaps from the raw data, and conversion of height coordinates (z-values) of the vegetation returns from absolute elevation into distance-to-ground using the DTM.

3.1.3 Satellite data

Medium-resolution Landsat images covering the entire study area were used. Four Landsat 5 (TM sensor) scenes of processing level 1T (Standard Terrain Correction level) with a resolution of 30 meters were received from the Landsat program. The data have been acquired during October/November of 2010 and 2011. The processing level includes radiometric and geometrical correction based on ground control points and the best available digital terrain model (U.S. Geological Survey 2012).

3.2 Methods

3.2.1 Sampling and processing of remote sensing data

LiDAR block sampling

To produce a LiDAR sample that reflects the full range of variation in biomass over the study area and that covers not only the most common forest types but also the rare ones, different weights were assigned to different vegetation types. Probability proportional-to-size sampling (Särndal *et al.* 1992) was used to select the areas for LiDAR data collection.

Processing of LiDAR data

The pre-processed LiDAR data was further processed by calculating LiDAR features following Junttila *et al.* (2010). These features are an extended and modified version of those published by Næsset (2002). They 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.

Satellite image calibration

A relative radiometric calibration of the satellite images was necessary due to their different acquisition times. To obtain a homogeneous reference data set, satellite image scenes were calibrated relatively to each other using scene mean intensity and intensity variance normalization based on overlapping areas between scenes. Thus, a uniform mosaic was created. Additional normalization steps to correct for seasonal effects, topographic shadows, and accurate co-registration of images were applied, too. These effects cause artificial peaks in the histograms of Landsat bands and derived fields, such as Normalized Difference Vegetation Index (NDVI) and Normalized Difference Fraction Index (NDFI). Statistical corrections remove those peaks and replace those values with locally calibrated random values from the true distribution. Furthermore, normalization is restricted to the area under the prevailing forest cover map only.

3.2.2 LiDAR-Assisted Multi-source Programme (LAMP) Estimation

LAMP phase 1: Estimating forest parameters for LiDAR block locations

In the first phase of the LAMP approach, a regression model was generated based on the relationship between LiDAR metrics (height and density distribution) and field measurement based biomass training data. 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 (Junttila et al. 2008, Junttila et al. 2010). The Sparse-Bayesian 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.

LAMP phase 2: Expanding the estimates to the entire study area using satellite data

In the second phase of the LAMP approach, the forest characteristics that are estimated for the "surrogate plots" from LiDAR data were applied as ground reference to generate a regression model between bio-physical forest parameters and features derived from satellite imagery. Again, the 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) and the spectral end members for Soil and Non-photosynthetic vegetation (NPV) that are used to derive it (Souza Jr. & Siqueira 2013).

The interpretation of medium-resolution satellite scenes resulted to a continuous biomass density map (ton/ha) over the entire study area. Aboveground carbon density values (tons/ha) were calculated by using carbon fraction 0.47 of aboveground biomass (IPCC 2006).

4. RESULTS

4.1 LAMP biomass estimation for LiDAR block locations (Phase 1)

The linear model that was used to estimate aboveground biomass within the LiDAR blocks (LAMP phase 1) showed strong correlation with ground-truth biomass when validated against an independent set of 46 field plots with 30 meters radius (2826 sq.m.). The relative Root Mean Square Error (RMSE) was 0.17 (17%), and the achieved coefficient of determination (R^2) was 0.92. No significant bias was present (relative bias 0.013). Full validation results are shown in Figure 3 and Table 1.

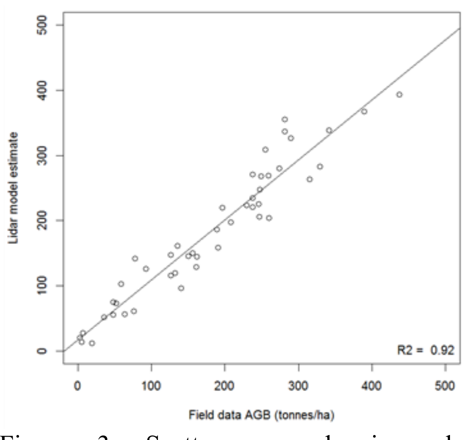

Figure 3: Scatterogram showing aboveground biomass (AGB) from independent field data against the estimates of the linear model from LiDAR data.

4.2 LAMP biomass estimation for entire study area (Phase 2)

The LAMP biomass/carbon estimates at 1ha-level (Figure 4) showed a relative RMSE of 0.42 (42.1%) without any bias, when validated against LiDAR estimates using k-fold cross-validation (k=100). The achieved R^2 was 0.48. The validation result for the estimates is presented in Figure 4 and Table 1. The preliminary result of the aboveground carbon estimates is presented in Figure 5.

