BIOREDD+ Program

DELIVERABLE 16: UNCERTAINTY OF CARBON ESTIMATES

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Uncertainty of Carbon Estimates

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1. Statement of task 16

The Report on Carbon Estimates Uncertainty will discuss the relative contribution of uncertainty associated with estimating carbon stocks in the aboveground biomass, and all other pools (belowground, dead, litter, soil). The report also includes a detailed explanation of the methodology used in the design and implementation of BIOREDD+ program over the nodes and the uncertainty associated with field sampling, Lidar sampling, estimation of forest carbon stocks from lidar, and estimation all carbon pools used in establishing the REDD+ projects and the MRV systems.

2. Background

A comprehensive and accurate assessment of uncertainty in the forest carbon stocks in all pools are critical for understanding the quantitative limits of the products and for ensuring their usefulness to the broader BioREDD community, and future carbon credit qualifications. The BioREDD project documents require a thorough evaluation of uncertatinties to meet the guidelines of the VM0006 methodology. In particular, the BioREDD project adopted new techniques that have not been previously used in any VCS tools due to the difficulty of the region for security, and access to establish ground based carbon estimates. The new techniques make use of extensive airborne high resolution lidar observations for estimating above ground carbon density in the proejct areas, and additional data from other sources from previous studies in the region or literature to quantify carbon pools in all BioREDD project regions. Our team has developed several reports on lidar estimation of vegetation biomass and other carbon pools and estimates in different BioREDD reports. These analysis are based on several years of experience in assessing uncertainty associated with complex products generated

from multiple sources of input data, models, and error sources (Hagen et al., 2006; Saatchi et al., 2011; Harris et al., 2012; Weisbin et al. 2013).

The forest carbon estimates are produced using a combination of tree level measurements and models. All ground measurements, remotely sensed observations, and process-based and statistical models are all imperfect and no matter how carefully obtained, managed, or processed. After models are fit to data, substantial noise (i.e. residual errors) will certainly remain. This residual noise is due to both measurement and model uncertainty (i.e. noisy data and imperfect models), with model uncertainty potentially due to both parameterization and choice of the functional form of the model. In addition, the variance of these residuals can be heteroscedastic (i.e. not constant with respect to one or more of the independent variables). The bootstrapping approach to uncertainty assessment, also known as resampling with replacement, is more appropriate than conventional analytic methods for data with heteroscedastic and/or non-normally distributed errors. This method assumes that the observed data represent only one possible realization out of many, and reconstructs a large number of alternate realizations based on random resampling of the residuals. Bootstrapping brackets the range of unobserved values conditioned on the assumption of the model and its associated likelihood function (Efron and Tibshirani, 1993).

Here, as in our past successful projects, we will estimate statistical uncertainty bounds associated with the final forest carbon stock and change estimates using a randomized, Monte Carlo-style sampling technique (Hagen et al. 2006; Robert and Casella, 1999; Harris et al, 2012). This technique relies on the bootstrapping approach described above. With bootstrapping and its Monte Carlo-style framework, we avoid making incorrect assumptions about the distribution of the underlying data sets, while combining the individual uncertainties from many different sources.

We will construct a minimum of 1,000 scenarios, each one generated from randomized alternative data sets, each providing a realistic set of parameters for each model component. At the conclusion of our simulation, each of the 1,000 scenarios will exist as a full resolution gridded map of carbon lost to the atmosphere as a result of forest loss and gain between 2000 and 2010. From these 1,000 scenario maps, we will construct the 95% prediction limits at the pixel, county, regional, and national scales by first aggregating each individual map to the targeted scale (e.g., country, continent) and then selecting the 0.025 and 0.975 percentiles (i.e., 25th and 975th) from the 1,000 sorted simulations. The identification of the percentile values is computed individually for net change of forest cover, carbon stock, and stock changes, such that the low emission value is not simply a combination of the low bound for forest cover change and the low bound for carbon stocks; it is the 50th out of 1,000 sorted simulations that combined change in forest cover and carbon stock.

3. UNCERTAINTY IN PLOT ESTIMATES OF AGB

Inventory plots have been established and tree level data have been collected in BioREDD project areas. The plot-based measurements are used for calibrating and validating lidar remote sensing estimates of forest aboveground biomass within the LULC class or forest stratum. Often in field base approaches, estimates of forest biomass

from tree dimensions data are considered the golden standard. According to the IPCC guidelines for REDD projects (A/R CDM tool 14), tree dimensions can be converted to forest carbon stocks (above and below) using either the biomass expansion factor or allometric equation method. In either case, the standard error is calculated by considering the number of samples within forest stratum or area without any consideration for other errors. However, in recent years, there has been efforts to consider the errors in inventory data in order to provide better estimates of biomass and changes that may be used for understanding ecological changes from climatic effects and climate mitigation policies as in REDD. This renewed interest in tropical forest inventories has also motivated a new literature on methodological aspects that have greatly improved our confidence in biomass data estimated from plots (see Chave et al. 2004).

The REDD methodology also provides guidance in the use of quality control/quality assurance (QA/QC) procedures prescribed under national forest inventory to establish protocols for data collection and uncertainty assessments. In the absence of these, QA/QC procedures from published handbooks, or from the IPCC GPG LULUCF 2003, are applied. In this section, we discuss the uncertainty in ground estimates of forest biomass from various error sources: 1. Measurement errors, 2. Allometry errors, 3. Sampling error, and 4. Plot location errors.

3.1 Measurement Errors

In the BioREDD project, the plots are only used for calibration and validation of lidar to AGB model. The minimum number of plots required for developing and validating the remote sensing to AGB predictive model was estimated to be 45, with 30 plots for calibration and 15 plots for validation. This requirements were based on a similar methodology as in CDM A/R tools for Calculation of the number of sample plots for measurements within A/R CDM project activities, and based on minimum number for developing remote sensing and AGB predictive model (Asner and Mascaro, 2014). In general one predictive model is enough to estimate forest biomass from lidar in BioREDD regions if the ground allometric model used in estimating AGB at the plot level is also one.

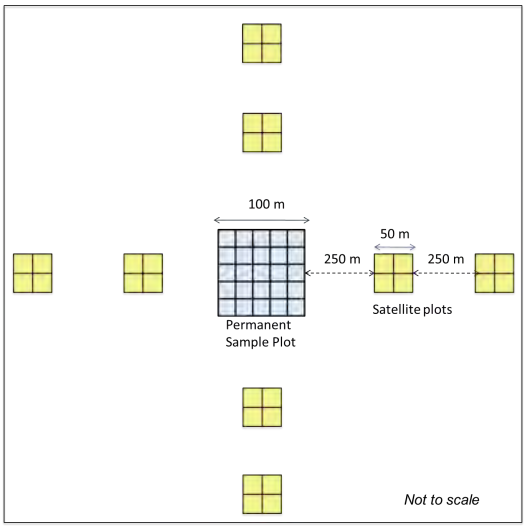

Fig. 3.1.1 Shape and size of permanent and satellite plots within the lidar transect

In the BioREDD project we increased the number of calibration and validation plots in order to make sure that the numbers are enough for developing more than one lidar to AGB predictive model if necessary. A total of 15 cluster plots were used in 15 lidar transects covering different strata in the BioREDD regions. Each cluster plot met the following requirements:

1. Each cluster plot had one permanent plot of 1-ha in size (100 m x 100 m) and 8 satellite or auxiliary plots at 0.25 ha in size (50 m x 50 m).
2. The center location of permanent plot was selected randomly in the lidar transect in the forest area to allow sampling all forest conditions as in fragmented, degraded or secondary forests. The satellite plots were located at 250 m and 500 m away from the center permanent plots in four cardinal directions (Fig. 3.1.1).
3. In addition to above plots, we also developed a set of 45 plots, each 0.25 ha in size for spatial uncertainty analysis of the lidar estimation of biomass. We selected one lidar transect with relatively easy access and with no previous plots and developed 45 systematically located plots.

Here, we use the ground plots to calibrate the lidar data for estimating forest biomass in project areas. Any errors in ground estimate of the forest biomass can readily propagate through the various models impacting lidar estimates of biomass. Using a generic allometric model as:

$$AGB = \sum_{i=1}^{N} a\rho_i D_i^2 h_i$$

We identified three measurement errors impacting the estimates of the forest biomass: 1. Errors in measuring the diameter (D), errors in measuring tree height (h), and error in identifying or measuring species wood density (ρ). During the project, we collected data to quantify errors associated with the measurements and using an error propagation approach to quantify the overall effect of ground measurements in estimating carbon stocks in project areas (Chave et al. 2004; Saatchi et al., 2011).

Measurements from QA/QC procedure from 45 sample plots collected within a lidar transect in a systematic fashion to examine the effect of measurement errors. Two teams were formed to collect data in the field and have replications to examine the potential errors in the data. The first team, collected data in a systematic fashion in 45 plots and the second team randomly sampled 10 trees in each of the 45 0.25 ha plots.

The QA/QC data are used in the following steps to estimate the uncertainty of measurements:

1. Errors in DBH measurements were calculated from the data collected in 45 plots and the uncertainty in estimating DBH were then propagated through the local allometric equation to assess the impact on the plot level biomass estimation.
2. Errors in tree height (H) measurements were quantified from the data collected in 45 plots and the errors were propagated in developing the local height diameter (H-D) relationship and then through biomass estimation at the plot level using the local allometry.

3. Errors associated with wood density of tree species were estimated by the knowledge of the number of species un-identified in the field and the wood density measurements of sample species collected during the field campaign. The errors in estimating the wood density were propagated through the allometric equation to assess the impact on the plot level estimates of biomass.

Error in Tree DBH Measurements:

The errors associated with DBH are shown in Fig. 3.1.2. It appears all trees except few have very accurate estimate of DBH. Out of 429 trees, 414 were measured with high accuracy (RMSE < 0.5 cm). About 15 trees have large measurement errors that may be due to factors different than measurement errors. Some trees have large differences in DBH (22 cm by group 1 and 59 cm by group 2). These differences may be due to registering the number of trees while recording the data or due to location of measurement above the tree buttress. The bias in measurements was small but was included in the measuremnet errors for estimating biomass at the plot level from the two data sets. The relative error associated with DBH varied from < 1% for 414 trees to about 11% for all QA/QC trees. We used the uncertainty in estimating DBH in evaluating the error in AGB at the tree level. The RMSE of tree biomass was about 182.64 kg (bias 0.82 kg, n=429) (Fig. 3.1.4). The bias in the estimate was negligible and therefore had impact of < 0.8% on the biomass estimation at the plot level when propagated to all the trees for 45 plots.

