Analyses of the feasibility of participatory REDD+ MRV approaches to Lidar assisted Carbon Inventories in Nepal

Stefano Puliti

Arbetsrapport 374 2012
Master thesis in Forest Management
MSc in European Forestry

Handledare:
Johan Holmgren

Sveriges lantbruksuniversitet
Institutionen för skoglig resurshushållning
901 83 UMEÅ
www.slu.se/srh
Tfn: 090-786 81 00

ISSN 1401–1204
ISRN SLU–SRG–AR–374–SE

Analyses of the feasibility of participatory REDD+ MRV approaches to Lidar assisted Carbon Inventories in Nepal

Stefano Puliti

Master thesis in Forest Management
MSc in European Forestry
EX0599
Supervisor: Johan Holmgren, SLU, Department of Forest resource management, Section of Forest Remote Sensing
Examiner: Håkan Olsson, SLU, Department of Forest resource management, Section of Forest Remote Sensing

Sveriges lantbruksuniversitet
Institutionen för skoglig resurshushållning
Utgivningsort: Umeå
Utgivningsår: 2012

ISSN 1401–1204
ISRN SLU–SRG–AR–374–SE

Preface

The Master thesis was carried out at the Swedish University of Agricultural Science (SLU) in cooperation with Arbonaut Oy Ltd., with the additional support of the International Centre for Integrated Mountain Development (ICIMOD). The Thesis has been complementary to the work conducted in the Forest Resource Assessment (FRA) Nepal Project (2010-2014), a bilateral cooperation between Government of Finland (GoF) and Government of Nepal (GoN).

I am grateful to my supervisor Dr. Johan Holmgren for his constructive feedbacks and continuous guidance throughout the entire research work. I like to thank Professor Håkan Olsson who provided this research framework and valuable suggestions for this work. I like to thank Arbonaut Oy and ICIMOD for providing me with the field and Remote Sensing data and for actively supervising the work with fruitful discussions on technical aspects.

My thanks also extend to Post Doc Alessandro Montaghi for support and guidance on the use of R project and other technical issues. I wish to thank the teachers and researchers from Forest remote sensing section at SLU for their kind responses and discussions whenever a question was raised. Two year Master of Science in European Forestry Program including thesis work was financially supported by European Commission.

Summary

Forests are estimated to sequester and emit respectively 15% and 20% of the CO_2 emissions. REDD+ aims at establishing a financial framework to compensate developing countries for reducing Green House Gasses emissions due to decreased deforestation and land degradation. An accurate Monitoring, Reporting and Verification (MRV) of the forest carbon pools is needed. The adoption of State-Of-The-Art remote sensing technologies, such as Lidar in combination with participatory approaches can potentially produce an accurate assessment of the forest resources, ensuring the sustainability of the process.
The study aims at defining the feasibility of Lidar assisted Above Ground Biomass (AGB) assessment with a participatory approach. The study compares AGB regression models built with wall-to-wall, low density (0.8 points m^{-2}) laser scanning data and two field datasets collected by professionals and Community Forest User Groups (CFUGs) teams. The models were built using ArboLiDAR©, a tool-box developed in ESRI environment by Arbonaut Oy, that uses a Sparse Bayesian approach to define a set of weights for each independent variable based on the variance of the field measured AGB and the Lidar metrics. Finally the models were validated with Leave-One-Out Cross Validation (LOOCV). The adjusted R^2, relative RMSE and BIAS as well as the analyses of the residuals were used to compare the models. In addition the study also analyzed the reliability of the models across different forest structures. The professional model described a greater part of the variability of the AGB (adj.R^2=0.75) compared the CFUG model (adj. R^2=0.55), moreover the first was slightly more accurate (professional: rel. RMSE= 45.6 %; CFUG: rel. RMSE= 47.2 %). Although both of the models proved to have the mean of the error term not equal to zero and did not follow a normal distribution, the CUFG model showed heteroschedastic residuals. The accuracy improved when applying the models to forests characterized by a more uniform height distribution (rel. RMSE= 32.1 – 45.2 %), whereas it drastically decreased for sparse forests (rel. RMSE= 91.4 -130.5 %). The study concludes that with the limitation of having different sampling designs and measuring techniques the CFUGs models were slightly worst than the professional ones. However, it is likely that with a more accurate retrieval of the GPS plot center and increase of plot size the results can be as good as the ones obtained with professionally collected data.

Keywords: Above Ground Biomass, remote sensing, forest inventory

Contents

1. INTRODUCTION 5

1.1 BACKGROUND 5
1.2 AIM OF THE THESIS 6

2 MATERIAL AND METHODS 8

2.1 MATERIALS 8
2.1.1 Study site 8
2.1.2 LiDAR data 9
2.1.3 Field data 9
2.2 METHODS 12
2.2.1 LiDAR derived metrics 12
2.2.2 Above Ground Biomass models – Sparse Bayesian approach 13
2.2.3 Models validation 13

3 RESULTS 17

3.1 ABOVE GROUND BIOMASS MODELS: SPARSE BAYESIAN APPROACH 17
3.2 ABOVE GROUND BIOMASS MODELS BASED ON LIDAR HEIGHT STRATIFIED FIELD DATA 20

4 DISCUSSION AND CONCLUSION 23

4.1 AGB MODEL ACCURACY 23
4.1.1 Comparison between Arbonaut and ICIMOD models 26
4.1.2 Suggestion for further studies 28

REFERENCES 29

1. Introduction

1.1 Background

During the past years, the role of forests in mitigating climate change has been increasingly acknowledged by the scientific and political community. It has been estimated, according to the IPCC (Intergovernmental Panel on Climate Change), that forests sequester approximately 15% of the total carbon emissions where tropical deforestation has been shown to account for approximately 20% of the total anthropogenic emissions (IPCC, 2000). This led to the development of policies and processes aiming at reducing the carbon emissions from tropical forests. The UNFCCC started the policy negotiations for REDD (Reducing emissions from Deforestation and Land Degradation) in 2005 and continued in 2009 at the Copenhagen conference (Zahabu, 2008). The negotiations continued in the Conference of Parties (COP 16) in Cancun, in COP 17 in Durban and will be further developed in the future. This process aims at establishing a financial framework to compensate developing countries for the reduced deforestation and land degradation (Gibbs et al. 2007).

The main limitations to the implementation of REDD have been institutional as well as financial regarding the transaction costs for carbon credits (Murdiyarso et al. 2006). The first issue relates to the fact that these policies have been developed only at a national level while they require to be implemented also at a local scale in order to be effective (UNFCCC, 2009). The second issue relates to the fact the actors involved in the monitoring have usually been expert teams, which are costly and scarcely available (Zahabu, 2008). To solve these two problems one of the key issues suggested has been to involve local communities in the monitoring and reporting of carbon resources (UNFCCC, 2009; Zahabu, 2008). The involvement of local communities, would result in more equitable benefit-sharing, would enhance the capacity building and create employment, as well as create a reduction in transaction costs (Gautam and Kandel, 2010). Under the KTGAL project (Kyoto: Think Global Act Local) several studies have tested the reliability of data collected by local communities in order to utilize it for carbon monitoring (e.g. Zahabu, 2008; Tewari et al. 2008) and the results have shown that locals with a 4-7 year education can be trained to carry out forest inventories fulfilling the IPCC Good Practice Guidance criteria for carbon accounting (Skutsch et al. 2009).

The monitoring and reporting of the present carbon resources can be achieved with many different approaches (Gibbs et al. 2007). Different methodologies reflect different quality of information which are described by the IPCC (2006) in three Tiers, each providing more reliable data and therefore higher financial return (Asner, 2009). Tier 1 represents the most general method, characterized by national level average estimates and therefore low resolution and high degree of uncertainty (Asner, 2009). Tier 2, represents an intermediate methodology which is characterized by country and species specific information but with coarser spatial resolution compared to Tier 3. Tier 3 is characterized by data produced with process based models allowing transparent and accurate reporting, providing reliable and valid information updated over time and site specific (IPCC, 2006).
In order to achieve Tier 3 level information, there is the need to have a robust methodology that can be repeated over the years. Remote sensing techniques in combination with ground

truth data can be used to build statistical models in order to fulfil Tier 2-3 requirements (Gibbs et al. 2007).

Laser scanning is one of the most promising technologies in Remote Sensing. The main advantage compared to other remote sensing data is the fact that it gives information about the height and vertical structure characteristics of the forest and produces accurate results taking into account the spatial variability of carbon stocks (Gibbs et al. 2007) allowing a fine retrieval of data over large areas otherwise inaccessible by standard data collection procedures. Furthermore, this technology does not suffer the limitations that other remote sensing techniques encounter such as topographical shading in mountainous areas (Gautam, 2010). Many studies proved that it is possible to produce accurate estimates of forest variables in different areas of the world (Drake et al. 2000, 2002, 2003; Lefsky et al. 2002; Næsset 2002, 2007; Holmgren 2004; Asner 2009, Gautam et al. 2010, Clark et al., 2011, Kronseder et al., 2012).

The REDD+ Monitoring, Reporting, and Verification (MRV) activity is mainly focused on tropical and sub-tropical forest. Even though Lidar forest inventories have been mostly applied with great success in boreal forests, there is a rich literature of studies that prove that the estimation of Above Ground Biomass (AGB) in more complex forest structures with Lidar assisted models is possible with a good level of accuracy (Drake et al., 2002). Drake et al. (2003) in tropical wet forests in Costa Rica, were able to describe the AGB with an R^2 of 0.89 with large-footprint full waveform Lidar. In a more recent study Asner et al. (2009) estimated AGB in a tropical Rain Forest in Hawaii with an R^2 of 0.78 and relative RMSE % of approximately 37.5-43.2 %. Equivalently, Clark et al. (2011), in the same Costa Rican site estimated AGB on a wall-to-wall Lidar data with a coefficient of determination of 0.89 and relative RMSE of 32.3%. Another study by Kronseder et al. (2012) estimated the overall AGB in a tropical rainforest with an adjusted R^2 of 0.7 and relative RMSE of 33.9%.

In order to model forest variables with LiDAR data, there is a need to combine this data with a teaching ground-truth dataset. Up to now the experience is based on forest inventories modeled with teaching datasets that have been collected by professional teams. The utilization of data collected by Community Forest User Groups (CFUGs) in combination with LiDAR data has not yet been explored.

