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Monitoring Aboveground Forest Biomass: A Comparison of Cost and Accuracy between LiDAR-Assisted Multisource Programme (LAMP) and Field-based Forest Resource Assessment (FRA) in Nepal

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Abstract

Analyzing forest monitoring costs and accuracy of forest carbon stock estimates are important criteria in the framework of Reducing Emission from Deforestation and forest Degradation (REDD), because Monitoring, Reporting and Verification (MRV) system has been seen as an investment that aims to generate financial benefits to forest owners. Thus, comparisons of cost efficiency and accuracy were carried out between the LiDAR-Assisted Multisource Program (LAMP) and the field-based multisource Forest Resource Assessment (FRA) applied in the 23 300 km^{2}of Terai Arc Landscape (TAL) of Nepal in 2011 to estimate Above-Ground Biomass (AGB). The model-based LAMP was applied by integrating 5% LiDAR (Light Detection and Ranging) sampling, wall to wall RapidEye satellite image and field sample plot inventory. The design-based FRA was carried out to generate comprehensive forest resource information. Administrative and initial variable costs of both approaches were calculated separately, and converted to unit costs for comparison. To compare the subsequent forest monitoring costs, cumulative costs were derived on the basis of the calculated present variable items and expenditures. The accuracies werecalculated by using mean error of mean biomass estimates (tons/ha) at different spatial scales ranging from 1 to 350,000 ha forests. Design-based FRA was found to be cost-efficient (US$ 0.22/ha) over the LAMP approach (US$ 0.28/ha) for baseline data collection, whereas administrative cost of multisource FRA (US$ 0.26/ha) was significantly higher. Although a huge amount of data were generated through multisource FRA in each cycle, the LAMP approach appears to be cost-efficient to estimate AGB in subsequent forest inventory. The mean errors in the LAMP-derived mean biomass estimate were significantly smaller at all spatial resolutions than the FRA plot-derived mean biomass estimate. The study concludes that spatial accuracy of LAMP is good enough to estimate biomass stock of Community Forests (CFs) where average size of CF was 150 ha in the study area.

Key words: Above ground biomass, cost, accuracy, LiDAR, Forest Resource Assessment

1. Introduction

Forests act as carbon sink, but turn into a source of carbon emissions when they degrade. As a consequence, political and public attentions to the world's forests have drastically increased due to the significant role of forests in the global carbon cycle (FAO 2010, IPCC 2007b). Tropical forests cover 15% of the world's land surface, and hold about 25% of the carbon in the terrestrial biosphere, emit 15-20

% of the total carbon dioxide in the atmosphere every year due to deforestation and forest degradation (FAO 2010, IPCC 2007b).

Recognizing this prospect, the United Nations Framework Convention on Climate Change (UNFCCC) agreed to encourage reductions in greenhouse gas emissions from forests via REDD+ program (Asner*etal.* 2012, FAO 2010, UNFCCC 2009). As a result, REDD+ has become an international policy instrument to mitigate climate change by reducing carbon emissions caused by deforestation and forest degradation, and by increasing carbon uptake through forest restoration and sustainable forest management (Herold and Skutsch 2011, IPCC 2010). However, effective implementation of REDD+ strategy depends on cost-effective forest monitoring systems to generate accurate baseline statistics of forest biomass, carbon stocks and emission levels (Asner *et al.* 2010, 2009).

Forest inventory methods have changed in the course of time due to the continuous technological advancement (Kandel 2010, Gatziolis and Andersen 2008). The key driving force behind the development of different FRA methods is the goal of obtaining accurate forest information at low cost (Tomppo *et al*. 2008, Kangas *et al*. 2006).

In the past, intensive field-based FRA focused on timber production and applied for estimating tree volume, growing stock and growth (Hummel and O'Hara 2008). Although traditional approach is accurate method, rigorous field measurement is time-consuming, costly, and difficult to implement in unreachable extensive forest areas.