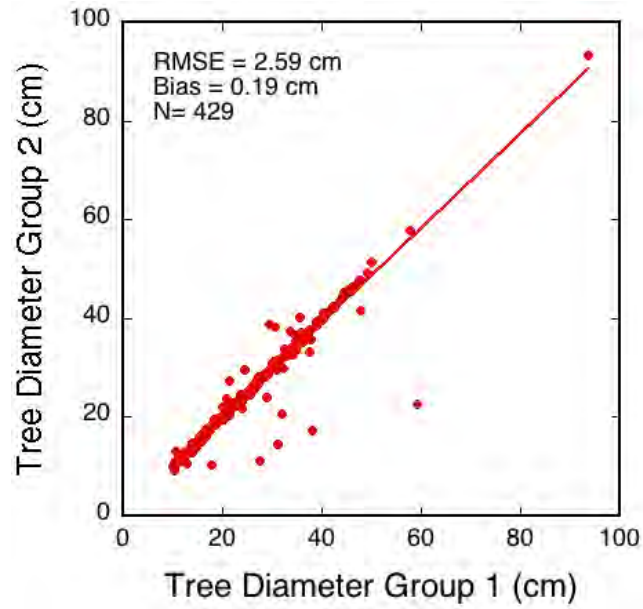

Fig. 3.1.2. Tree diameter measurement error developed from the QA/QC data collected in 45 0.25 ha plots.

Error in Tree Height Measurements:

The errors associated with the height measurements are shown in Fig. 3.1.3. The errors in height estimation appear to be large at the individual tree level but have approximately no bias between the two groups (RMSE=4.21 m, bias=-0.29 m). For the first 400 trees, the RMSE drops to about 2 m in height and negligible bias (0.08 m). Similar to the DBH measurements, it appears that the difference in measurements between the two groups is a combination of errors in measurements and recording. However, using the two measurements, we develop height-diameter relationships for the 45 plots and find that the two equations appear to be idenitical. Using both H-D equations in local allometry results in negligible uncertainty (< 0.5%) in biomass estimates at the plot level. The aggregate effect of tree diameter and height measurement errors on the tree level biomass

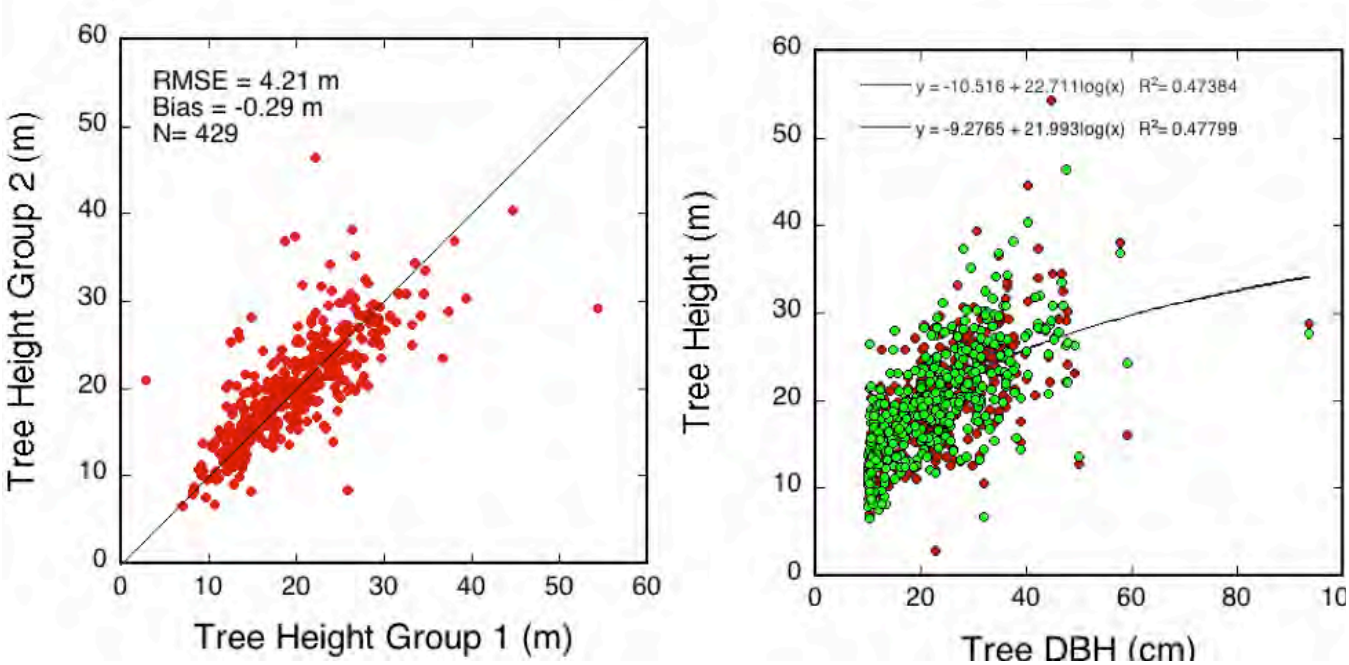

Fig. 3.1.3. Height measurement error estimated from the QA/QC measurements reported from two groups in 45 0.25 ha plots. The height-diameter relationship in the right panel shows approximately no difference in estimating tree height from diameter from the two sets of measurements.

estimation from the local allometry is provided in Fig. 3.1.4.

Error in Tree Wood Density Estimation:

In most applications wood density is not measured but extracted from published tabulated values from global or tropical wood density data. In the field, tree species are identified and then matched with scientific names in the published tables. For the BioREDD project, we used the recommended methodology of using the tree identification, extracting values from tables, and applying an avarage plot level estimate for those trees that were not idenitified in the field. In most plots, more than 90% of trees were idenitified at the species and genus level. In addition, the BioREDD project

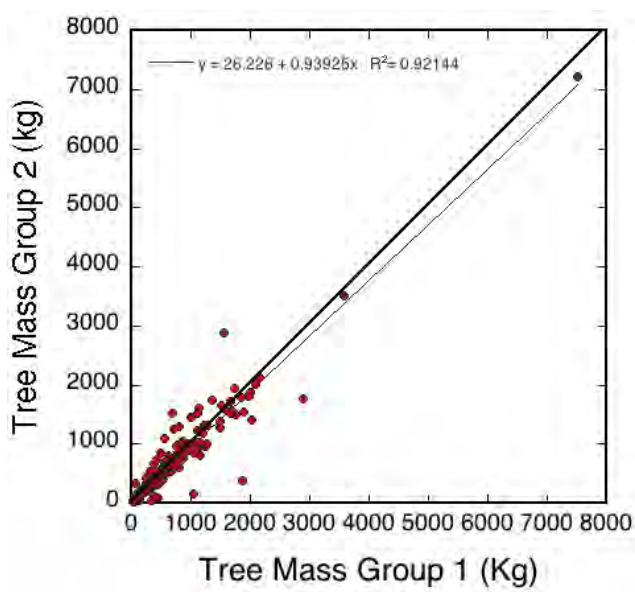

Fig. 3.1.4. Tree level biomass estimation error associated with differences in the DBH and height measurements between group 1 and group 2.

collected measurements of wood density of trees at stem and branch level for a selected number of trees.

The BioREDD project developed a method based on the fit of a model that would estimate the density of wood from tree trunks (WD_T) based on wood density of branches (WD_R). For this the hypothesis of linear relationship with a slope of 1 and intercept 0 between WD_T and WD_R of felled trees 296 to construct models evaluated allometric relation. Regardless of the test for the hypothesis, the measurements were used to improve estimation of species and compared with data from tabulated data to estimate the potential errors assocaited with the wood density values.

The team develpoed a regression model to estimate the tree trunk wood density from branches and used this relationship to estimate the wood density of all tree species with measurements. A minimum of 30 random collections of branches that were approximately 2-3 cm thick and 10 cm long on each of the permanent plots of 1-ha were used for this calculation. Based on the value of WD_R, each individual WD_T was estimated using the regression model, and then used to obtain an average WD_T per plot. This average wood density was then compared with a similar number from tablulated data. At the plot level, this average value WD_T per plot was the one assigned to each individual in each plot system for unidentified trees.

At the plot level the impact of wood density measurements and tree identification is given by RMSE=0.02 (g/cm^3). The wood density uncertainty can impact the biomass estimation through allometric model and as a linear coefficient. On the average on the plot level the impact of this error is < 1% of the mean plot level biomass.

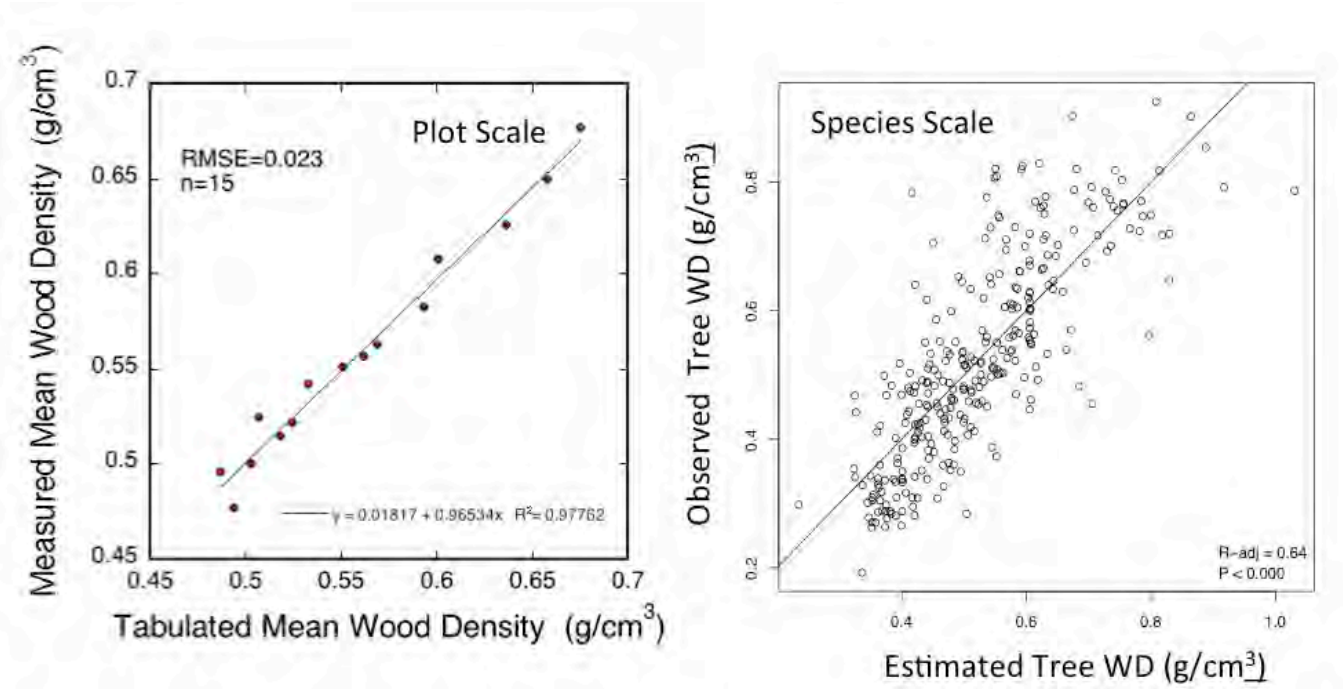

Fig. 3.1.5. Errors associated with the tree and plot level wood density. The right panel shows the wood densit estimation error from regression model compared with the observed values. The estimated values of species were used in each plot to develop average values. The left panel shows plot level average values againsted th tabulated values.