1.2 Aim of the thesis

The aim of this study was to test the possibility of integrating laser scanning data with ground truth data collected by local communities in Ludikhola watershed in Nepal to built models to estimate carbon stocks. This was achieved by comparing the AGB Lidar assisted models built with professional and CFUGs ground truth data, referred respectively in this report as Arbonaut and ICIMOD datasets. Consequently, after an overall evaluation of the models performances based on the comparison of statistical indexes presented in previous studies in tropical regions (e.g. adjusted R^2, relative RMSE), the study focused on the comparison of the Arbonaut and ICIMOD AGB models.

In case the CFUGs AGB model would produce similar results as the professional one it would allow this technique to be implemented in other geographical areas. This would enhance the involvement of local communities in the REDD+ MRV process, reducing the transaction costs, developing a strong and reliable methodology to support the results, fulfilling the IPCC recommendations for Tier 3 inventories as well as enhancing the sustainable development of the communities that manage the forests.

2 Material and Methods

2.1 Materials

2.1.1 Study site

The present study, considers Nepal as a typical example of a nation where REDD+ can be implemented. In fact, the conservation efforts started in 1978 in Nepal, created a solid base for improving the state of the forest resources by redefining the property rights of Community Forest Users Groups (CFUGs) (Gautam, 2005). Since Nepal's Ministry of Forests and Soil Conservation, has committed to objectives of conservation for the reduction of GHG emissions (Readiness Preparation Proposal, RPP, April 19th 2010), several REDD+ pilot projects started to be implemented to guide the development of participatory CO2 monitoring schemes and the establishment of payment schemes (ICIMOD, 2010).

The study was carried out in a Nepalese watershed, included in the biomass sites projects developed by the cooperation of the International Centre for Integrated Mountain Development (ICIMOD) together with the Asian Network for Sustainable Agriculture and Bio-resources (ANSAB) and the Federation of community Forestry Users (FECOFUN) with the financial support of the Norwegian Agency for Development (NORAD).

The Ludikhola watershed (Gorkha district) is located in the Hill region characterized by sub-tropical broad leaved forests, ranging from 318 m to 1714 m above sea level, has a total area of 5750 ha, a forest area of 4869 ha, and includes 31 Community Forests that cover 1888 ha (Table 1). The dominant tree specie is *Shorea robusta* associated with *Schima wallichii* and *Castanopsis indica* (ANSAB, 2010).

Table 1. Main abiotic and biotic site characteristics. The land use was derived from the Land cover analyses report (2010)

	Watershed	**Ludikhola (Gorkha)**
Site characteristics	**area (ha)**	5750
	Altitude range (m a.s.l)	318 - 1714
	Average temp. (°C)	23.1
	Average rainfall (mm)	1972-2000
	Close to open Broadleaved (dense) forest (ha)	3873 (67,3%)
	Open Broadleved (sarse) forest (ha)	996 (17,3%)
Land use	**Natural water bodies (ha)**	9 (0,2%)
	Bare soil (ha)	241 (4,2%)
	Grassland and degradated forest (ha)	0
	Clouds (ha)	0
	Agricultural land and build up areas (ha)	632 (10,9%)
	Forest Area TOT (ha)	4869 (84,6%)

2.1.2 LiDAR data

The laser scanning data was provided by the Forest Resource Assessment in Nepal, Ministry of Forests and Soil Conservation in the project developed by the joint venture of FRA (Forest Resource Assessment) Nepal project, WWF, Arbonaut Oy Ltd and ICIMOD. The data set was collected during the spring (March-April) 2011 with Helicopter (9N-AIW) at a flight altitude of 2200 m above ground level using Leica ALS50-II Lidar-scanner with footprint size of 50 cm, average laser beam density 0.8 points m^{-2} and scan frequency of 52.9 kHz. The Lidar block object of study was collected within the study (Lidar Assisted Multisource Program LAMP) of a larger area. With regard to this study case the Lidar data is characterized by a wall-to-wall coverage.

2.1.3 Field data

The field data was composed by the Arbonaut and the ICIMOD datasets. The Arbonaut data collection was also done within the project cited above by DFRS/FRA and WWF personnel during spring 2011. The ICIMOD data was collected during the ICIMOD REDD Pilot Project during spring 2011. MENRIS (Mountain and Natural Resources Information) section of ICIMOD was in charge of the field campaign and a total of 118 representatives of local communities participated actively in the measurements.

These two field datasets presented differences and similarities that were highly relevant to the purpose of the study.

The differences are represented by:

- Sampling design: for the Arbonaut dataset the field plots were generated using a systematic clustered random sampling within the LiDAR coverage. Each cluster was composed by a maximum of 8 plots (Figure 2), located in two parallel columns distant 300 m from each other and with a distance of 300 m between rows. The original sampling design included 15 clusters for a total of 115 plots in the Ludikhola watershed. The actual number of plots available for the purpose of the study was less due to the fact that some plots were either inaccessible or in non forested areas (water, agricultural and bare soil areas). The total number of plots available for the study is therefore 92 (Table 2). Differently the ICIMOD sampling design was based on a stratified random plot generation. The stratification was carried out using high resolution satellite images (Geo-eye). The area was divided into two strata: dense (canopy cover >70%) and sparse forest (canopy cover<70%). Secondly, the plots were randomly generated using Hawt´s Analysis Tool for ArcGIS. The number of measured plots was 191.

- Plot size: The Arbonaut plots were fixed circular plots with area= 500 m^2 and radius = 12.62 m, whereas the ICIMOD plots were fixed circular plots with area= 250 m^2 and radius = 8.92 m.

- DGPS: The Arbonaut´s GPS plot center points were geometrically corrected with a real-time Differential GPS (DGPS) station (Promark 3, Magellan) located in the watershed, while this was not available for the ICIMOD dataset.

The similarities are represented by:

- Plot quantitative measures: Stem count, species composition, Diameter at Breast Height (DBH) >5cm (caliper or measuring tape), height (clinometer or VertexIV and Transponder T3), GPS plot center (Map 60CSx or 62s, Garmin).

- Sampled area: regardless the difference in plot number between the two datasets the total sampled area was similar: Arbonaut = 4.6 ha; ICIMOD= 4.8 ha (Table 2).

- Above Ground Tree Biomass (AGTB) model: similarly to other studies in tropical areas (Asner et al., 2009; Kronseder et al., 2012), was estimated using the allometric equation described by Chave (2005):

  $$AGTB = 0.0509 * \rho D^2 H$$

  Where: ρ is the wood specific density (Kg m^{-3}) (MPFS, 1988), D is the DBH (cm) and H is equal to the tree height (m). Moreover the biomass value was converted to t ha^{-1}.

- Quality assurance (QA) and quality control (QC) was carried out for both datasets.

Table 2. Comparison of the professional and community plot data in the two watersheds object of study

Watershed	**Ludikhola (Gorkha)**	
Source	Arbonaut	ICIMOD
n_plots	92	191
sample plot size (m2)	500	250
sampled area (ha; % of forest area)	4.6 (0.1%)	4.8 (0.1%)
Tree_AGB mean (t/ha)	126	189.9
AGB_stdev (t/ha)	111.4	131.8
Tree_AGB max (t/ha)	478.3	625
Tree_AGB min (t/ha)	4.11	0

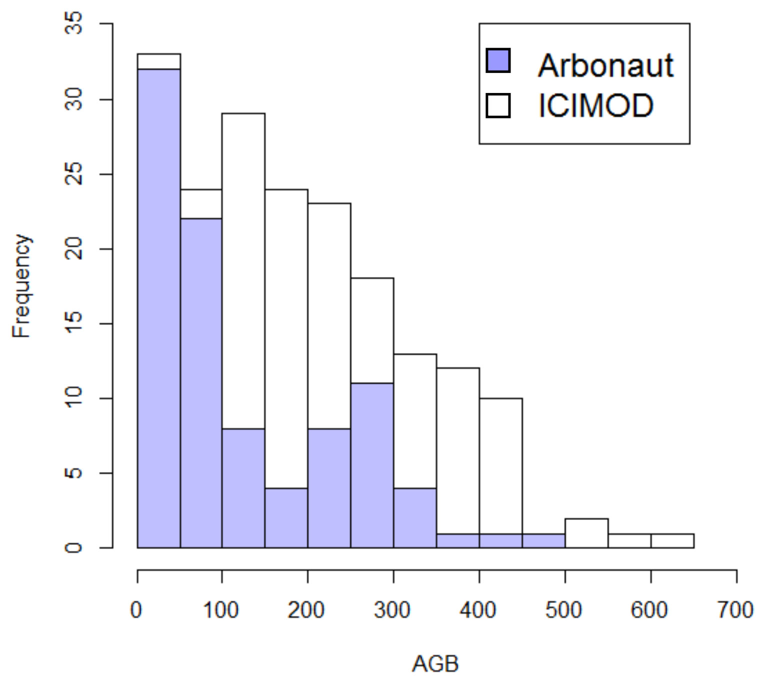

Figure 1. Tree biomass (t ha^{-1}) frequency distributions from Arbonaut and ICIMOD field data in Ludikhola watershed. The blue bars represent the Professional data while the white ones the Community data. Even though the distributions follow similar patterns, the professional dataset presents a narrower range.