Satellite RS has become key tool to collect large amounts of image data over a wide geographical area with high temporal frequency and provide 2D (x, y) information on species composition. However, optical RS cannot penetrate through the forest canopy to generate information about forest structure (Gautam *et al.* 2010). Besides, intensive field inventory and ground verification are required to validate the data and to generate tree level statistics (Gautam and Kandel 2010).

LiDARis an active RS technology that is able to penetrate the vertical profile of dense forest canopy and quantify its structure (Asner *et al.* 2012, Pascual *et al.* 2010, Gatziolis and Andersen 2008). Compared to traditional passive optical RS, LiDAR has the capacity to capture 3D (x, y, z) data of objects, and can precisely estimate height and size of individual trees or forest stands and thereby volume and AGB (Lim *et al.* 2003, Nelson *et al*. 2003b). However, a key obstacle in using LiDAR is due to its relatively high cost for scanning in challenging flying condition (Asner *et.al* 2010, Gautam *et. al.* 2010, Hummel *et al.* 2011, Næsset 2002a-b, 2009).

When combining LiDAR from sample areas with satellite data covering the entire area of interest and in-situ measurements at sample locations, high-resolution maps of forest carbon stocks and emission can be produced in an efficient way (Asner *et al*. 2010, Arbonaut 2010). The integrated approach is known as the LAMP – a term that was coined by the World Wildlife Fund U.S. (WWF-US) and Arbonaut Ltd. in early 2011. LAMP has been tested in Peru, Laos, Madagascar, Columbia and Nepal. However, so far a cost and accuracy analysis that would allow a comparison between the LAMP approach and field-based forest inventory methods has not been carried out.

Comparison of cost and accuracy of different FRA approaches applied for the same objective such as monitoring forest carbon stocks and emissions has become one of the key research areas in forestry in order to draw conclusions on their cost efficiency, robustness and accuracy (Hummel *et al.* 2011). This paper presents the results of a study which compares the cost and accuracy of LAMP and multi-source FRA methods applied in TAL-Nepal for the estimation of AGB.

2. Materials and methods

2.1 Study area

TAL is a trans-boundary landscape that extends between Nepal and India, and includes two globally outstanding eco-regions viz. the Terai-Duar Savanna Grasslands, and the Himalayan Subtropical Broadleaf Forests (Gurung and Joshi 2009). The study area covers an area of 23 300 km^2 within Nepal, extending over Bagmati River in the East, Mahakali River in the West, Siwalik ridge in the North and Terai flatland in the South (Figure 1).

Altitude varies from 300 m in the South to 1500 meters in the northern hills from above mean sea level. The area is a spatial mosaic of tropical and subtropical forest types, and covers 75% of the remaining forests of Terai and foot hills of Siwalik (HMGN/MFSC 2004, HMGN/ADB/FINNIDA 1988). The region is home to the world's most impressive wildlife species such as Royal Bengal Tiger (*Pantheratigris*), the Greater One-horned Rhinoceros (*Rhinoceros unicornis*) and the Asian Elephant (Joshi and Bhatta 2010). The area is inhabited by 6.7 million people, and the majority of them are rural poor (Joshi and Bhatta 2010). As a result, forest resources have declined in extent and quality due to deforestation and degradation.

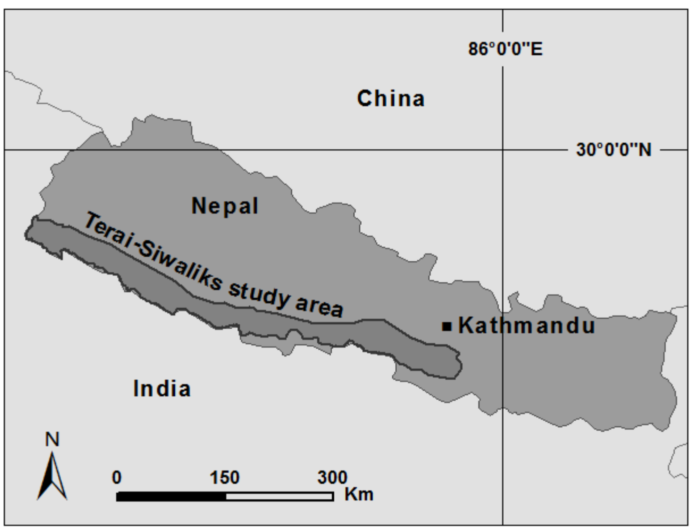

Figure 1. Map showing the study area in the Terai Arc Landscape.