3.2 Ground Allometric Errors

Tree biomass is estimated from size measurements and species wood density from allometric models. These models can be variable depending on the forest type, environment and edaphic conditions controling growth and mortality of trees and other factors that impacts species composition and structural variations. There are several models in the literature that can be used to estimate the tree biomass and hence the biomass of a plot when inventory is available.

For developing local allometric equations trees have been harvested from different locations representing the species and diameter and height classes for the forests of the region. The allometric equations were also separated for three types of forests as in terra firme (Colinas), flooded forests (Guandal) and mangrove (manglar). These equations were used to calculate the forest above ground biomass from field data that in turn were used to calibrate and validate remote sensing estimates of forest biomass. For other carbon pools direct measurements and/or existing allometric models were used.

To examine the accuracy of allometric relations, we used six models to estimate the biomass of mature forests of coastal Colombia. Of the six models, three are to estimate the biomass of mature forests generally three to estimate biomass as forest type, guandal, mangroves and colinas. In addition, three models were developed to estimate the biomass of secondary forests. Trees of all diameter classes including individuals with larger diameters found in the study are also included. Finally, two models to estimate the biomass of palms were developed. The three groups of models, mature forest, secondary forest and palms, are solid from a statistical point of view. However, it is considered that the models found for mature forest can more accurately estimate the biomass of all forests including successional forests, because the database of trees in mature forest includes individuals of all size classes including large trees, palms, and species from secondary forests. The following models have been used in the BioREDD projects.

Colinas	$\ln(AGB) = -2.130+2.015\times\ln(D)+0.724\times\ln(H)+1.002\times\ln(WD)$
Guandal	$\ln(AGB) = -2.328+1.833\times\ln(D)+0.724\times\ln(H)+0.151\times\ln(WD)$
Manglar	$\ln(AGB) = -2.818+2.185\times\ln(D)+0.724\times\ln(H)+0.650\times\ln(WD)$

For biomass values estimated in individual permanent and satellite plots see (GeoEcoMap Report 8&9)

For trees smaller than the threshold of 10 cm, we used a model based on several plot data including data in Panama, Colombia consulated from literature (Chave et al., 2003; Sierra et al., 2007; Usuga et al., 2010). The following model was used to estimate the ratio (R_t) of AGB for trees > 1 cm to AGB for trees > 10 cm. Once the ratio was applied, the total biomass was caluclated by:

$$R_t = 1.483 AGB_{10cm}^{-0.0613} \qquad n = 65, \quad R^2 = 0.91$$

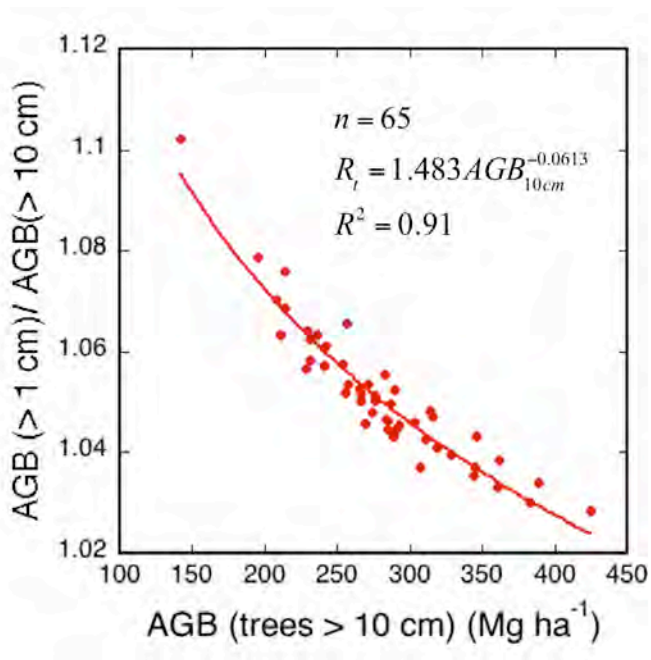

Fig. 3.2.1. The ratio of forest biomass with all trees > 1cm to biomass of trees above the threshold of 10 cm measured in the field. The ratio will correct the biomass from measurements to total biomass.

We used the carbon fraction value of $C_F = 0.485$ to convert the biomass to carbon numbers. This number is smaller than the conservative value of 50% suggested by the IPCC guideline, but is the average of values reported in the region and most Amazonian forests (Higuchi et al., 1994).

For estimating the uncertainty in biomass estimation from allometric models, we performed two assessments:

In the first assessment, we used the local model and compared the values of biomass with other existing models used for the region or tropical forests. We used three models, assuming model 1, as the local model, we assigned Saldarriaga (2014) allometry as model 2, Alvarez et al. (2012) as model 3, and Chave et al. (2014) as model 4. When comparing the biomass from these tree models for the region from the same diameter, height, and wood density, we found no significant differences among them (ANOVA; P> 0.5). However, model 1 from local allometry produced on the average the lowest values among all models, since when the average error (100 × (AGB-est - AGB_model) / AGB_model) was calculated, model 2 from Saldarriaga (2014) produced higher values by 3.9% , model 3 Alvarez et al. (2012) 10%, and model 4 Chave et al. (2014) 7.2%. This analysis provided us with the conclusion to use the local allometry, although

developed with less number of harvested trees, as the model to estimate biomass from ground measurements of structure.

The error in local allometry itself was calculated from the regression model development from harvested trees. For trees > 10 cm in diameter, the model provided an error of approximately 4% for a sample size of 240 trees (number of harvested trees). This error increaseted to about 10% for 50 individuals. The average error for estimating the biomass of individual tree was about 29%:

$$\sigma_A = 0.29 < AGB >$$

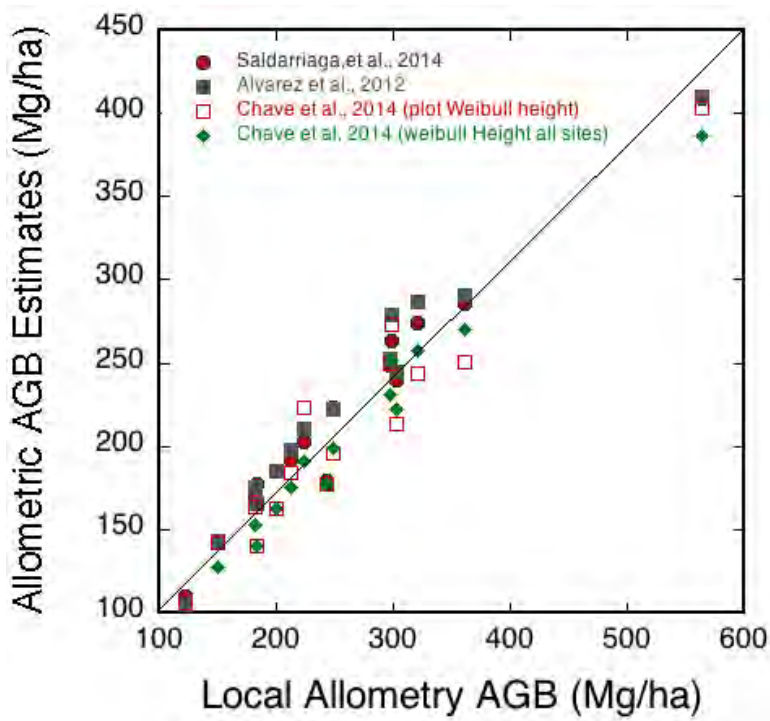

Fig. 3.2.2. Allometric model errors in comparison with locally developed allometry.

Error Associated with Tree Size Limit of Allometry

The choice of allometry also creates another condition for its implementation at the plot level. In general, allometric equations are developed as a regression model from harvested trees of different sizes and tree structure. Once the equation is developed, it can be used over all ranges because the regression model can predict biomass values outside

the range of the data used to develop the model. However, according to the VCS methodolog and the IPCC guidelines, the allometric equations are not recommended to be used for trees greater than the size of the largest harvested tree used in the equation. In developing the local allometry, the size of the largest diameter tree was 155.4 cm (55.4 m height). In our study, we used the common scientific method of applying the allometry to all tree sizes present in the plot. In order to demonstrate that our approach is not different from the recommended methodology, we estimated the biomass for each plot using the recommended methodology and compared it to the one used for all trees (Fig. 3.2.3).

The results show that there are only 3 plots with trees > 155.4 cm diameter with slightly lower biomass values when the local allometry with DBH threshold was used. Using the new estimates with DBH threshold to relate to the mean canopy height, we find negligble impact on the biomass estimate. The biomass height model cannot be distinguished from the model with original biomass. Using the two models and estimating biomass created and RMSE=1.58 Mg/ha that was less than less than 1% error (1.58/199.5).