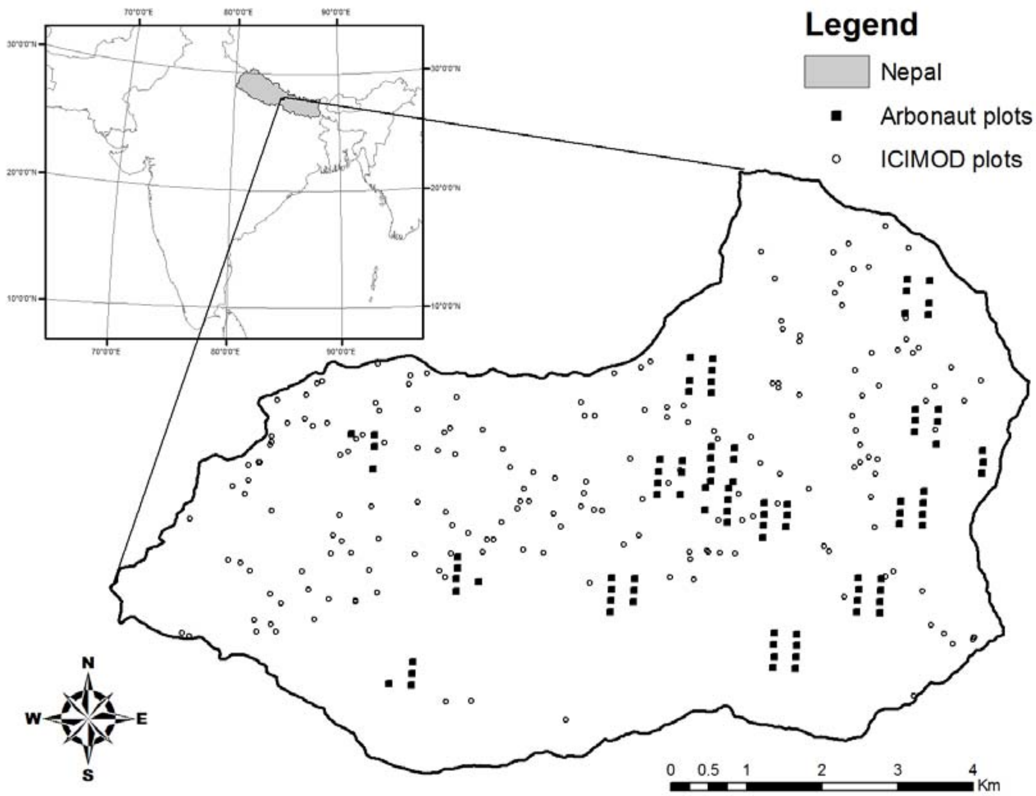

Figure 2. Location of the Ludikhola watershed and sampling design differences between the Arbonaut plot data (squares) and ICIMOD plot data (circles).

2.2 Methods

The two plot datasets were used as the training datasets, together with the Lidar data for two different inventory calculations. The modeling was done using ArboLiDAR©, a forest inventory process and tool package developed in ESRI environment by Arbonaut Oy Ltd.

2.2.1 LiDAR derived metrics

Initially, a number of Lidar metrics were extracted from the Lidar data (Table 3) correspondingly to the area of each plot (Junttila et al. 2010). Afterwards, the plot dataset with the correspondent Lidar variables was used as the input for the statistical models.

Table 3. Lidar Variables (Junttila et al. 2010)

X1,…10 = H*fpr*, height for which the cumulative sum of ordered first pulse heights is closest to *k*% of the total height sum, *k* _ 10, 20, …, 100 (m).
X11,…20 = H*lpr*, height for which the cumulative sum of ordered last pulse heights is closest to *k*% of the total height sum, *k* _ 10, 20, …, 100 (m).
X21,…23 = I*fpr*, Intensity for which the cumulative sum of ordered first pulse intensities is closed to 30%, 60% and 90% of the total intensity sum.
X24,…26 = I*lpr*, Intensity for which the cumulative sum of ordered last pulse intensities is closed to 30%, 60% and 90% of the total intensity sum.
X27 = H*f,m5*, Mean height of first pulse high vegetation points (points over highveg_threshold= 5m).
X28 = H*f,std*, Standard deviation of first pulse heights
X29 = H*f,empty*, The ratio of the below vegetation first pulse points (points under ground_threshold= 1 m) and all first pulse points.
X30 = H*l,empty*,The ratio of the below vegetation last pulse points (points under ground_threshold= 1 m) and all last pulse points.
X31,…38 = Ratio of last pulse points with height lower than lpdensity_class + i * lpdensity_cllssize for i = 0..7 and the total number of last pulse points. Where: lpdensity_start="1.5"; lpdensity_clssize="3".
X39,...41 = Ratio of first pulse points with intensity I ≤ 0.5+i for i = intensity_classes and the total number of first pulse points. Where: intensity_classes="10;30;50"
X42,…44 = Ratio of last pulse points with intensity I ≤ 0.5+i for i = intensity_classes and the total number of first pulse points. Where: intensity_classes="10;30;50"
X46 = Logarithm of the ratio of the number of first pulse points below "highveg_treshold" (5 m) and the total number of first pulse points.
X47 = Mean of the largest three heights within first pulse points.

2.2.2 Above Ground Biomass models – Sparse Bayesian approach

The regression was based on a sparse Bayesian approach (Tipping 2001; Bishop & Tipping 2003; Junttila et al. 2008) that integrates LiDAR and field measurements to estimate forest variables. The Sparse Bayesian approach relies on a non-parametric, locally linear Bayesian method (Junttila, 2008) that ranks the regression models based on the variance in the variable of interest (e.g. , basal area, biomass) and the variable's correlation with another dataset, in this case the LiDAR metrics.

The strength of the method is the ability to weigh the relevance of each variable in the prediction with a high degree of automation (Junttila, 2008).

The input data and parameters in the model were constituted by the plot data with the correspondent Lidar metrics, the stand data for the output calculation and by the value of the hyperparameter α (Junttila, 2008). Finally the inventory results were calculated for the same plots used to train the models.

2.2.3 Models validation

The models' evaluation and comparison was done based on the most common statistical indexes found in the literature. First, the RMSE % and BIAS % of the mean AGB were calculated with Leave One Out Cross Validation (LOOCV). Secondly, as previous studies have reported (Drake et al., 2002; Asner et al, 2009; Clark et al., 2011; Kronseder et al., 2012) the adjusted R^2 was used to determine how well the models can describe the variation in the sample population. The adjusted R^2 was used since the model relies on more than one independent variable. Finally the analyses of the observance of the assumptions of a linear regression model were tested. The mean of error term and its normality were tested analytically and respectively with a t-student test and a Shapiro-Wilk test using the R functions (R-project) found in the base package. Additionally, the normality, linearity and homoschedasticity of the error term were analyzed graphically.

The comparison of the models was affected by several factors, such as differences in plot size, sampling design and DPGS plot center geometric correction. In fact the ICIMOD field data presented several outlier plots that had exceptionally high biomass that skewed the AGB distribution to the right and significantly affected the model's RMSE. The RMSE was then calculated also for a narrower AGB range, spanning from 0 to 350 t ha^{-1}. Furthermore, in order to produce more comparable results the model's accuracy was also tested for both datasets based on the real-time GPS measure, without a post geometric correction.

In addition to the analyses of the statistical indexes, further investigation included the analyses of AGB models constructed using a stratification of the original field data, in order to describe the uncertainty of the AGB estimates within different forest structures. A fundamental aspect that needs to be taken into account when modeling biomass in a tropical/subtropical context is the heterogeneity of forest structures and its variation within a landscape (Clark and Clark, 200; Chave, 2004). As other studies previously reported, different forest structures corresponded different uncertainties of the AGB models. Clark et al. (2011), in a tropical context in Costa Rica (mean annual precipitation= 4244 mm) demonstrated that the R^2 and relative RMSE are highly variable between different forest types, the overall results of the research (n=83; R^2 =0.90; RMSE rel= 32.77%) significantly improved when the modeling was restricted to plantations plots (n=32; R^2 =0.95), alternatively when the model was built on the old-growth forest plots (n=51; R^2 =0.43) the results worsened. Similarly, in a recent study Kronseder et al. (2012) estimated AGB using Lidar data in Borneo across forests at different degrees of degradation. Also in this study the overall model performance (n=142; adj. R^2 =0.70; RMSE rel= 33.85%), improved significantly when the models were restricted to lowland dipterocarp forests (n=70; adj. R^2 =0.82; RMSE rel= 21.37%) and worsened when modeling peat swamp forests (n=72; adj. R^2 =0.31; RMSE rel= 41.02%).

In this study case the two field data sets available did not contain common information about the forest structures, thus the plots have been stratified based on the Coefficient of Variation (HCV) of the Lidar height raster, described by Evans et al. (2009) with 4m x 4 m pixels, a resolution at which it is possible to identify even small gaps due to tree fall in the canopy (Clark and Clark, 2000).

In order to produce strata that are relevant at a landscape scale, a grid of 500 m^2 (Arbonaut plot size) was created over the watershed, the Height CV was calculated for each cell and the median value (0.6587) was used to define the two strata (Figure 3).

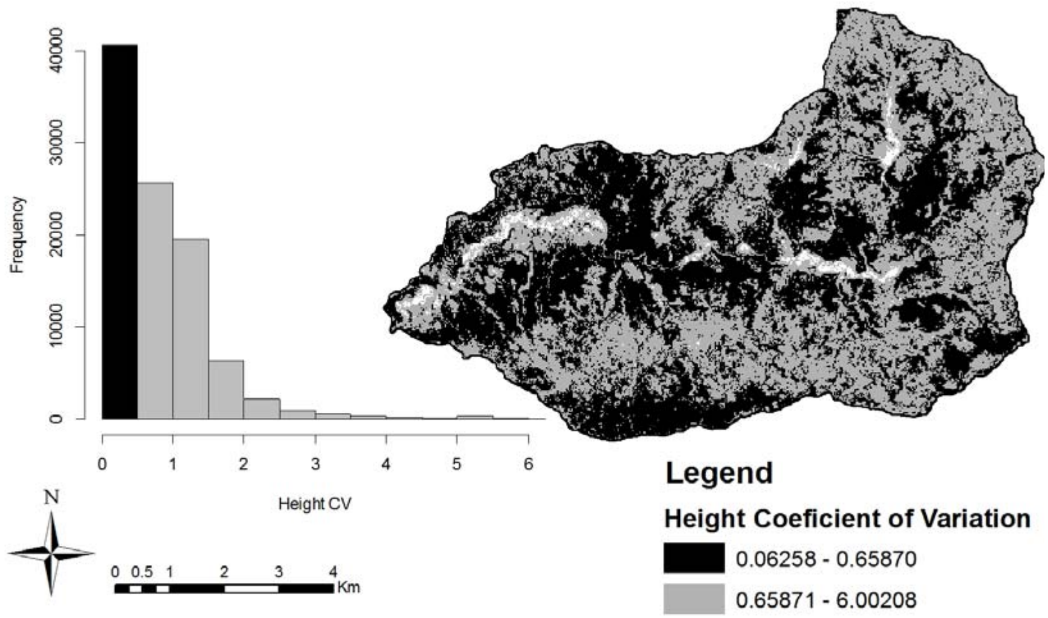

Figure 3. Frequency and geographical distribution of the Height Coefficient of Variation (HCV) within the Ludikhola watershed. The two strata are defined by the median HCV value (0.6587), in black the first strata representing the denser and uniform forests, while in grey are the more sparse forests and trees outside forests.