2.2 Inventory methods considered in the study

2.2.1 LiDAR Assisted Multisource Program

LiDAR data was collected from 5% of the study area. For the LiDAR campaign, 20 rectangular forest blocks of 5 km × 10 km size were designed by a weighted random sampling. Wall-to-wall Airborne Laser Scanning (ALS) was conducted during March and April 2011 using a Leica ALS50-II- scanner. Average recorded point density was 1.26 pulses/m^2.

Systematic cluster sampling was applied to collect field data in the LiDAR sample areas. Six clusters were designed in each LiDAR block. Altogether, 792 forest-located circular plots of size 500 m^2were measured in the field. The measurements at tree-level included all living trees and shrubs above 5cm diameter within the plot area. Plot volume and biomass were calculated using species-group specific volume and biomass equations prepared by Sharma and Pukkala (1990).

LiDAR metrics describing the canopy height distribution were used to predict growing stock, biomass and other related characteristics of a forest stand (Lim *et al.* 2003, Næsset 2002a, 2009). The LiDAR model was established by regressing field measurements with 30 lidar variables defined by Junttila *et al.* (2010). The selection of variables was done using the Sparse Bayesian methodology (Junttila *et al.*2008). The ArboLidar tools developed by Arbonaut, Finland were used to apply this method.

2.2.2 Field based Multi-source FRA approach

The FRA Nepal Project (2010-2014) has applied a stratified two-phase systematic cluster sampling. In the first phase sampling, a 4 km by 4 km systematic grids were overlaid for visual interpretation. Out of the total, 4883 (56%) points were located in the forests. Altogether, 128 sample clusters consisting of 676 sample points were selected for field inventory which represents about 13.8% points of the first phase forest-area samples.

In the Terai region, each cluster consisted of a group of 4 sample plots while there were 6 plots per cluster in the Siwaliks region. A concentric circular sample plot with radii thresholds of 20 m, 15m, 8 m and 4 m was designed for tallying and measuring different size of trees. Field inventory was carried out by a number of inventory crews. Altogether, 10-12 personnel were engaged in one inventory crew to measure field plots. The measured tree characteristics were used to calculate the volume of each species at plot-level, later extrapolated to the whole target area and finally estimated per unit area (Sharma and Pukkala 1990).

2.3 Costs of forest inventory

Hardcastle and Baird (2008) have described the cost of forest inventory under variable and fixed/ administrative **c**osts. Variable costs depend on methods, spatial coverage, required accuracy, sampling intensity, materials to be used and the capacity of the executing organization. The administrative costs include costs of planning and organizing sampling events such as staffing, formulating inventory tools and techniques, personnel/experts involved, procurements and other costs which do not much vary with sampling design and other variables of inventory, if system is well institutionalized. In the case of the project based FRA, the total cost becomes the allocated budget to perform the task.

2.3.1 Extent of variable costs of LAMP

Variable costs of LAMP comprise the expenditure required for wall-to-wall LiDAR scanning in 20 sample blocks, insitu measurements at 792 field plots, purchase of RapidEye satellite imagery, data processing, modeling (LiDAR model and satellite-based model) and biomass estimation for the whole study area. The cost-related data were collected from the records of the FRA Nepal project and Arbonaut, Finland. The costs for data processing and model building were derived from the number of working days spent on these tasks and the respective hourly rates of the experts involved.

2.3.2 Variable cost magnitudes of field-based FRA

Several variable costs were associated during the implementation of field-based FRA. All relevant cost items, their composition and data sources are presented in table 1 below.