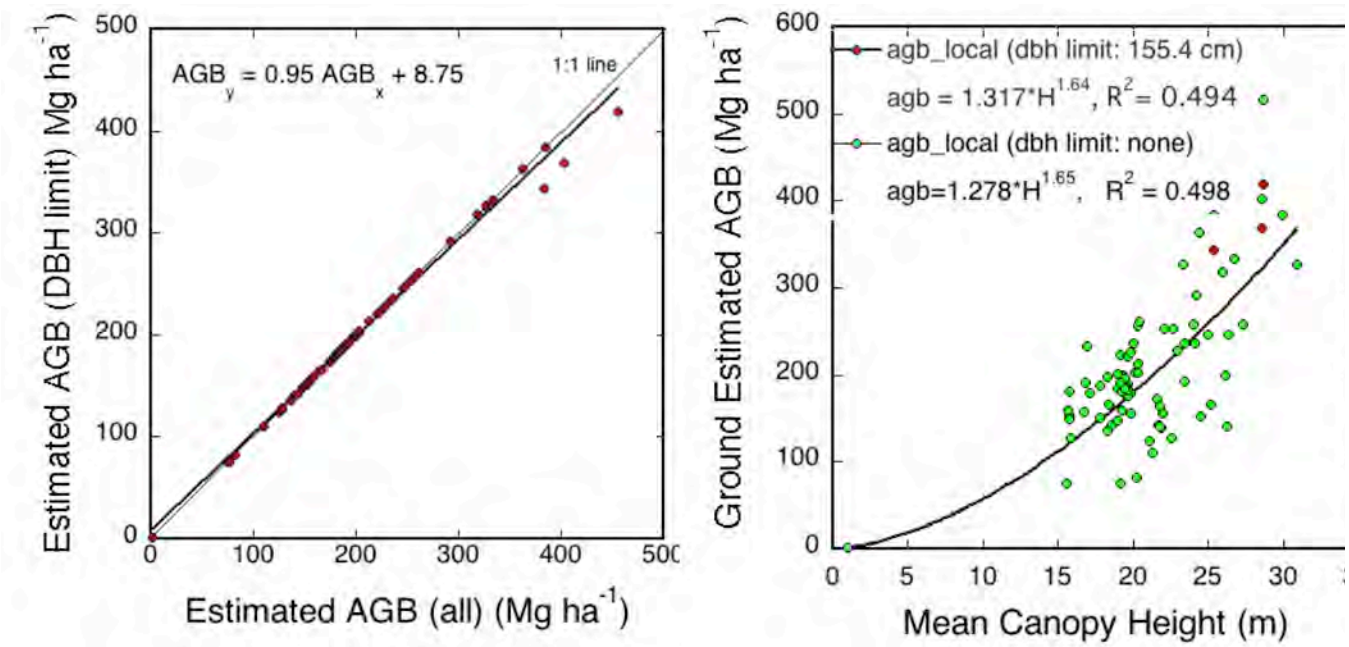

Fig. 3.2.3. Comparison of biomass estimates from allometry applying on all trees without DBH limit and with the DBH limit of 155.4 cm. The left panel shows the differences in estimates, and the right panel shows the indistinguishable regression models relating the biomass to mean canopy height similar to models that are used in estimating biomass from lidar data.

3.3 Error Propagation

We propagated errors from different sources into the local allometric model used for the BioREDD project and evaluated the ensemble effect of errors on the estimation of plot level forest biomass carbon stock. In the following, we assume that the measurement and the allometric uncertainties are independent sources of variability. The overall uncertainty on the AGB estimation of a single tree therefore:

$$\sigma = \sigma_A + \sigma_M$$

To estimate the error in tree level biomass estimation, we need to quantify the allometry and measurement errors. The allometry error was definited to be approximately 34% for trees > 10 cm diameter

$$\sigma_A = 0.34 < AGB >$$

For measurement errors, we included different sources of errors, including DBH measurement error, height model error, wood density error, and allometric model error. To combine the errors, we first converted the standard errors for each term in units of Mg/ha as the effect they may have on the biomass estimation. Second, we assumed these errors are independent in nature. The argument in independence is justified as measurement errors for size, wood density, and model errors are not related and can be considered independent source of error. To estimate the ensemble effect, we use the following error propagation formula:

$$\sigma_M =< AGB > \left[\alpha^2 \frac{\sigma_D^2}{D^2} + \beta^2 \frac{\sigma_H^2}{H^2} + \delta^2 \frac{\sigma_\rho^2}{\rho^2} + 2\alpha\beta \frac{\sigma_{DH}}{DH} \right]^{1/2}$$

$$\alpha = \frac{\partial \ln(f)}{\partial \ln(D)}, \quad \beta = \frac{\partial \ln(f)}{\partial \ln(H)}, \quad \delta = \frac{\partial \ln(f)}{\partial \ln(\rho)}$$

$$f = a\rho D^2 H$$

where the function *f* represents the general form of the allometric equation and in our case, it is the local equation. For the diameter measurement error, we use 2.59/23.5 = 0.11 (11% of the mean), for height measurement error we use, 4.21/19.85=0.21 (21%), and for wood density we use 0.023/0.56=0.04 (4%), and for the correlation coefficient of 0.68 between diameter and height in the above equation. These will provide the measurement error of about 21.4% of the AGB:

$$\sigma_M = 0.214 < AGB >$$

The total uncertainty of AGB estimation for a single tree is on the average 55.4%,

partitioned into 29% due to allometric error and 21.4% due to measurement errors.

At the plot level the uncertainty will go down as a function of number of trees per plot.

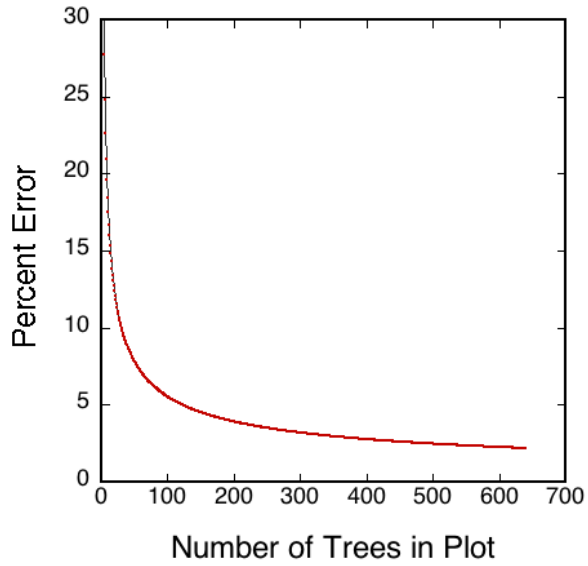

Fig. 3.3.1. Percent error associated with the size of plot and the number of trees (Sample size) within a plot. Small plots having less than 100 trees may have large errors associated with their biomass estimation even from a local allometry.

The tree-level uncertainties shown in the above figure average out at the stand scale when the number of trees in sample plots increases. The above figure also suggests that biomass estimation of individual plots with less 50 trees can be much larger than. For example, in a typical plot of one-quarter of a hectare, the error on the AGB estimate is 10% of the mean. In Chave et al. (2003), the uncertainty on AGB estimate was assessed based on limited sampling plots and was shown the AGB held in the sub-plots of a 50 ha plot is not autocorrelated, even for very small sub-plots: two neighbouring sub-plots of size10 m °— 10 m to 100 m °— 100 m are not significantly more similar in their AGB stock than two randomly chosen plots. We also developed a test of normality for the data. This suggests that for ground plot estimate, there is no need to include any spatial auto-correlation error. In addition, the test of normality at plots at difference sizes indicate that the size of one-quarter of a hectare is the minimal size such that the normality criterion is satisfied in this forest, in agreement with other published results in tropical forests. Although this figure might vary slightly with the stem density in the plot, it can be taken as a reasonable guideline. In the BioREDD region, we used the minimum size of 0.25 ha for field surveys and biomass estimation to calibrate the lidar metrics.

4.0 UNCERTAINTY IN LIDAR ESTIMATE OF AGB

4.1 Lidar Measurement Errors

This section provides the basic information about the lidar measurements of forest height and accuracy at the plot level. We used several height metrics in developing the lidar biomass estimator. These included the percentile heights (RH10, ….RH100). However, we used the mean top canopy height (TCH) as the metric for biomass estimation. The processing provided the TCH for each 50 m area over all lidar data developing (83,000 x 4) sample area for biomass estimation. The processing steps to develop 0.25 ha scale height metrics from lidar data included:

We assessed the classification of the lidar raw data into ground and canopy using the point cloud data and las files. In Microstation (using the Terrascan/Terramodel extension) and ArcGIS 10.2 (using the LP360 extension) the las files were imported and the triangulated ground model was visualized to assess the quality of the client classification. If larger interpolations in the DEM are present, they are flagged and analyzed to determine whether the DEM could be improved via additional processing.

In forested ecosystems the outlier values are generally high points caused by low clouds or birds or any objects on the path of the lidar and top canopy height that appears well above the top of the forest canopy. If the client classification does not re-classify these points as error points, we removed them manually so they don't provide large errors canopy height values. We re-classified all error points by first flagging them in ArcGIS and reclassifying them in Terrascan. Majority of lidar sample areas do not have these high and low points. However, when they are present, they are often sparsely scattered throughtout the lidar transects but are sparse and have very low impact on the overall accuracy of lidar top canopy estimates at the plot scale.

To quantify the errors associated with lidar estimation of forest height we use the following approach:

1. There is no true forest height measurements from ground in order to estimate the lidar measurement error, we estimate the error statistically using the lidar observations alone. In general, over tropical forests, tree height is much better measured from lidar observation from the above of canopy using laser ranger. This measurement is only subject to errors related to ground classification from lidar point clouds.
2. To estimate the error, we perform a new ground classification of lidar point clouds using a random sample of lidar scenes and compare the classification with the data provided by the commercial vendor. We also visually examine the location of true ground in the point cloud and make sure the different between CSM and DEM represent the true height.
3. We compiled 10 lidar scenes and in each scene used transects of more than 200 m long to compile a statistical sample of ground elevation DEM. We evaluate the error by comparing the following two data sets:

$$CSM - DEM_1 \,, \qquad CSM - DEM_2$$

where DEM_1 is the original ground classification elevation received from the commercial vendor, and DEM_2 is the ground elevation classified using the terrascan software and GeoEcoMap Macro program and visual examination. Note that, here we do not necessarily imply that any of the DEM classification is supperior, even though we prefer DEM_2 as the values are processed with several iteration of Macro and appears to be more accurate when compared visually to DEM_1.