This metric provided information on how uniform the forest structure are, figures 4 and 5 show the range for the Height CV for the Arbonaut and ICIMOD dataset. The first strata represents forests that are more uniform in the distribution of heights and where the forest cover is more homogeneous, while the second strata represents more open woodland areas and *trees outside forest* (Figures 4 and 5). *Trees outside forest* are important in the determination of the AGB in developing countries due to widespread agricultural land use and the importance of trees in rural landscapes, yet it has been proven to be difficult to estimate such category due to the lack of official statistics (FAO, 2011).

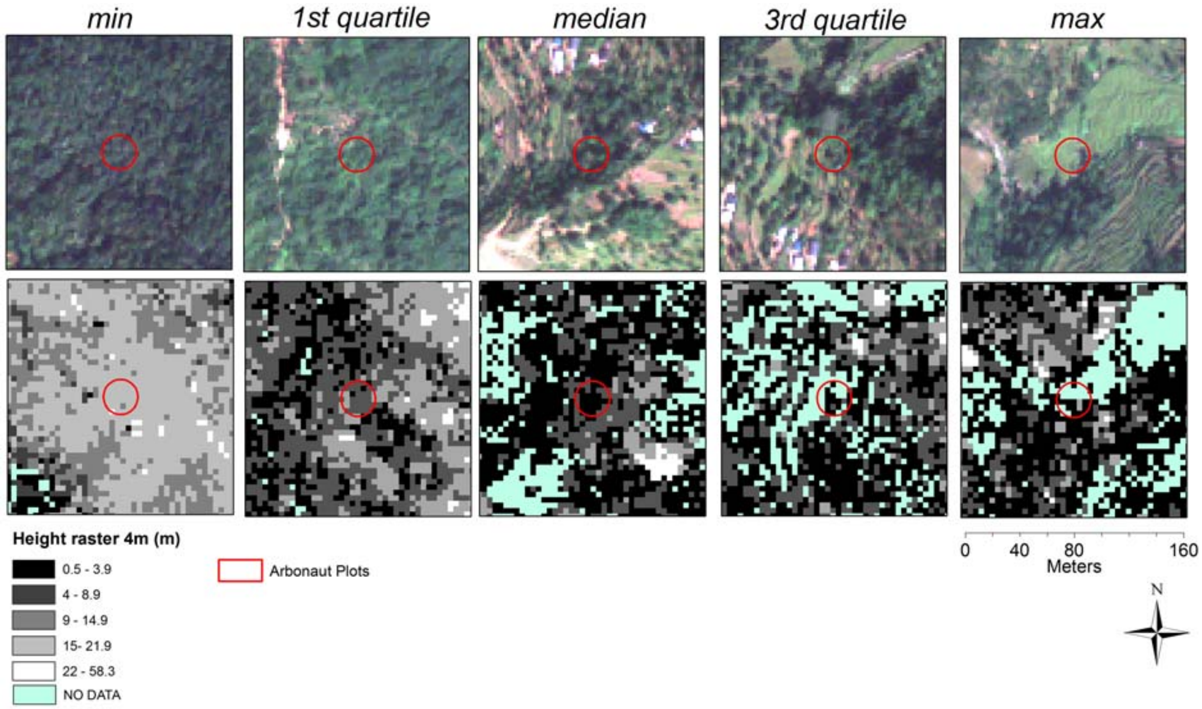

Figure 4. Range (minimum, 1st quartile, median, 3rd quartile, maximum values) of height Coefficient of Variation (CV) for the Arbonaut plots. No data values are pixels where there is no vegetation laser hit.

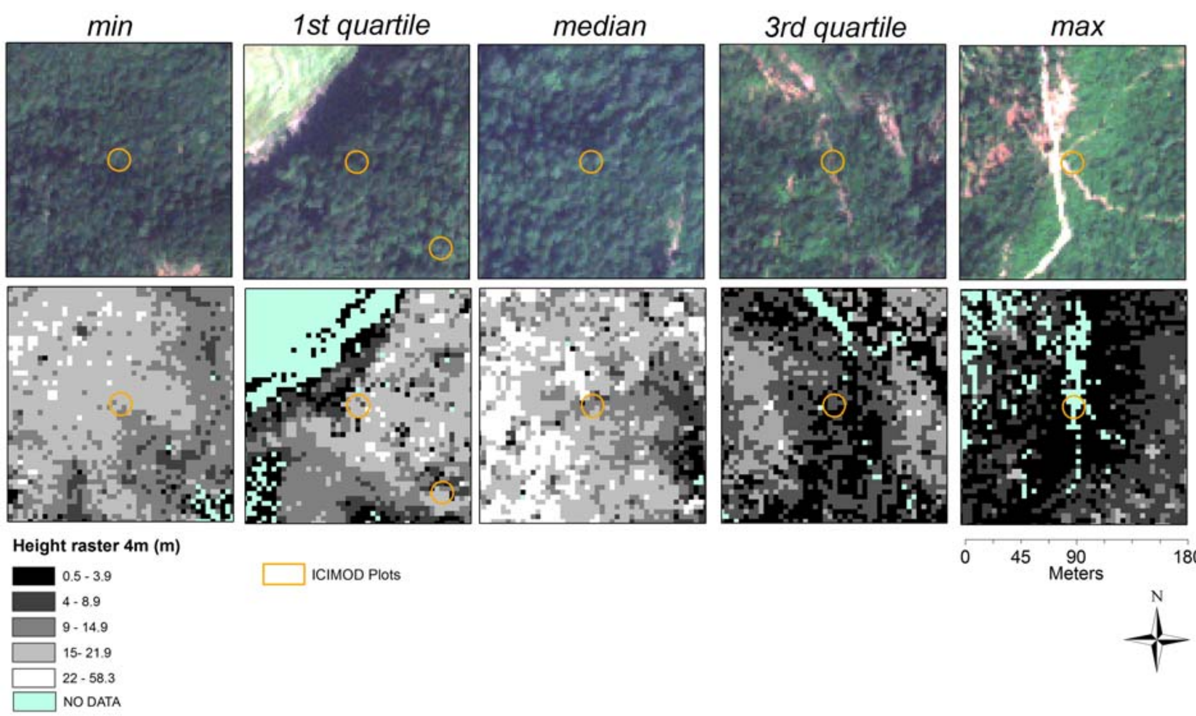

Figure 5. Range (minimum, 1st quartile, median, 3rd quartile, maximum values) of height Coefficient of Variation (CV) for the ICMOD plots. No data values are pixels where there is no vegetation laser hit.

3 Results

3.1 Above Ground Biomass Models: Sparse Bayesian approach

The biomass modeling was performed with all the plots available from both datasets (Arbonaut: n=92; ICIMOD: n= 191). However, it is important to mention that these had substantial differences with regard to the forest structures that they described. The best results were achieved with multiple independent variables, these varied in number between the two field datasets, for Arbonaut four and for ICIMOD six independent variables were selected. The different field data produced also different results in the variable selection process. In fact, the Arbonaut model was more parsimonious, including only one height percentile (first return 60th percentile), two intensity metrics and one vegetation ratio measure. On the other hand, the variable selection for the ICIMOD model included three height percentiles, including the first pulse 100th percentile, the ratio of below vegetation points, the ratio of vegetation points and another ratio of points with intensity under a threshold. Furthermore, the transformation of the independent variables has shown to improve the results. In the Arbonaut models the logarithmic and power transformations were preferred. The square root and power produced better results for ICIMOD dataset. Table 4 summarizes the variables that showed the best correlation with the AGB with the correspondent transformations.

Table 4. Variables used as predictors in the Biomass models. For the description of each variable see Table 3 in section 2.2.1

Plot Data set	Arbonaut	ICIMOD
Independent Variables	log(X6)	sqrt(X10)
	log(X23)	sqrt(X14)
	X34	sqrt(X16)
	X42^2	X30^2
		X34
		X41^2

The results of the regression analyses (Table 5) showed that the Arbonaut AGB model better describes the variability of the sample (adjusted R^2= 0.75) compared to the ICIMOD model (adjusted R^2= 0.55). Regardless of the lower adjusted R^2 in the ICIMOD model, the overall model accuracy and bias calculated with a Leave-One-Out cross validation (rel. RMSE = 47.2%; rel. BIAS= 0.04 %) is similar to the one of the Arbonaut model (rel. RMSE = 45.58%; rel. BIAS= -0.28 %). It is however important to mention that the absolute RMSE is notably higher for the ICIMOD model (RMSE=89.7 t ha^{-1}) compared to the Arbonaut's one (RMSE= 57.4 t ha^{-1}). Additionally, Figure 6 shows that for both datasets there was a tendency of underestimating high AGB values, even though this was more prominent in the ICIMOD AGB model.

The accuracy assessment conducted on a narrower measured AGB range, showed that when few of the exceptionally higher values from the ICIMOD dataset were removed the relative RMSE (35.3%) was smaller than the one for the Arbonaut model (46.1%), even though the absolute RMSE was still higher (Arbonaut= 53.5 t ha^{-1}; ICIMOD= 72.3 t ha^{-1}). Similarly, the Arbonaut's non-differentially corrected relative RMSE was higher (51.3%)

than the ICIMOD's one (47.2%) despite the fact that also in this case the absolute RMSE was higher for the ICIMOD dataset (Table 5).