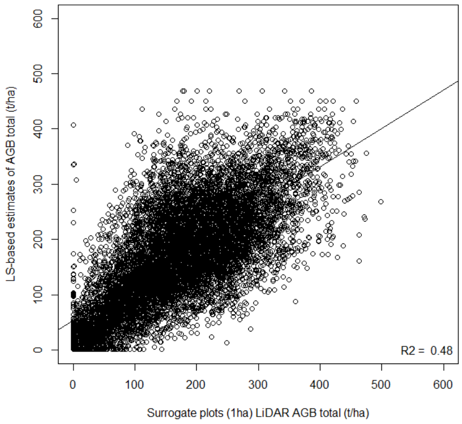

Figure 4: Scatterogram showing the LAMP estimates of aboveground biomass (AGB) against LiDAR estimates at 1ha.

Table 2: Statistics for the LiDAR (Phase 1) and LAMP (Phase 2) estimates of aboveground biomass.

Total AGB (t/ha)	LiDAR (Phase 1)	LAMP (Phase 2)
Mean of estimates	182.8	175.4
Standard deviation of estimates	104.2	94.4
Mean of reference plots	180.4	175.4
SD of reference plots	108.5	94.4
RMSE	30.8	73.8
Relative RMSE (%)	17.1	42.1
Bias	2.4	0.0
Relative bias (%)	1.3	0.0
R^2	0.92	0.48

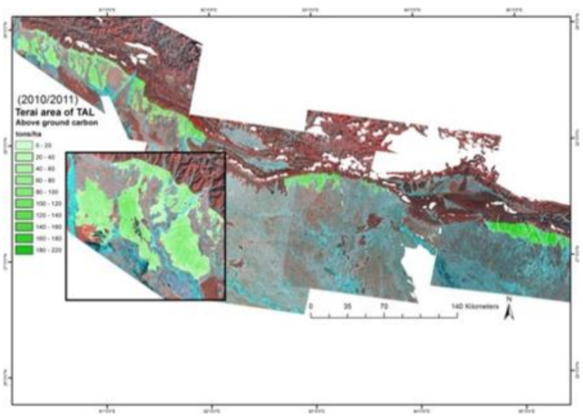

Figure 5: Aboveground carbon estimates at 1ha resolution in Terai area of TAL (preliminary result).

5. DISCUSSION AND CONCLUSIONS

For this study there was no full coverage of LiDAR data and there was a need to use wall-to-wall optical satellite data to calculate landscape level results. Optical sensor being a two-dimensional technique does not capture information below dense canopy covers. This results in a saturation effect which leads to underestimation of biomass in areas with high aboveground biomass concentrations (Næsset 2009, Garcia *et al.* 2010). This problem does not affect LiDAR which can penetrate even through a closed canopy cover to return information from ground-level and precisely estimate the tree biomass. The described approach uses thousands of LiDAR estimates as simulated ground-truth plots for the interpretation of optical satellite images and thus improves the interpretation process compared to conventional methods with limited amount of field plots

Around 5% LiDAR sample data and a set of 738 available field plots (after removal of outliers) were used to calibrate the LiDAR model. The LiDAR data and calibrating plots were more than necessary strictly for modelling, however as this work was conducted for the first time in Nepal sufficient data were needed to make sure that our method works and that the results are statistically reliable. It is anticipated that less than half of this amount would be sufficient to calibrate an accurate model. It can be concluded that future LiDAR campaigns may not require the collection of such a large LiDAR and field plot sample as was used in this analysis.

The allometric equations by Sharma & Pukkala (1990) that have been applied to estimate volume and biomass for the field plots introduce modelling errors into our ground-truth biomass data. The available volume and biomass equations for Nepal consider groups of species, but they are certainly not optimal at single-species level. Furthermore, the used equations are based on the data collected in the sixties and are not up-to-date.

The described LAMP methodology makes the best use of techniques that have been shown suitable for biomass inventories: well-measured field plots from sample locations, LiDAR data from sample areas, and freely available medium-resolution satellite imagery for the entire area of interest. It can be considered as a compromise between highly costly LiDAR data collection which would provide very accurate, high-resolution biomass estimates for the entire study area, and a multi-source method based on field plots and satellite data, which gives very low estimation accuracies (Asner et al. 2009, Gautam *et al.* 2010, Asner *et al.* 2012, Asner *et al.* 2013). The LAMP method has high potential to contribute to the development of the accurate, precise and high-resolution forest carbon baseline and monitoring in

Nepal as well as for other countries.

The method development is still in progress and new results (especially carbon related temporal estimates) are expected to be available soon. Nepal is preparing to submit a jurisdiction based sub-national REDD+ forest reference level proposal to the UNFCCC and the Forest Carbon Partnership Facility (FCPF) considering twelve districts in the Terai and Siwaliks. The current results will hopefully be helpful for Nepal to achieve the Tier 3 emission level estimation. The COP decision states that parties can submit a reference level proposal using best available methodology in accordance with national circumstances. The submission can be updated periodically as appropriate, taking into account new knowledge, new trends and any modification of scope and methodologies.

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