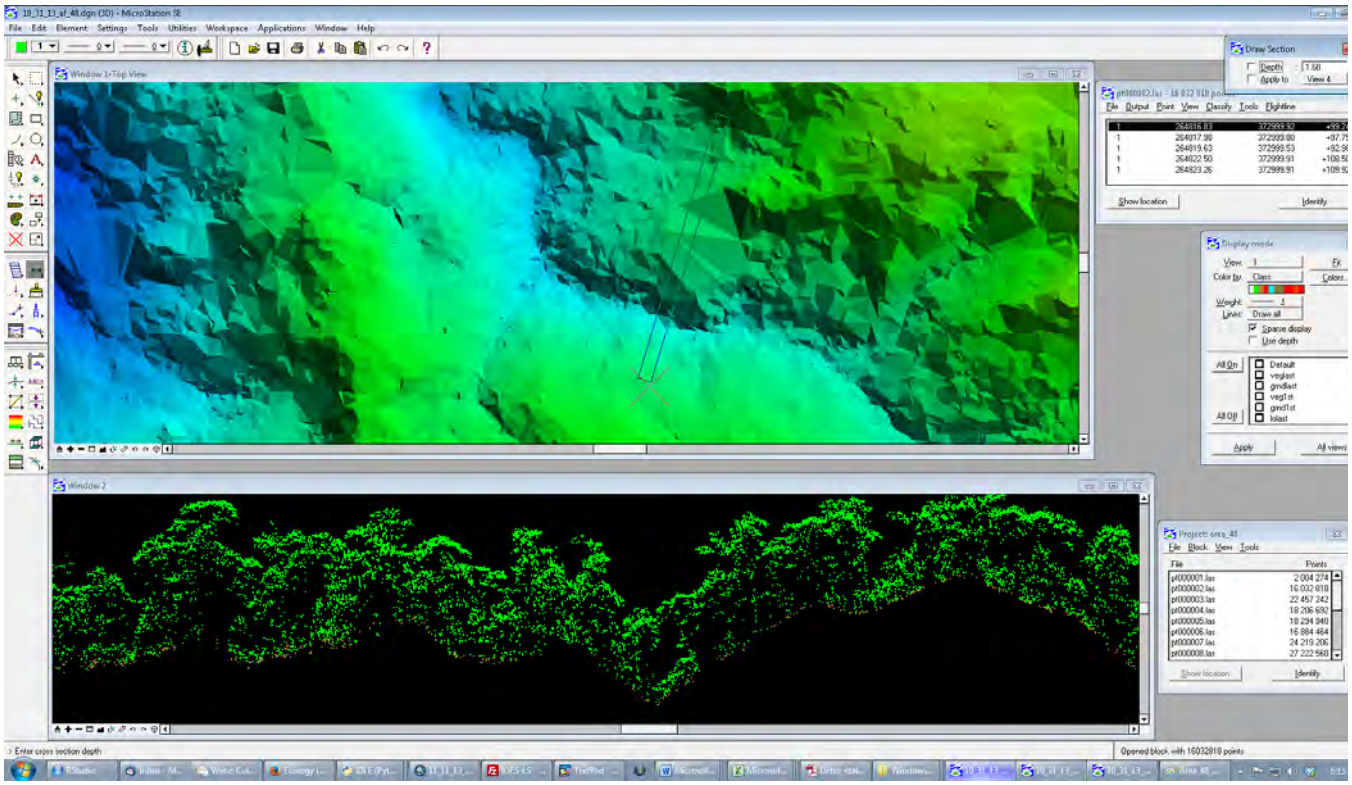

Fig. 4.1. Sample transect of approximately 200 m with ground classification DEM_2. We selected the transects randomly over both flat and complex terrain as shown in this figure.

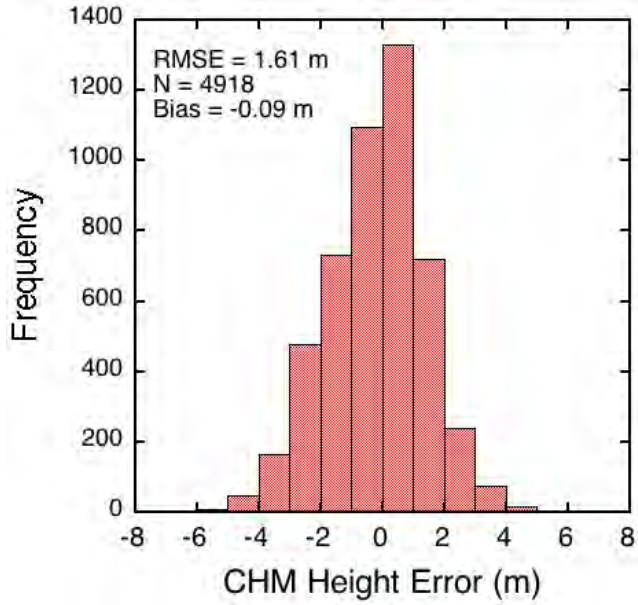

Fig. 4.2. Estimated error of forest canopy height at 1 m spatial resolution by quantifying the error in DEM from two classification approaches.

The tree canopy height error as shown in Fig 4.2 is evaluated at 1 m spatial resolution. In propagating the tree height error to canopy height metric used in biomass estimation at 0.25 ha, we will use 50 m x 50 m= 2500 pixels and estimate the standard error at 0.25 ha to be $SD = \frac{1.61}{\sqrt{2500}} = 0.032\ m$. We conclude:

Lidar height measurement error impact on the biomass estimation at 0.25 ha is negligble and can be ignored.

4.2 Lidar Geolocation Errors

Here, we examine the geolocation errors from two sources: 1. Geolocation error of the lidar data acquisition and processing. 2. Geolocation error associated with ground plot location from the ground GPS measurements.

Lidar Geolocation Error

During the lidar surveys, often ground GPS stations or base receivers within the flight lines are installed in order to calibrate the lidar data for accurate geospatial location of lidar grid celsl. Due to security problems in the region and within the flight lines of lidar,

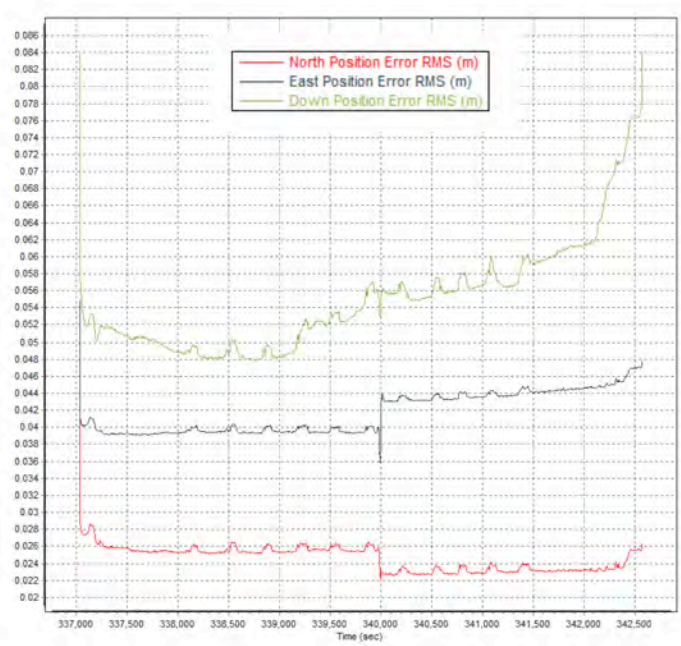

Fig. 4.3. Calculation of geolocation accuracy from the IN-

the deployments of ground stations were not allowed. Instead we implemented the IN-Fusion Precise Point Positioning (PPP) approach. PPP provides positioning accuracies on the order of a few decimeters without a base receiver, and hence is useful for those applications where a base receiver cannot be found or installed. Such applications include airborne surveying in remote areas or open-ocean hydrographic surveys far from land. The typical PPP algorithm implements a floated ionosphere-free (IF) solution that requires up to 30 minutes to converge from an initial meter-level position accuracy to a desired decimeter-level accuracy. Significant loss of coherent carrier phase tracking such as due to aircraft sharp turns will require the GNSS-only PPP algorithm to restart this convergence. IN-Fusion PPP implements Applanix's Inertially Aided PPP (IAPPP) algorithm that overcomes this shortcoming by preserving positioning accuracy through GNSS outages using inertial coast. IN-Fusion PPP uses optimal smoothing to carry the converged decimeter-level position accuracy backwards in time and thereby achieve PPP-level position accuracies throughout the survey trajectory.

The lidar data were processed and calibrated using the IN-Fusion PPP methodology. The error associated with this method is considered neglible compared with other sources of errors. An example of the errors along the lidar swath is shown below:

Plot Geolocation Error

The main soure of error is due to location of the calibration and validation plots within the lidar image (raster) data. The source of error in plot location is the GPS measurements in the field. Without any differential GPS, regular GPS measurements from commercial units can have large errors (5-50 m) depending on the forest cover, the measurement time, and the time of the day. In BioREDD field experiments the ground team crew collected GPS measurements at the corner of permanent plot and the center or four corner of the satellite plots. We examined the gelolocation errors of the plots by locating them on the lidar image and comparing the relative location of large trees in plots and in lidar data. This error can be readily examined by first extracting the mean canopy height (MCH) over the plots and relating the height from lidar to height or biomass from the ground observation. If the location

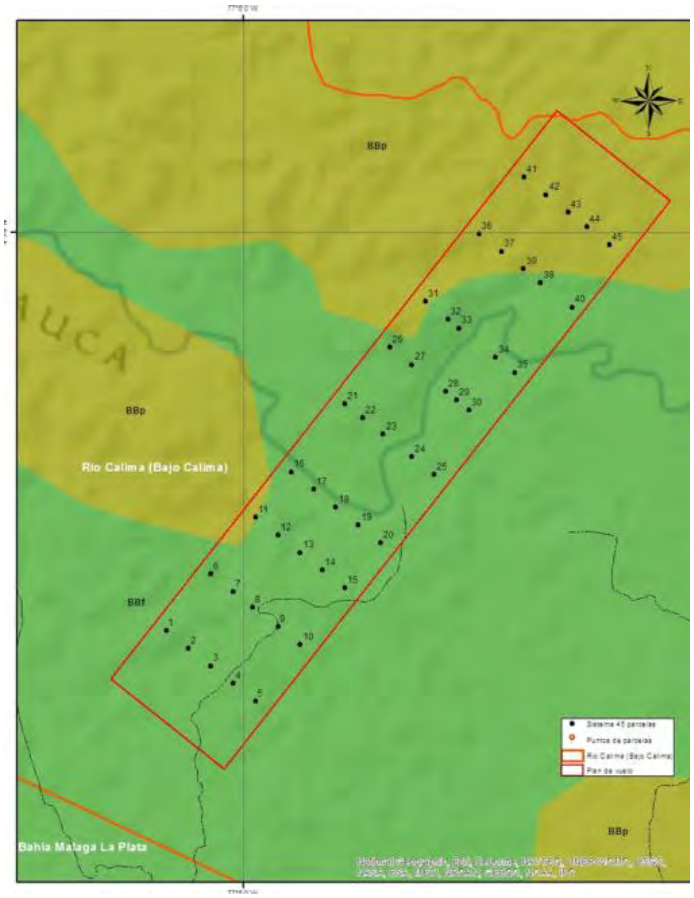

Fig.4.4. Location of 45 plots distributed systematically within a lidar scene. The center of all plots are located o

has large errors, the lidar height metrics and ground data show poor relationship.