Table 5. Main statistical indexes used to compare the Biomass models from Arbonaut and ICIMOD. The indexes were calculated with the functions below

	Arbonaut	ICIMOD
n plots	92	191
R2*	0.77	0.57
adjR2**	0.75	0.55
RMSE (t ha-1)	57.4	89.7
RMSE (%)***	45.58	47.2
BIAS (%)****	-0.28	0.04
RMSE AGB range 0-350 (t ha-1)	53.5	72.3
RMSE AGB range 0-350 (%)	46.1	35.3
RMSE no DGPS correction (t ha-1)	64.7	89.7
RMSE no DGPS correction (%)	51.3	47.2

* cal.r2 <- function(obs, pred) 1-(sum((obs-pred)^2) / sum((obs-mean(obs))^2))
** adjR2<- 1 - (1-R2)* ((n-1) / (n-p-1)) where: n=sample size; p= number of predictors
*** cal.rmse <- function(obs, pred) sqrt(mean((obs-pred)^2))
**** Bias= (mean (obs - predict)) / mean (obs) *100

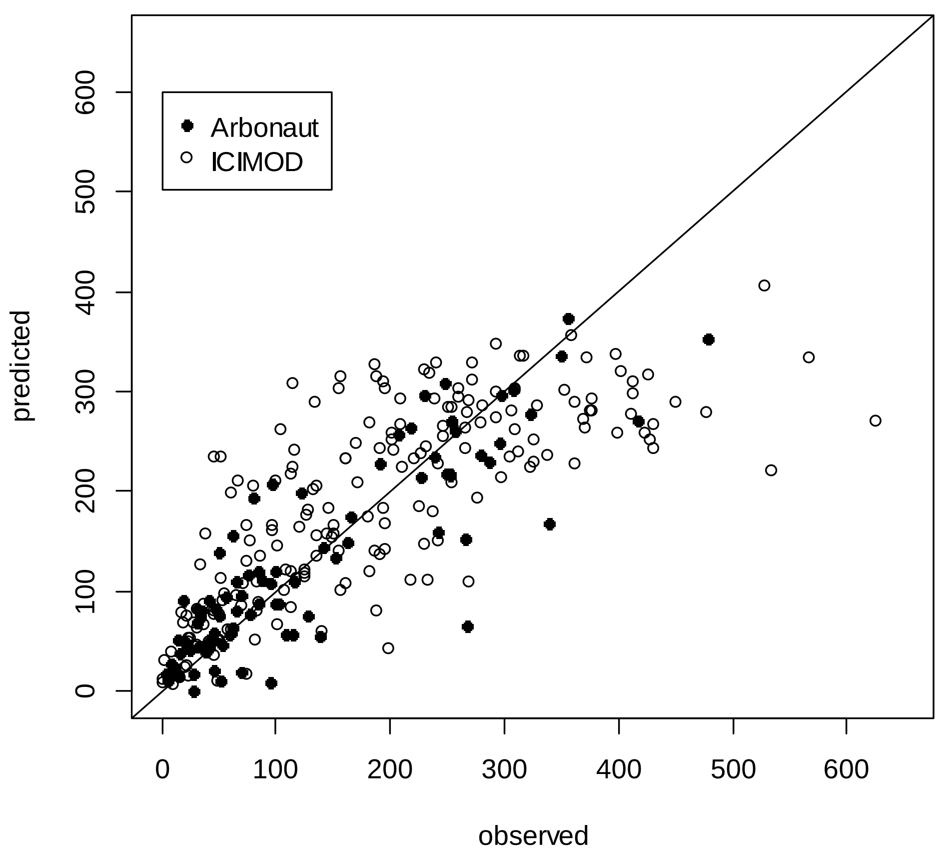

Figure 6. Lidar estimated AGB (T ha-1) using the previously mentioned variables (Table 1) plotted against field measured AGB for Arbonaut and ICIMOD AGB models.

The analyses of the assumptions of the linear regression showed that according to the T-student test, both of the models had a mean of the residuals not equal to 0 (Arbonaut: t= -0.0011, p-value= 0.99; ICIMOD: t= 0, p-value= 1). Additionally, the Shapiro-Wilk test the null hypothesis was rejected (p-values < 0.05), resulting in a non-normal distribution of the residuals. The graphical analysis of the assumption of normality is shown in figures 8 and 9 with a histogram of the distribution of the standardized residuals and a QQ plot. The graphical analyses (Figure 7) of the assumptions of linearity and homoschedasticity showed that neither one of the models is seriously affected by non-linearity of the residuals (figure 7), whereas it is important to notice the variance in the error term is not constant for the ICIMOD model (Figure 7 b). Another aspect worth mentioning is that both of the models had potential outliers. The investigation of these plots revealed that many were the potential causes, including high biomass and density values which could explain a greater displacement of GPS plot center due to thicker canopies.

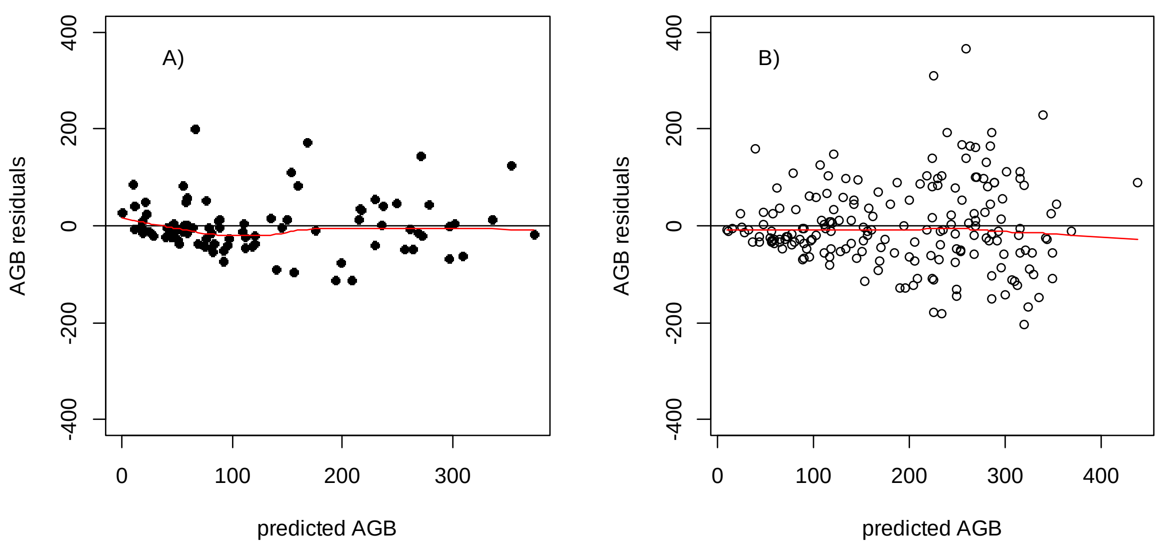

Figure 7. AGB residuals plotted against the predicted values for Arbonaut (A) and ICIMOD (B) AGB models. The red line represents the locally-weighted polynomial regression (lowess function, R project).

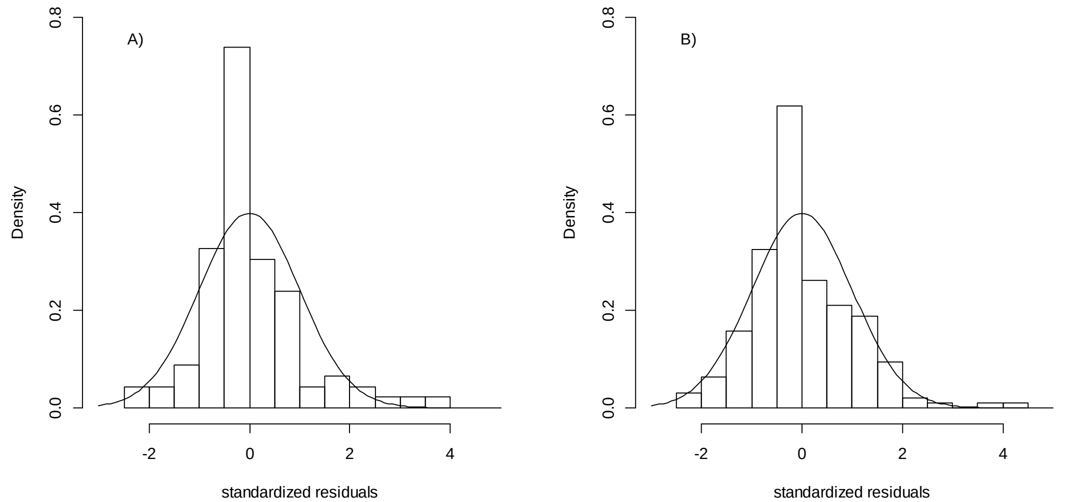

Figure 8. Standardized AGB residuals frequency distribution for Arbonaut (A) and ICIMOD (B) models.

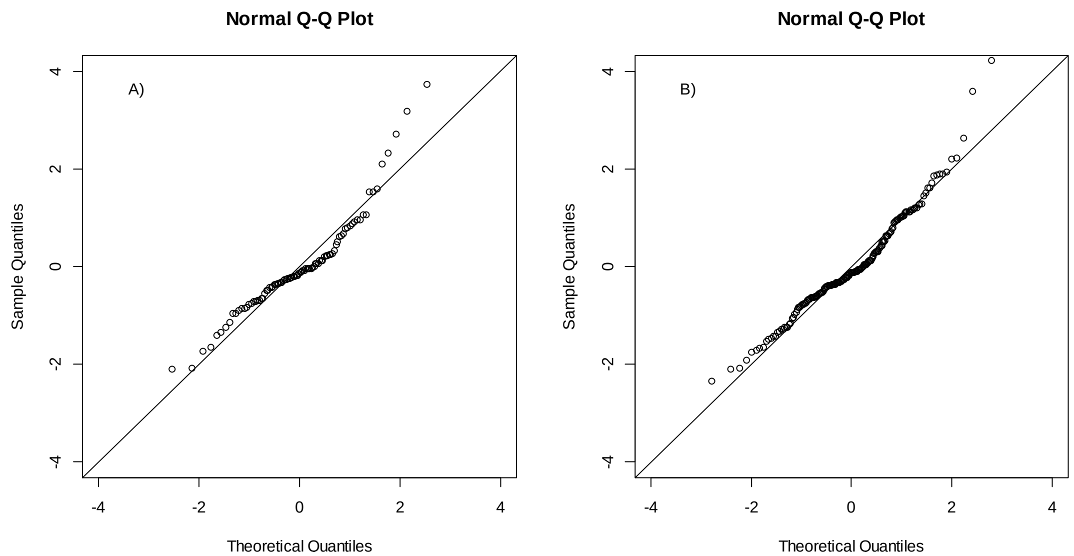

Figure 9. QQ plot of the residuals for Arbonaut (A) and ICIMOD (B) models. The graph shows that neither one of the models produced residuals that are normally distributed.

3.2 Above Ground Biomass Models based on Lidar height stratified field data

The AGB models stratified according to the median Coefficient of Variation of the Lidar height (HCV) in the watershed were built with the same variables described in section 3.1 (Table 4). The performance of the stratified models is described in Table 6. Regardless the fact that the R^2 remained stable between the original model (Table 5) and the first strata models (Table 6) the relative RMSE decreased significantly for the Arbonaut with a decrease of 13.46% dataset and by only a 2% for the ICIMOD dataset (Table 6).