To demonstrate the geolocation errors in the BioREDD project, we use two data sets. The first data set includes plots from the 15 permanent and satellite plots disturbuted in all project areas and the second data set from the 45 systematic plots on one lidar scence as shown below (Fig. 4.4).

We derive two lidar allometry models from the two data sets and demonstrate that the errors in the model derived from the systematic plots with less geolocation errors is significantly better. To further demonstrate the effect of the geolocation error, we simulated the effect of plot location error by adjusting the plots to fall in the right location on the lidar scene through a 3x3 or 5x5, 7x7, etc. pixels search model. Here the pixel is assumed to be 1 m. However, we move the 0.25 ha aggregate pixels used for biomass estimation from lidar data at steps of 10 m and then calculate the effect of average geolocation error on the allometry on estimating the biomass of all plots. The RMSE errors from geolocation errors are shown in Fig. 4.6.

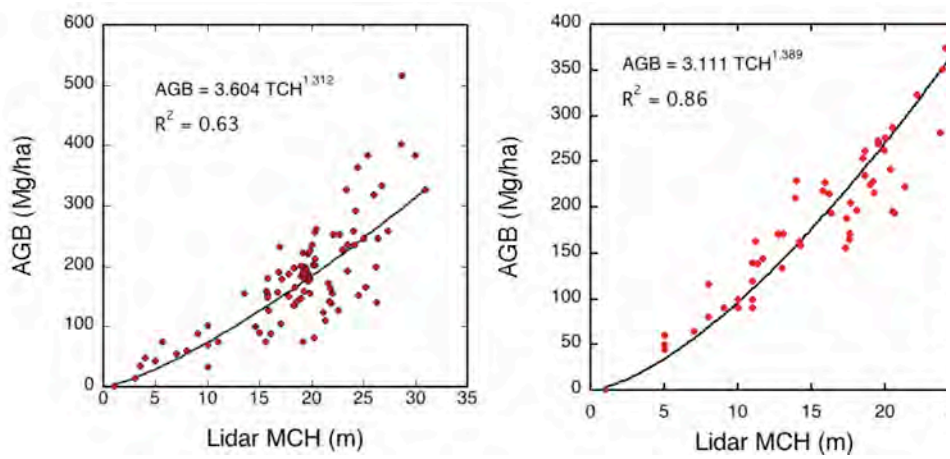

Fig. 4.5. Two allometry models derived from the plots with systematic plots (right panel) in one lidar scene and randomly distributed plots in 15 lidar scenes in project areas.

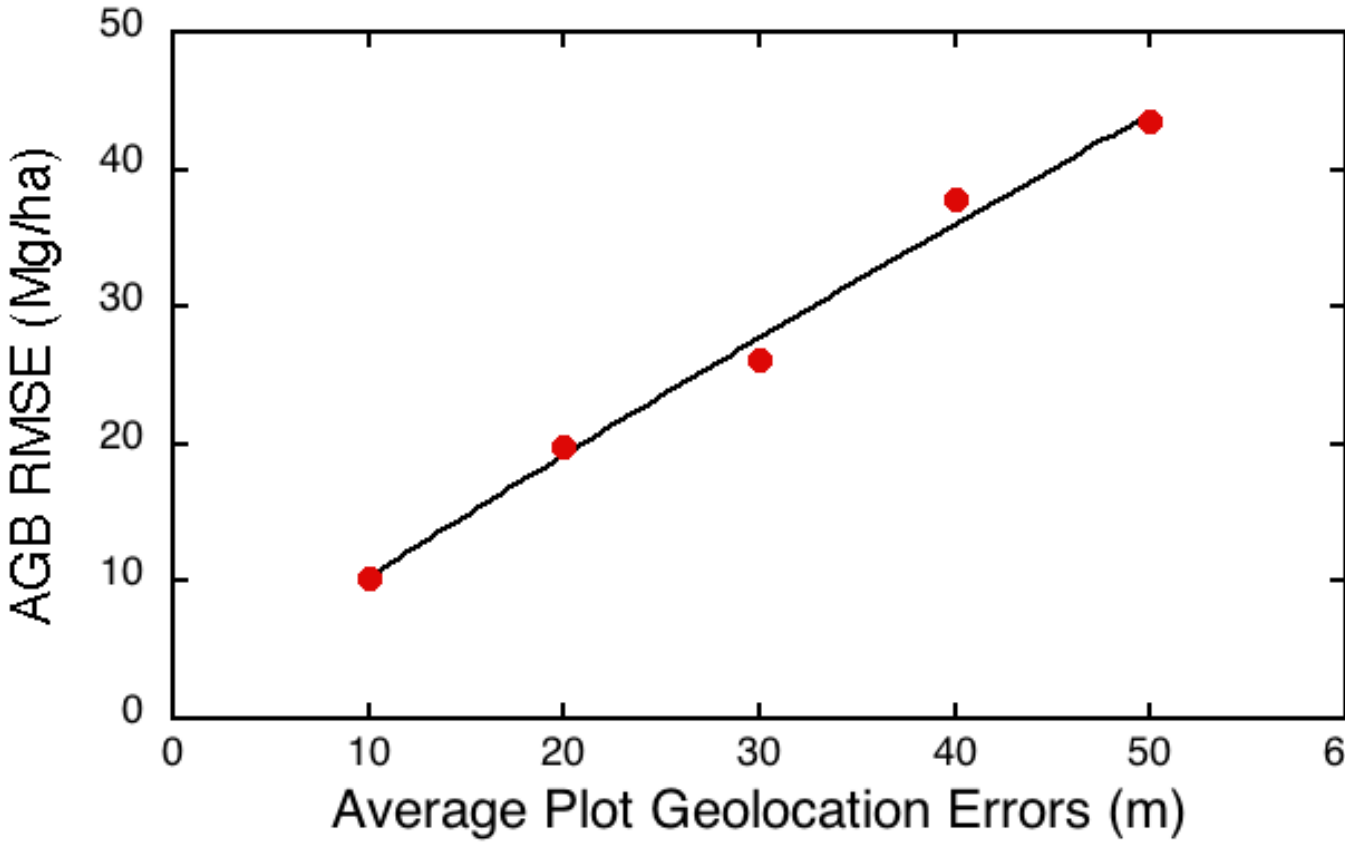

Fig. 4.6. Average above ground biomass root mean square error from plot location errors. The plot size is 100 m by 100 m and the errors are associated with the center location of the plots. When the center location is off 50 m off, the plot is misplaced in the lidar image and the biomass is highly decorrelated.

Using the two models shown in Fig. 4.5, we calculated the impact of the geolocation error on the estimates of forest biomass from the lidar data and propagated this error through the entire system of equations when calculating the errors associated with the biomass estimation at the project area and for different land use types. Using the two models, we estimated the impact of the geolocation error can be significant and reach an average value of about 26.4 Mg/ha at the 0.25 ha lidar pixels. We require to propagate this error when calculating the average biomass estimation at the project level.

4.3 Lidar Biomass Allometry Errors

Lidar Biomass Predictive model

From lidar data we derived various height metrics to examine the accuracy of the best relationship for aboveground biomass estimation. These metrics included the percentile of energy from lidar data using the point cloud information or only the top canopy height for each lidar pixel (1 m). As shown in various earlier work, the top canopy height at the native pixel level of

lidar is the most reliable metric to use for biomass estimation (Meyer et al. 2013; Asner and Mascaro, 2014). The quality of point cloud data is highly variable over individual lidar transects or between transects if data were taken at different dates with different lidar flight configuration or environmental conditions such as canopy moisture because of the impacts on NIR (Near Infrared Lidar) signal penetration into the canopy.

Using the top canopy height at each pixel as the basic measurement of lidar data, we developed several metrics such as mean top canopy height (TCH) and 25, 50, 75, and 100 (maximum height) percentiles of 2500 points at 50 m x 50 m scale. We tested three types of equations for evaluating the contribution of these metrics for biomass estimation:

$$AGB = ah_{TCH}^{b} + \varepsilon$$

$$AGB = a_0 + a_1 h_{25p}^{b_1} + a_2 h_{50p}^{b_2} + a_3 h_{75p}^{b_3} + a_4 h_{100p}^{b_4} + \varepsilon$$

$$AGB = a_0 + a_1 h_{25p} + a_2 h_{50p} + a_3 h_{75p} + a_4 h_{100p} + \varepsilon$$

Where h_{TCH} represents the mean top canopy height, and the metrics are 25, 50, 75, and 100 percentiles. In all equations $\epsilon \sim N(0, \sigma^2)$ represents the uncertainty in measurements or when observations deviate from a power-law by accounting for the heteroskedasticity. After testing all three equations, we arrived to the conclusion that the first equation using the simle mean top canopy height (TCH) is the most reliable model as the other models, although slightly improve the coefficient of derminiation with AGB and the RMSE error of estimation, the are more subject to errors and sometimes require a higher number of plot data for robust estimations of model coefficients. The TCH model has only two coefficients (a,b) and can be readily developed using a minimum number of 30 points or ground plots.

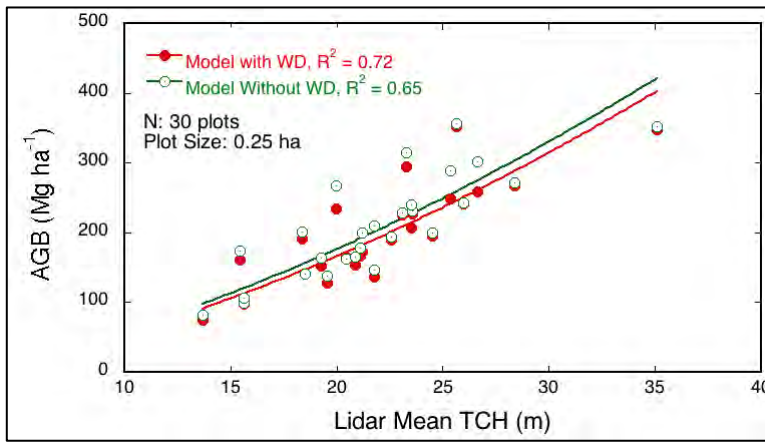

Fig. 4.7. Lidar biomass model derived from mean top canopy height (TCH) and aboveground biomass estimated from ground data. The model with WD performs better than the model without WD because of variations of WD over the landscape and within the BioREDD project areas.

We then tested the following two models in terms of their accuracy in estimating biomass in different forest types.

$$AGB = a(WDh_{TCH})^{b} + \varepsilon$$

$$AGB = ah_{TCH}^{b} + \varepsilon$$

where WD represents the average WD density at the plot level added as linear term to improve the estimation of AGB over areas with different WD. We have already calculated the average WD of each plot within the cluster plots (permanent and satellites) and also calculated estimates of mean WD for forest type identified during the ground measurements and comparison of coordinates with the land cover map of the region. The advantage of model 1 withiout WD component is its straightforward application with the lidar data. Model 2 with WD requires that the regional or landscape variations of WD is known. Using the above two equations, we tested

the goodness to fit of both models to the plot data evaluated by AIC (Akaike Information Criterion) . The AIC is a measure of the goodness-of-fit that penalizes parameter-rich models, as required by the principle of parsimony (Burnham & Anderson,2002). The results as shown below:

$$AGB = 1.484(WDh_{TCH})^{1.575} \quad (AIC = 2780, \sigma = 0.32)$$
$$AGB = 1.707h_{TCH}^{1.548} \quad (AIC = 2850, \sigma = 0.34)$$

The model with WD performed slightly better than the model without WD (higher AIC and σ). We removed the plots with significant numbe of mangrove trees and Guandal, we noticed that the models were not significantly different. We concluded that the model with WD performs better than the model without WD only in forests with mangrove trees and in inundated forests (guandal) by improving the RMSE of estimation by approximately 10%. Figure 7.2 shows the difference between the models and the improvement.
The uncertainty of the above models have been evaluated using cross validation approach and using plots not used in developing the model. In the above equation we only used 30 plots to develop the model in order to demonstrate how the methodology works with the minimum number of plots. Overall, we have the following number of plots to evaluate the lidar model: 1) 15 1-ha permanent plots within the lidar transects. We divided each plot to four 0.25 ha plots to increase the number of plots for calibration and validation. This resulted to 60 plots at 0.25ha, 2) we have 15 sets of satellite plots falling in the lidar transects with each set having 8 satellite plots at 0.25 ha for a total number of 120 with 109 plots accuractely located in lidar images, and 3) we collected 45 plots in 0.25 ha systematically within one lidar transect. Overall, we had 214 plots at 0.25 ha in size to develop and test the accuracy of lidar predictive model.

Statistical Analysis

The statistical analysis includes evaluating the performance of the model selected above based on regressing a dependent variable (AGB) against one or several independent variables (in our case, WD and H). We follow the general form of the model as shown above by assuming ε as an error term as a normally distributed with zero mean and SD of σ. If the model as the one selected above as p parameters (p=2 for WD and h), then the σ is defined as:

$$AGB = a(WDh_{TCH})^b + \varepsilon$$
$$\ln(AGB) = a + b\ln(WDh_{TCH}) + \varepsilon$$
$$RSE = \sigma = \sqrt{\frac{1}{N-p}\sum_{i=1}^{N}\varepsilon_i^2}$$
$$N(\varepsilon) = N(0,\sigma^2): \quad \text{Distirubtion of errors}$$

The model as shown above can be linearized in the ln form to simplify the model as a linear regression model. The model be used to estimate AGB from the parameters developed at the plot

level, i.e. average wood density *WD (g cm^{-3}) and h_{TCH} (m)*. The estimated value of AGB can be written as:

$$AGB_{est} = \overline{\exp\left[a + b\ln(WDh_{TCH}) + \varepsilon\right]} = \overline{\exp(\varepsilon)} \times \exp\left[a + b\ln(WDh_{TCH})\right]$$

where

$$\overline{\exp(\varepsilon)} = \int \exp(\varepsilon) N(\varepsilon)\, d\varepsilon \quad \text{with } N(\varepsilon) = N(0, \sigma^2)$$

$$\overline{\exp(\varepsilon)} = \exp(\sigma^2 / 2)$$

then

$$AGB_{est} = \exp\left[\sigma^2 / 2 + a + b\ln(WDh_{TCH})\right]$$

The last equation provides the unbiased estimator for AGB using the height and wood density. To examine the model, we used the plot data and calculated the average systematic error (bias) and the coefficient of variation (CV) as follo

$$bias = \frac{1}{N}\sum_{i=1}^{N} \frac{(AGB_{est}(i) - AGB_{obs}(i))}{AGB_{obs}(i)}$$

$$RSE = \sqrt{\frac{1}{N-P}\sum_{i=1}^{N}\left[AGB_{est}(i) - AGB_{obs}(i)\right]^2}$$

$$MAGB = \frac{1}{N}\sum_{i=1}^{N} AGB_{obs}$$

$$CV = \frac{RSE}{MAGB}$$

where RSE is the residual standard error representing the random errors. The standard deviation of estimation error can be computed as: $SD = \sqrt{RSE^2 - bias^2}$.

The table below provides the model fit and the accuracy of the model in estimating the AGB. The bias can be readily excluded in the estimator. From the table, it appears that having a minimum of 30 plots for calibration and 15 plots for validation will be enough to acheive at the required lidar biomass predictor model and uncertainty assessment. More plots provides only slighty improved results. Note that here, we used one allometric model for all forests. In the case, more allometric models, for each model, a minimum of 30 plots are required for calibration.

Table 7.2. Lidar biomass predictive model Model goodness of fit and uncertainty assessment using the plot data available for the BioREDD project.

Calibration Sample Size	**Model fit Assessments**			**Validation Sample Size**	**Cross Validation Results**		
	σ	**AIC**	**DF**		**RSE**	**Bias**	**CV**

30	0.329	47	3989	15	37. 96	2.27%	18.8%
50	0.326	45	3990	25	35. 24	2.01%	16.2%
100	0.319	45	3980	50	33. 96	2.20%	15.8%
150	0.311	43	3980	75	31. 96	1.98%	14.8%

5.0 UNCERTAINTY IN CARBON POOLS

The methodology to estimate carbon pools has been described in earlier reports (deliverable 12). Here we repeat some of the main points from the report before addressing the uncertainty associated with the carbon pools.

1. Ground estimation of carbon pools: We developed a series of field plots as described in earlier reports to sample the forest carbon pools in BioREDD regions. The field survey and data collection occurred in summer of 2013 and ended in early 2014. The field plots included permanent (1-ha) and temporary plots (0.25 ha) over 16 study regions covering a variety of forest types including intact and degraded forests. The measurements included tree diameter for all trees > 10 cm. The 10 cm threshold was selected to meet the requirement of the VCS REDD methodological and IPCC guidelines. The measurements were converted to forest above ground biomass using a combination of existing allometric equations. However, we found large differences between the allometric equations, particularly between wet and moist forests from Chave et al. 2005. The Choco region has large variations of rainfall and species composition different from the central Amazonian trees where most of the harvested trees in Chave et al. (2005) equation are based on. Ground measurements also included the dead trees both the standing and lying to provide the carbon in standing and lying organic matter.
2. The BioREDD team developed a local allometric equation to convert the tree structure measurements in the field to biomass. The allometric models were developed based on a set of harvested trees. To develop the project based allometric model for biomass and carbon content measurements were performed by CONIF at four sites, two sites were in the Northern Pacific region near the Mutatá and Rio Pepe Indigenous Community Councils/ The other two sites were in the Southern Pacific region where fieldwork was conducted in late 2010 and early 2011 by CONIF and members of the Community Council in Bajo Mira and Frontera and Concosta (Saldarriaga, et al., 2011). All these four sites are within the BioREDD region with the aim of establishing REDD + projects in the future. The field work for the allometry model lasted four months, ~75 days of fieldwork and ~ 45 days of laboratory work. The main objectives of the study were:
    1. Adjust existing allometric functions for upland forests, including a greater number of species and individuals distributed in diameter classes from 10 cm with special emphasis in the higher classes (D> 70 cm).

2. Develop models to estimate the biomass of secondary forests.
3. Develop models to estimate the biomass of some species of palms.

The selection of sites were based on several criteria such as community interest, state forest and diversity, coverage and scientific interest, safety in the work area, operating costs, logistics and transport. Working with communities was instrumental in achieving the objectives. We harvested 296 trees ≥ 5 cm diameter at four sites, two in the North Pacific and two in the South Pacific, including 240 from the mature forest trees, 56 trees of secondary forest and 97 palms. In turn, of the 240 individuals in the mature forest, 160 are from the terra firme forests in middle and low hilly regions (Colinas), 46 from the inundated forests near the coastal plain (Guandal), and 34 tree from the mangrove forests (Manglar).

3. Estimation of carbon pools in BioREDD regions: To extrapolate the ground measurements to the entire BioREDD regions, we made use of the estimates of aboveground biomass from lidar data randomly sampled in forest strata and LULC classes. From ground measurements, we developed carbon pools and ratios of the carbon pools to aboveground carbon density and used the aboveground carbon density derived from lidar and LULC map to extrapolate the estimates over larger regions. The estimates also included error propagation approaches to derive the uncertainty of carbon pool estimates at LULC units within the BioREDD project areas.
4. The statistical approach included estimates of mean and variance of carbon pools from the plot data and extrapolating the mean and variance to the entire BioREDD regions. The methodology to extrapolate the estimates to the BioREDD region is described in section 11 below.