On the other hand, the results from the second strata showed a significant worsening of all the indexes, in the worst case the mean root square errors were higher than the mean AGB value producing results of relative RMSE of 130% for Arbonaut (Table 6). Also the Bias significantly increased in the second strata. It is important to highlight that due to different sampling designs the number of plots between the two strata in the ICIMOD dataset are highly different (n strata1= 164; n strata 2= 27), therefore affecting the models. Figure 10 shows that for both strata the models tend to underestimate the higher values within their ranges, this applies both to the Arbonaut and to the ICIMOD models.

The analyses of the residuals show that the distribution of the residuals is linear for both datasets for the first strata, even though for the ICIMOD models there are still problems of heteroschedascticity (Figure 11). The second strata show in both cases that it is possible to identify problems of non linearity and heteroschedasticity.

Table 6. Statistical indexes for the Lidar height CV stratified models

	Arbonaut		ICIMOD	
	strata 1	strata 2	strata 1	strata 2
% of tot forest area	50	50	50	50
n plots	47	45	164	27
R2*	0.75	0.32	0.52	0.27
adjR2**	0.73	0.25	0.5	0.05
RMSE (t ha-1)	61	77.3	93.7	69.2
RMSE (%)***	32.12	130.5	45.2	91.39
BIAS (%)****	-0.32	-10.01	-0.18	1.15

* cal.r2 <- function(obs, pred) 1-(sum((obs-pred)^2) / sum((obs-mean(obs))^2))
** adjR2<- 1 - (1-R2)* ((n-1) / (n-p-1)) where: n=sample size; p= number of predictors
*** cal.rmse <- function(obs, pred) sqrt(mean((obs-pred)^2))
**** Bias= (mean (obs - predict)) / mean (obs) *100

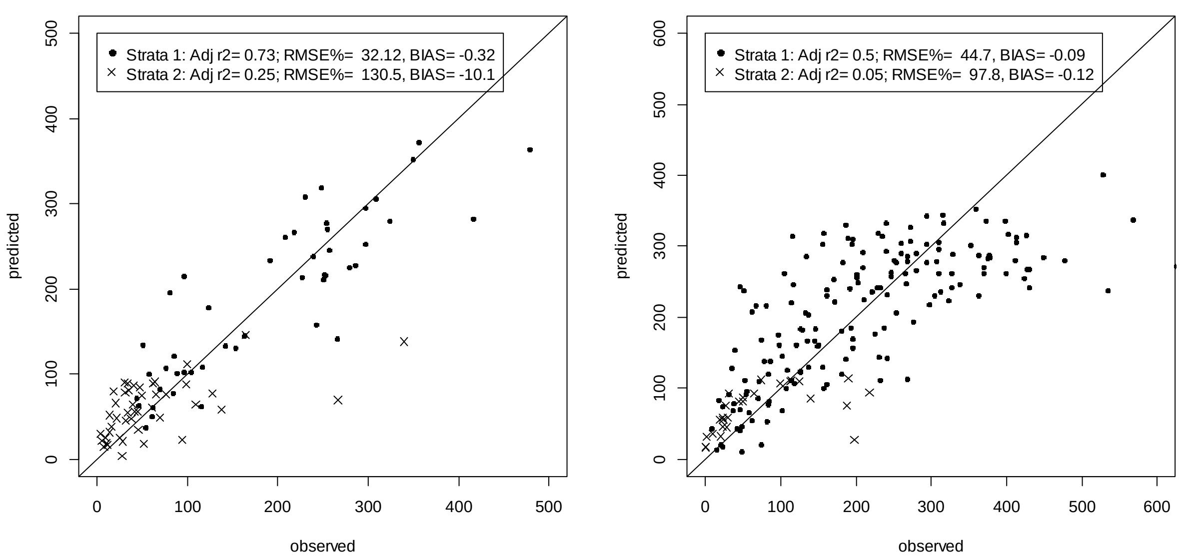

Figure 10. Lidar estimated AGB (T ha-1) plotted against field measured AGB for Arbonaut and ICIMOD AGB stratified models.

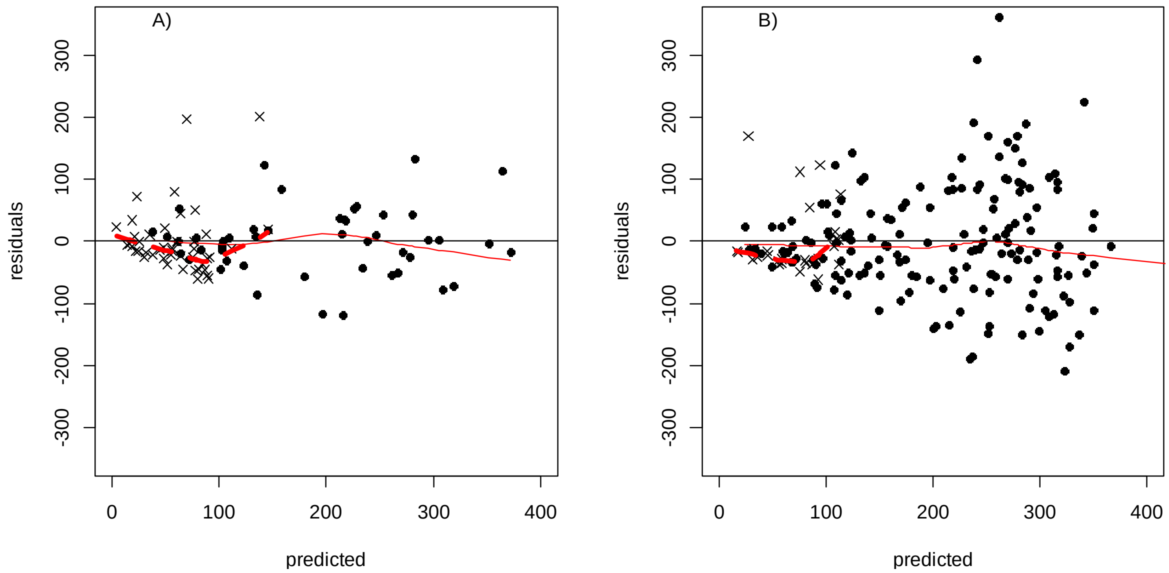

Figure 11. AGB residuals plotted against the predicted values for Arbonaut (A) and ICIMOD (B) AGB models and for strata 1 (dots) and strata 2 (crosses) representing respectively dense and sparse forests. The red continuous line represents the locally-weighted polynomial regression for the strata 1 while the dashed line represents the locally-weighted polynomial regression for the strata 2 (lowess function, R project).

4 Discussion and Conclusion

4.1 AGB model accuracy

Recently, Nguyet (2012) conducted a study in the Ludikhola watershed using a single tree method to predict AGB (Dalponte et al., 2011), obtaining for other species and for the main specie (*Shorea robusta*) respectively values of adjusted R^2 of 0.65-0.75 and relative RMSE of 23.8% and 36%. Other studies were successfully conducted in other Tropical and temperate areas. Comparing the results from this study with previous experiences, it is possible to determine that Arbonaut model´s adjusted R^2 (0.75) is comparable to previous studies (Drake et al. 2000, 2002, 2003; Lefsky et al. 2002; Næsset 2002, 2007; Gautam et al. 2010, Clark et al., 2011, Kronseder et al., 2012) where they obtained values of R^2 ranging from 0.89 to 0.7. On the other hand, the ICIMOD model showed a low ability in describing the variability of AGB in the sample (adjusted R^2= 0.55). The relative RMSE (Arbonaut= 45.58 %; ICIMOD=47.2 %) was higher than most of the previous studies, which ranged between 32.3 and 43.2 %, proved to be acceptable for the more dense and uniform first strata forests (Arbonaut=32.12 %; ICIMOD=45.2 %).

The investigation of the residuals and of the assumptions of the linear regression was not present in any of the studies found in the literature, therefore was not possible to compare the results from the present study.

The analyses of the stratified models showed some important figures regarding the available data and building know how for further studies. The results from the first strata models showed a relatively good ability to predict AGB in areas where the forest cover and structure is more uniform (Arbonaut: adj.R^2= 0.73, RMSE= 61 t ha^{-1}; rel.rmse=32.12 %, rel.bias = -0.32 ; ICIMOD: adj.R^2= 0.5, RMSE= 93.7 t ha^{-1}; rel.rmse=45.2 %, rel.bias= -0.18), whereas produced unreliable and biased results for the strata representing sparse, open forest or other wooded areas (Arbonaut: adj.R^2= 0.25, RMSE= 77.3 t ha^{-1}; rel.rmse=130.5 %, rel.bias= -10.01 ; ICIMOD: adj.R^2= 0.05, RMSE= 69.2 t ha^{-1}; rel.rmse=91.39 %, rel.bias= 1.15). The effect of the stratification was more evident for the Arbonaut model since the field data was relying on a stricter sampling design and some plots that were located in open areas were measured, whereas the ICIMOD data was describing only forested areas. This aspect needs to be carefully considered when generating the sampling design, since the inclusion of plots that lie in sparse forests will reduce the overall accuracy of the model's predictions unless some other metric is found to describe these types of forests. One of the main issues with these forest types and their estimation with Lidar assisted models is the fact that when the Lidar data is summarized in Lidar metrics (e.g. height percentiles) the three dimensional information is simplified into a two dimension type of data. Therefore to describe the vertical and horizontal distribution of forests, would be useful to extract several Lidar metrics able to describe the spatial variation of the forest and therefore within the sample plot.

The process of AGB estimation is characterized by a stepwise process where each step has different level of uncertainty (Chave et al., 2004, Asner et al., 2009). Initially, each tree is measured in each plot, then the diameter and height measures from each tree are used to estimate the AGB through allometric relationships, moreover the plot AGB estimates are converted to per ha values. Finally the AGB is modeled with the Lidar data in order to produce the estimates over a landscape. Regarding the field measurements, Chave et al.

(2004) notes that the diameter measurement error is proportional to the trunk diameter, reporting errors of 0.27 cm on trees with 30 cm diameter (95% probability), height and wood density errors are estimated to be ca. 10%. In this case study, the errors due to diameter and height measurements are different between datasets due to subjectivity between different measuring teams and differences in the instruments used. The ground truth height measurements were available only for the Arbonaut plots and resulted in 25 plots with field measured mean height basal area Weighted (HGW) higher than Lidar 100th percentile (maximum height) with a maximum difference of 12 m. The cause of the mismatching of field and Lidar heights lies either in a displacement of the plot GPS center or in a difficulty in visualizing the tree top when measuring height for dense broadleaved forests. It is also likely also that these two factors could occur at the same time since in dense canopies the GPS signal is lower.