Estimating carbon pools in all LULC classes for BioREDD project areas are based on the aboveground live carbon pool derived from 83,000 lidar data interesected by land use and land cover classes as described in report 8&9. We estimate the belowground, standing and lying deadwood, the non-tree carbon pool, litter using models and factors developed above on each ha of lidar derived aboveground pool. The approach is summarized as follows:

$$AGT = CF_{AG} \times (1.483 AGB_{10cm}^{-0.0613})$$

$$AGNT = CF_{AGNT} \times (0.832 AGB_{10cm}^{0.346})$$

$$BG = CF_{BG} \times (0.489 AGB^{0.89})$$

$$LDW = CF_{LDW} \times (\frac{0.0353}{f} AGB_{10cm}^{1.093})$$

$$SDW = CF_{SDW} \times (\frac{0.000484}{f} AGB_{10cm}^{1.614})$$

$$DTS = CF_{DTS} \times (0.01538 AGB_{10cm}): \quad \text{Intact Forest}$$

$$DTS = CF_{DTS} \times (0.09438 AGB_{10cm}): \quad \text{Degraded \& Seconadry Forest}$$

where

$$CF_{AG} = 0.485, CF_{BG} = 0.485, CF_{AGNT} = 0.47, CF_{LDW} = 0.485, CF_{SDW} = 0.485, CF_{DTS} = 0.485$$

5.1 Belowground Carbon

We used this equation to estimate belowground biomass from aboveground biomass:

$$BGB = 0.489 * AGB^{0.89}$$

where BGB is the belowground and AGB is the aboveground biomass in units of Mg ha^{-1} of dry weight. To develop an uncertainty in the above relationship, we used the measurements from Mokany et al. and examined the variations in the ratio of below:aboveground biomass or root:shoot biomass ratios with respect to vegetation types used in the study. By including sites in forest plantations and grasslands and tundra, the RMSE in predicting the belowground biomass was 9.46 Mg ha^{-1} and relative error of approximately 23.2% (See deliverable 12 for details). The application of the above model to estimate of BGB had standard error of 0.659 Mg ha^{-1}. For converting the belowground biomass to carbon(BG) , we used the carbon fraction value of 0.485 similar to aboveground carbon pool.

The RMSE error will be propagated to project level carbon estimates and through an error propagation routine to calculate the error on the total carbon pool for the project areas. The error in BGB is estimated from both the error in the prediction of BGB from AGB through the allometric equation *above* and the error in AGB:

$$\varepsilon_{BGB} = \left[(23.2)^2 + (0.89\varepsilon_{AGB})^2\right]^{1/2}$$

where ε_{BGB} is the relative uncertainty in BGB. The coefficient, 0.89 is the power of AGB in the allometric relationship used in the above equation.

5.2 Standing and Lying Dead Wood

In developing the model or the ratio for estimating deadwood biomass from the aboveground live biomass, we also explored the use of ancillary parameter such as the degree of fragmention or canopy cover derived from lidar data over each plot to improve the estimation of deadwood. Introudcing ancillary parameter such as fraction cover is based on the fact that the biomass of deadwood increases in degraded and secondary

forests compared to intact old growth forests. The use of ancilary data improved the estimate to some extent

$$AGB_{SDW} = \frac{0.000484}{f} AGB_{10cm}^{1.614}$$

$$AGB_{LDW} = \frac{0.0353}{f} AGB_{10cm}^{1.093}$$

$$AGB_{Total} = \frac{0.0424}{f} AGB_{10cm}^{1.106}$$

where *f* is the fraction cover of trees within each plot. The fraction cover is estimated from the lidar data by separating the gaps from tree crown cover within each permanent plot. The same method can be used during the ground survey of deadwood by fisheye photography or other forestry techniques. To convert the biomass to carbon, we used the default value of 0.485 as in live tree components to estimate the carbon pool values.

The error associated with the standing and lying dead wood can be estimated from combining the error associated with the above equations and the error associated with the AGB. We used ground data on deadwood to develop the above models and the methods for measuring the carbon stocks in dead wood, both lying and standing, are detailed in the standard operating procedures outlined in field measurement protocols used by CONIF for the BioREDD project. The basic methods are as follows: (1) For standing dead wood, the volume of the main stem is estimated from measures of base diameter and height, This is then multiplied by the density of the species (if known or by the average density of 0.65). (2) For lying dead wood, measurements are taken to estimate the volume and its density class (sound, intermediate, and rotten) according to the methodology. Multiple samples of the three classes of dead wood are then collected to determine their average wood density (t m^{-3}) according to the methodology. The volume by density class times the dead wood density results in an estimate of the carbon stock in lying dead wood.

The uncertainty in AGB_{SDW} and AGB_{LDW} are estimated from the following equations:

$$\varepsilon_{SDW} = \left[\varepsilon_S^2 + 1.614\varepsilon_{AGB}^2\right]^{1/2}$$

$$\varepsilon_{LDW} = \left[\varepsilon_L^2 + 1.093\varepsilon_{AGB}^2\right]^{1/2}$$

where ε_S *and* ε_L are respectively the errors associated with the regression models associated with SDW and LDW respectively (see deliverable 12 for model formulation). These error are:

5.3 Litter Carbon

5.4 Soil Carbon

We used the stratified map developed during the Task 1 of the project to design the lidar data acquisition and the field sampling plots. The stratification was developed by combining four data layers: climate, soil, topography, and the land cover map. We colored the stratified image into 30 distinct colors to demonstrate the potential variations of the landscape features that may influence the forest structure, carbon stock and dynamics. The stratified map has been used to define areas for forest inventory and airborne Lidar samples. We selected 49 locations randomly in 30 stratified regions within the original project areas. We designed the 49 lidar transects to cover approximately 83,000 ha of forests randomly selected over an area of approximately 1.7 million ha along the Pacific coastal forests of Colombia where the BioREDD project has been established. The number of transects and the size of each transect was designed to reduce the variance in biomass estimation by taking into account the errors in lidar estimates of biomass, allometry, sampling errors, and natural variations of biomass. The area sampled by lidar was > 1000 ha and several lidar transects were located within each strata depending on the size of the stratum. The over-sampling compared to the ground inventory was done intentionally to meet two key requirements: 1) sampling had to be random and large enough in each stratum to reduce the standard error in estimation. We aimed at < 10% error at 95% confidence interval. However with a large number of samples acquired by the lidar data, we achieved errors with approximately one order of magnitude better with lidar data. 2) The samples were clustered along the lidar flights and therefore required to be large enough to provide the balanced sampling to estimate the mean and variance of biomass in each stratum.

6.0 REGIONAL ESTIMATES OF UNCERTAINTY

The lidar data acquired over the BioREDD region followed a stratified random sampling approach where the remote sensing sampling units (RSU) are the flight lines of lidar with a minimum area coverage. Each flight line has a given swath with regular grid cells of 0.25 ha with biomass estimations that are considered the population elements. Flight lines or sampling units are designed to provide a balanced random sample of stratified classes and therefore for each strata j there are η_j sampling units and within each sampling units there are η_{ij} lidar grid cells. The lidar grid cells within each flight line are considered clustered and the estimator for the mean and variance of biomass density for each stratum are given as follows (Naesset et al., 2013; Neigh et al., 2013; Stahl et al., 2011).

$$\mu_j = \frac{\frac{1}{n_j}\sum_{i=1}^{n_j} F_{ij}(\alpha_j)}{\frac{1}{n_j}\sum_{i=1}^{n_j} \eta_{ij}}$$

$$\mathrm{var}(\mu_j) = \frac{1}{\bar{\eta}_j^2}\frac{\sum_{i=1}^{n}\left(F_{ij}(\alpha_j) - \mu_j \eta_{ij}\right)^2}{n(n-1)} + \frac{1}{\bar{\eta}_j^2}\sum_{k_1}^{p_j}\sum_{k_2}^{p_j} Cov(\alpha_{k_1 j}, \alpha_{k2j})\bar{F}'_{k_1 j}\bar{F}'_{k2j}$$

where

$$\bar{F}'_{k_1 j} = \sum_{i=1}^{n}\sum_{t=1}^{T}\frac{\partial f(x_{it}, \alpha_{k_1})}{\partial \alpha_{k_1}}$$

where

$$AGB = f(x, \alpha, \varepsilon) = a(WDh_{TCH})^b + \varepsilon$$

where μ_j is the mean carbon density of stratum j, F_{ij} is the carbon density estimates for sample i in stratum j, n_j is the number of RSU intersecting stratum j, α_j represents the vector of parameters used in the biomass model (e.g. a and b in lidar model in above AGB equation, and η_{ij} is the number of lidar biomass units (cluster size) in each sample unit i intersecting stratum j. Note that if lidar biomass estimates are at 1-ha units, η_{ij} represents the size of the lidar transect or RSU in ha. In above equation, $cov(\alpha_{k_1 j}, \alpha_{k_2 j})$ is the covariance of k_1 and k_2 coefficients of the lidar biomass predictive model, represented by function *f* for stratum j. The first term in equation in variance estimate represents the sampling error and the second term describes the model error for each stratum. The above relations will be simplified if only one lidar model is used for all strata.

The lidar model-assisted estimator of biomass (carbon density) is approximately a design-unbiased estimator irrespective of the model of choice when the number of samples collected in each RSU is large (which is the case in airborne lidar collection). The design is unbiased because

within each stratum, ground plots are used to make the lidar predictor model unbiased (as discussed above) (Naesset et al., 2011). The variance estimator also propagates the error from the lidar predictive model for estimation at the statra and land cover class scales.

We collected 45 ground samples in a lidar sampling unit or transect to also estimate if there has been any bias in estimation of biomass at scale of sampling unit (lidar flight transect). The mean for each sample unit can be readily rewritten as:

$$\mu = \frac{\sum_j \hat{\mu}_j}{N} + \frac{\sum_j \hat{e}_j}{n}$$

$$\hat{e}_j = \mu_j - \hat{\mu}_j$$

where $\hat{e}_j$ is the difference between ground estimated biomass μ_j and lidar estimated biomass $\hat{\mu}_j$ using the lidar model. If the number of plots n used for estimating $\hat{e}_j$ is large (> 10) (Särndal, 1984).

Having more than 30 ground plots will allow us to remove the bias in the system and have an unbiased estimate of mean and standard error.

Using the above relations, we followed the following steps to estimate the mean and variance of biomass density in each strata and also based on the land cover types used in the VM0006 methodology.

We used the following steps to estimate the aboveground biomass for the BioREDD regions at the scale of strata, LULC, and project areas:

1. The unbiased lidar predictive model was used to estimate the biomass for each grid cell within the lidar sampling units. Since the grid cells are 0.25 ha each, we developed approximately 332,000 (i.e. 4 x 83,000) estimates at grid cells. Each grid cell has a lattitude and longitude identifier that can be traced to a location within each strata in the BioREDD project region. Each estimate has an error associated with it according to relations provided in the previous section.
2. The grid point estimates and the form of the mean and variance estimator shown in this section are used to estimate the mean biomass in each strata and the BioREDD project area by using the proportion area of each stratum in the project area as given by:

$$\hat{\mu}_{PA} = \frac{1}{PA}\sum_{j=1}^{m} w_j \mu_j$$

where w_j is the proportion area of each stratum in *PA* (Project Area)

μ_j is the biomass density for stratum j

m is the number of strata in the project area

3. For the LULC classes, we use the same methodology as the strata and replace the stratification by LULC map and use the lidar grid cells as samples for estimating biomass mean and variance of LULC class types.