In addition, allometric models are affected by errors, especially in tropical areas where they are constructed from limited samples and are often applied beyond their original diameter range (Chave et al., 2004). In the same study Chave et al. (2004) report an average uncertainty of the estimate of 20% of the mean AGB, with a minor relevance of the measurement error and a bigger fraction due to allometric equation errors (10%) and sampling errors (10%). With regards to the intrinsic errors due to the Biomass conversion model used in the present study, Chave et al. (2005) estimated a standard error of 12.5% and an R^2 of 0.97.

Another important factor affecting the accuracy of AGB estimates in tropical, sub-tropical forests is the plot size chosen for field data collection. In fact, the overall accuracy and ability of the model to describe the variability of AGB are closely related to the sampling size (Drake, 2002). This is referable to the degree of variation in forest structures (Clark and Clark, 200; Drake, 2002) at different spatial scales and to errors from displaced Lidar metrics extraction due of GPS plot center point errors. With regard to the first point, Clark and Clark (2000) as well as Drake et al. (2002) found that the inter-sample coefficient of variation (CV) for forest structural characteristics is two to three times higher at a scale of 0.05 ha compared to 0.5 ha, due to distribution and size (average size= 0.01-0.02 ha) of treefall gaps in old growth Tropical Rain Forest. Concluding that the estimation of forest variables in a tropical context it is necessary to sample forest characteristics at a scale of 0.35-0.5 ha (Clark and Clark, 200). Chave et al. (2004) also produced a similar figure, suggesting a minimum plot size of 0.25 ha. The plot size highly affects the strength of the relationship between Lidar metrics and the field measured forest characteristics. More precisely, with bigger plot size, the error derived from the displacement of the GPS plot position is attenuated by the fact that a significant part of the Lidar metrics are still extracted from the actual measured plot, while for small plots the metrics could be extracted from an adjacent forest patch with different structural characteristics, therefore reducing the correlation between AGB and Lidar data. Differing from the Nepalese study case where the plot sizes were in the order of 0.025 - 0.05 ha, most of the previous studies (Drake, 2002; Drake, 2003; Asner, 2009; Clark, 2011) in tropical areas utilized plot sizes greater than 0.2 ha and mostly of 0.5 ha. This partly explains the lower adjusted R^2 and higher RMSE of the Nepalese study compared to previous studies (see section 1.1).

More importantly, in case of Lidar assisted forest inventories are the errors of geolocation of the plot centers that cause a mismatching between the ground truth data and the remotely sensed Lidar data (Asner, 2009), especially in a sub-tropical mountainous context. This type of error is believed to have a high influence on the overall accuracy especially when the plot size is reduced. In this case study, the differential GPS (DGPS) correction was available for the Arbonaut dataset. The errors measured in the Arbonaut dataset can give an idea of average errors in the studied area also for the ICIMOD dataset. The DGPS correction was not available for 7 out of 92 plots due to the absence of records in the SD card, in the GPS or in the absence of the base station. Figure 12 shows the plotted easting (x) and northing (y) errors calculated as the difference between the real-time field measured GPS position minus the Differentially corrected GPS position. The vendor´s accuracy assessment for the Promark 3 DGPS base station reports accuracies below 10 mm for the differentially corrected measures. The easting error had minimum, mean and maximum values of respectively: -7.95 m, 0.66 m and 13.02 m. The northing had minimum, mean and maximum values of respectively: -6.18 m, 2.15 m and 12.46 m. This mostly agrees with the vendor´s accuracy assessment, which reports 95% typical errors less than 10 m and less than 5 m for the differentially corrected positions for the GPS Map 60CSx Garmin and Garmin 62s. Only two plots showed errors bigger than 10 m.

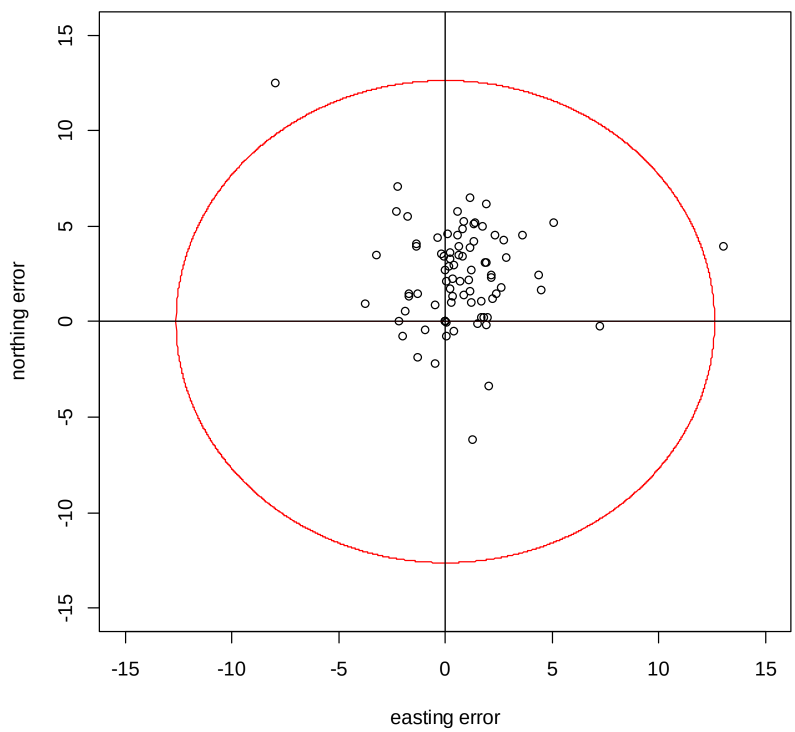

Figure 12. scatter plot of the easting (x) and northing (y) GPS errors (m) calculated by subtracting the differentially corrected GPS position from the real time GPS position measured in the field (Arbonaut dataset). The red circumference represents the Arbonaut´s plot area in order to give an idea of the relevance of the GPS displacement across the dataset.

Another source of error is derived from an incorrect Digital Elevation Model generation. Hyyppä et al. (2000) quantified this error for boreal forests to 15 cm in flat areas while it increased to 40 cm when the slope was 40%. The fact that the error is positively related to the slope added to the steep terrain conditions encountered in the Ludikhola watershed (e.g. mean watershed slope ~ 29.7 %; maximum ~ 57.3 %) are likely to be increase significantly this type of error. The 85th Lidar height percentile showed maximum vegetation heights in the order of 60 meters while the maximum height for these forests

types is exceptionally 45 m. This produces errors in Lidar vegetation height measurements that are not easily quantifiable that propagate into the model and decrease the correlation between the Lidar and field data because it is likely that the error is not systematic over the all area due to different slope gradients in different plots.
The investigation and quantification of such errors is extremely relevant to improve the model's overall accuracy, therefore further studies should dedicate particular attention in the DEM generation.

4.1.1 Comparison between Arbonaut and ICIMOD models

The aim of the thesis was to compare the two models in order to determine whether the model built with the data collected by Community Forest User Groups (ICIMOD) was as good as the model built with professionally collected data. As mentioned in section 1.1 the only study found in literature that studied the feasibility of participatory REDD+ MRV processes was conducted in Tanzania and in the Himalaya by Skutsch et al. (2009). This study compared the measurements from the CFUGs and professional teams and showed that the mean AGB values differed no more than 7 % and mostly 5 %. Moreover, the same study reports that the variance was higher in the CFUGs measurements, therefore indicating that even though the accuracy was as good as professional measurements the precision was weaker. This was also due to the fact that the two datasets were collected with different sampling designs. The use of these measurements in combination with wall-to-wall Lidar data is an aspect that has not been investigated yet. Lidar assisted AGB models have the advantage of producing estimates at relevant spatial scale (in this case study = 0.05 – 0.025ha) for the implementation of REDD+. Therefore, a clearer picture for the feasibility of participatory REDD+ MRV processes with higher Tier level (IPCC, 2006) will be produced by a comparison between the two Lidar assisted AGB models. Within the present case study, the difference of the mean AGB between the two datasets was of 63.9 t ha^{-1}, which represents an overestimate of 50.7 % of the ICIMOD dataset compared to the Arbonaut dataset (Figure 13). This figure does not agree with the previous experience (Skutsch et al., 2009), yet it is important to mention that the sampling design was different and therefore the sample plots did not match. Similarly to the study conducted by Skutsch et al. (2009), the standard deviation was greater for the ICIMOD dataset (131.79 t ha^{-1}) indicating a weaker precision (Figure 13).

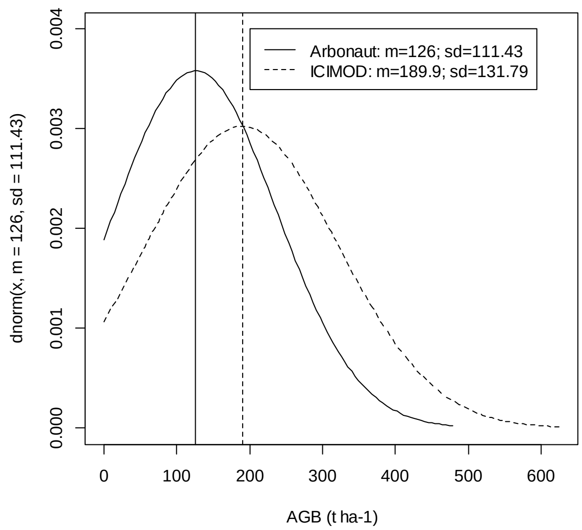

Figure 13.Above Ground Biomass (t ha^{-1}) density distribution function for the Arbonaut and ICIMOD datasets. The vertical lines show the mean values.

The comparison of the two AGB models (table 5) shows that even though the relative RMSE is similar (Arbonaut= 45.6%; ICIMOD= 47.2%), the Arbonaut model adjusted R^2 (0.75) is comparable with previous studies while the ICIMOD model could only explain the 55% of the variation of AGB in the sample, which contradicts previous studies. It is important to note how the RMSE is greatly dependent of the mean and variance of the sample and therefore it can be a misleading index when comparing different datasets.

When comparing the models' accuracy based on an equal range of measured AGB and therefore leaving out exceptionally high biomass plots, the relative RMSE proved to be lower (35.3%) for the ICIMOD AGB model compared to the Arbonaut's one (46.1%). Another result that favors the ICIMOD model is produced when calculating the RMSE on the Arbonaut model built without the DGPS correction, in fact the relative RMSE is lower also in this case (47.2%) compared to the Arbonaut model (51.3%). These two figures produce a more reliable basis for comparison of the two models since they are not affected as much as the original models by the different sampling designs and the DGPS correction, which are two of the main potential factors affecting the models' performances.

The analyses of the residuals (Figure 10 and 11) shows that even though both of the models had the mean of the error term not equal to zero and their distribution was not normal, the Arbonaut model did not show an increased variance of the residuals for higher values of AGB, while the ICIMOD model showed heteroschedastic residuals causing a greater under estimation errors for plots with bigger values of AGB.

In conclusion, with the given datasets and the limitations intrinsic in the study lying in a different sampling design, plot sizes and different plot location accuracies it is not possible to state that the CUFGs dataset was worst than the professional one to build AGB models in combination with Lidar data. In fact, if on one side the Arbonaut model produced better results for the original models, the ICIMOD showed to be equally or even more accurate than the Arbonaut's one when the AGB range was reduced to a maximum of 350 t ha-1 and when the differential correction was not applied. The study concludes that with small improvements (e.g. increase the plot size, DGPS correction), the CUFGs data could potentially produce results as good as the ones derived from models built on professionally collected data for Lidar assisted forest inventories.

4.1.2 Suggestion for further studies

Previous studies (Skutsch et al., 2009) concluded that it is possible to utilize data collected with participatory approaches for traditional forest inventories. These types of inventories are limited in the geographic representativeness (Asner, 2009), especially when the aim is the estimation of carbon resources for the remuneration of local communities, since the Community Forests are relatively small compared to the landscape scale. With regard to the spatial variation of Biomass, Lidar data is used to produce accurate results at a fine resolution with relatively low costs.

This study was the first attempt to utilize field data collected by CFUGs in Lidar assisted Carbon inventories within a REDD+ context. The implementation of participatory methods for the Monitoring, Reporting and Verification (MRV) of the forest carbon resources with high quality standards is a fundamental step for the implementation of REDD+ projects. The results showed that in order to have a more reliable comparison the professional dataset needs to geographically matching the one collected by local communities. Moreover, despite the mismatching of the locations of the plots the community measures need to be improved in order to be used to build models in correlation with laser scanning data. The main improvement relates to increasing the accuracy of the GPS location of the plots. This could be directly improved by retrieving more accurate GPS measurements with the introduction of the DGPS correction in site during the field campaign.

Another option to mitigate the effect of the displacement of the GPS location, as proved in previous studies (Clark and Clark 2000; Chave, 2004; Asner, 2009) would be, when defining the sampling, to reduce the number of plots and increase their size. This last option would be the one that would most likely produce the best results at a lower cost since it would reduce the time for the navigation from different plots without additional costs for equipment.

In conclusion, in order to improve the accuracy of the AGB models, the field measures would need to accurately take into account the forest structures and eventually model separately those plots where the tree cover is less than a certain threshold since these are not representing forest but other wooded land which have been proven by the present study to produce errors that are bigger than the error of not including them in the estimation (rel. RMSE=130.5 %).

References

ANSAB, 2010. Report on Forest Carbon Stock of community Forests in three Watersheds (Ludikhola, Kayarkhola and Charnawati). Nepal: NORAD, ICIMOD, ANSAB and FECOFUN. Available from: http://www.ansab.org/wp-content/uploads/2011/01/REDD-CStcok-Year-One-Report.pdf

Asner, G.P. (2009) Tropical forest carbon assessment: integrating satellite and airborne mapping approaches. *Environmental Research Letters* (4).

Asner, G.P., Hughes, R.F., Varga, T.A., Knapp, D.E., Kennedy-Bowdoin, T. (2009) Environmental and Biotic Controls over Aboveground Biomass Throughout a Tropical Rain Forest. *Ecosystems* (12) 261-278

Bishop, C.M., Tipping, M.E., (2003) Bayesian regression and classification. In: Suykens, J. (ed) Advances in learning Theory: Methods, Models and Applications. Proceedings of the NATO Advanced Study Institute on Learning Theory and Practice. Vol.190 267-285. Amsterdam: IOS Press.

Chave, J., Condit, R., Aguilar, S., Hernandez, A., Lao, S., Perez, R. (2004) Error propagation and scaling for tropical forest biomass estimates. *Philosophical Transactions of The Royal Society Biological Sciences*. 359, 409-420

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

Clark, D.B., Clark, D.A. (2000) Landscape-level variation in forest structure and biomass in a tropical rain forest. Forest Ecology and Management 137, 185-198.

Clark, M.L., Roberts, D.A., Ewel, J., Clark, D.B. (2011) Estimation of tropical rain forest aboveground biomass with small-footprint lidar and hyperspectral sensors. *Remote Sensing and Environment*. 115, 2931-2942.

Dalponte, M., Bruzzone, L., Giannelle, D. (2011) A system for estimation of single –tree stem diameter and volume using multireturn LIDAR data. Geoscience and Remote Sensing. Vol.49 (7), 2479-2490.

Drake, J.B., Dubayah, R.O., Clark, D.B., Knox, R.G., Blair, J.B., Hofton, M.A., Chadzon, R.L., Weishampel, J.F., Price, S.D. (2000) Estimation of tropical forest structural characteristics using large foot-print data. Remote Sensing of Environment 79 (2002) 305-319.

Evans,J.S., Hudak, A.T., Faux, R., Smith, A. M.(2009) Discrete Return Lidar in Natural Resources: Recommendations for Project Planning, Data Processing, and Deliverables. *Remote Sensing,* 1, 776-794.

Gautam, B.R., Tokola, T., Hamalainen, J., Gunia, M., Peuhkurinen, J, Parviainen1, H., Leppanen, V., Kauranne, T., Havia, J., Norjamaki I., Sah, B.P. (2010) Integration of airborne LiDAR, satellite imagery, and field measurements using a two-phase sampling method for forest biomass estimation in tropical forests. In: International Symposium on "Benefiting from Earth Observation". Kathmandu, Nepal, 4 - 6 October 2010.

Gautam, B.R., Kandel, P.N. (2010) Working paper on LiDAR mapping in Nepal. Submitted to: the Ministry of Forests and Soil Conservation. March 26, 2010. Available from: http://www.forestrynepal.org/publications/article/4771

Gautam, A.P. (2005) Forest Land-Use Dynamics and Community-based Institutions in a Mountain Watershed in Nepal: implications for forest governance and management. In: Zoebisch, M., Cho, K.M., Hein, S., Mowla R. Integrated watershed management. Studies and experiences from Asia. Asian Institute of Technology (AIT), Pathumthani Thailand.

Gibbs, H.K., Brown, S., O Niles, J., Foley, J. (2007) Monitoring and estimating tropical forest carbon stocks: Making REDD a reality. Environmental Research Letters. Issue 4, October-November 2007.

Holmgren, J. (2004) Prediction of tree height, basal area and stem volume in forest stands using airborne laser scanning. *Scandinavian Journal of Forest Research*, 19:6, 543-553.

Hyyppä, J., Pyysalo, U., Hyyppä H., Samberg, A.(2000) Elevation accuracy of laser scanning-derived digital terrain and target models in forest environment. *Proceedings of the 20th EARSeL Symposium and Workshops, Lidar Remote Sensing of Land and Sea*, 14–16 June, Dresden, Germany.

IPCC (2000) Land use, land-use change, and forestry. Cambridge university press.

IPCC (2006) Guidelines for National Greenhouse Gas inventories. ed Eggleston, H.S., Buendia, L., Miwa, K., Ngara, T., Tanabe, K.. Greenhouse Gas Inventory Programme, IGES, Japan.

Junttila, V., Maltamo, M., Kauranne, T. (2008) Sparse Bayesian estimation of forest characteristics from airborne laser scanning. *Forest science*. vol. 54 (5) 543-552(10).

Junttila, V., Kauranne, T., Leppänen, V. (2010) Estimation of Forest Stand Parameters from Airborne Laser Scanning Using Calibrated Plot Databases. Forest Science, Volume 56, Number 3, June 2010 , pp. 257-270(14).

Lefsky, M.A. (2002) Lidar remote sensing of above ground biomass in three biomes. *Global Ecology & Biogeography*. 11, 393 – 399.

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.

MPFS. (1988). Master Plan for the Forestry Sector Nepal. Appendix Table 2.2 Forest types, representative species, uses and wood density. Ministry of Forests and Soil Conservation, His majestry Government of Nepal (HMGN), Kathmandu.

Murdiyarso, D., Skutsch, M. (2006) Promoting Carbon Benefits from Community Forest Management. In: Murdiyarso, D., Skutsch, M. Community Forest Management as a carbon mitigation option. 1-7. Bogor, Indonesia: Centre for International Forestry Research (CIFOR).

Næsset, E., (2002) Predicting forest stand characteristics with airborne scanning laser using a practical two-stage procedure and field data. *Remote Sensing of Environment*. Vol. 80 (1), 88-89.

Naesset, E., Gobakken, T. (2008) Estimation of above- and below-ground biomass across regions of the boreal forests zone using airborne laser. *Remote Sensing of Environment*. Vol. 112 (6), 3079-3090.

Nguyet, D.A. (2012) Error propagation in carbon estimation using the combination of airborne LiDAR data and very high resolution GEO-EYE satellite imagery in Ludikhola watershed, Gorkha, Nepal. MSc Thesis University of Twente, Nederland.

Skutsch, M.M., Van Laake, P.E., Zahabu, E., Karky, B.S. , Phartiyal, P. (2009) The value and the feasibility of community monitoring of biomass under REDD+1. Available from: http://www.communitycarbonforestry.org/NewPublications/CIFOR%20paper%20Nov%205%20version.pdf

Tamrakar, P. R. (2000). Biomass and Volume Tables with Species Description for Community Forest Management. Kathmandu: MoFSC, NARMSAP-TISC.

Tewari, A.,Singh, V., Phartiyal, P. (4 december 2008) The potential of community managed forests for carbon credits. LEISA Magazine 24, pp. 32-33.

UNFCCC (2009): Decision on methodological guidance for activities relating to reduced emissions from deforestation and forest degradation and the role of conservation, sustainable management of forests and enhancement of forest carbon stocks in developing countries. Draft decision -/CP.15 Bonn, June 2009. Available from: http://unfccc.int/files/na/application/pdf/cop15_ddc_auv.pdf

Zahabu, E. (2008) A strategy to involve forest communities in Tanzania in global climate change policy. Diss. University of Twente.