Table 1: Details of cost items involved in field-based multisource FRA

Expenditure items	Details under each items	Data sources
Procurement of satellite imagery	• Cost calculated from actual price involved to buy RapidEye imagery.	FRA Nepal Project
Training cost to train field crews	• Cost required for training the inventory crew members involved in field plots measurement.	FRA Nepal Project
First-phase sampling (image interpretation)	• Cost required interpreting the points fall in the study area.	FRA Nepal Project
Second-phase field inventory (in-situ measurement)	• Preparatory cost • Hardship allowance for field crews and local staff paid by the project • Expenses required for social survey • Accommodation cost for field crew • Cost of vehicles and fuel • Salary of crew members • Field gear	Mission-wise record from FRA Nepal Project Salary sheet
Quality control of second-phase field inventory	About 7% cost of second-phase sampling	Quality control team
Data entry, processing analysis.		

The second phase field inventory was organized in a mission-wise approach by sending the crews to the locations of different field sample clusters. To derive the related costs, the average number of days spent by a crew for the field inventory and the average number of sample plots measured by a crew in each mission were calculated. On average, the field inventory crews spent 24 days on a mission, and measured 12 sample plots. Including all the expenditure items, the average total cost of each crew mission was computed. Cost per plots was figured out by using the following formula:

Cost/plot= Total cost per crew mission/12 plots

The total cost was determined by adding the overall cost of all direct expenses. Finally, per-hectare cost for the study area was derived.

2.4 Estimation of Subsequent Monitoring cost

Subsequent forest monitoring is needed in successive cycle to update the forest information (Angelsen *et al.* 2011, FAO2010, Tomppo *et al.* 2008, Kangas *et al.* 2006). Field based FRA approach necessitates repeating forest inventory in the same way during successive time periods. However, LAMP needs to update the model by interpretation of new satellite images for successive years at least does not repeat other items up to certain cycles (Asner *et al.* 2010, Gautam *et al.* 2010, Lim *et al.* 2003, Næsset 2002a). The LAMP model can also be applied to estimate historical biomass from satellite imagery of the past. In the case of TAL-Nepal , after collecting the baseline data, three succeeding cycles of five year interval have been set by assuming that the LAMP model does work up to the next 15 years. In this case, cost only requires for updating the model through interpretation and processing of new satellite images to produce AGB estimates.

In consequence, a postulation has been set that includes the base line data collection, forest monitoring up to the next three rounds is a single task required for MRV. An additional assumption is that both systems will be institutionalized within the Department of Research and Survey (DFRS) of Nepal thus, no cost is required to hire international experts. Hence, calculation of cumulative cost is required for the set subsequent forest monitoring series. We approach this buildup of activity cost so that each successive total cost includes activity costs that precede it (Jhingan 2002). Although the per-hectare cost for consecutive inventory cycles could be significantly increased in the future, due to increasing prices of materials and labors, the given estimates of future inventory costs (table 4) were derived on the basis of the calculated present initial expenditures which reveal the indicative minimum cumulative cost required for successive cycles. The set of assumptions allow us to compare cost efficiency between the two approaches up to the defined sequence of measurement cycles.

2.5 Estimation of method accuracy

The mean error of an estimator ME (θ) assesses the quality of an estimator in terms of its variation and unbiasness. Two or more statistical models applied for the same purpose can be compared using the values of the ME *(θ)* to explain the reliability of two sets of observations (Lebanon 2010, Moore *et al.* 2001). For the purpose of this study, both field plot-based FRA method and the LAMP approach were compared with respect to their accuracy in estimating mean AGB at different spatial scales. The ME (θ) is calculated as the root of the sum of the variance and the squared bias of the estimator:

$$ME(\theta)=\sqrt{var(\theta)+bias(\theta)^2} \qquad \text{Eq. 1}$$

In order to derive the mean error at different spatial scales, the formula was modified by replacing variance with the square of the standard error of the mean. The standard error of the mean is the standard deviation of the error in the sample mean relative to the true mean:

$$SE_x=\frac{s}{\sqrt{n}} \qquad \text{Eq. 2}$$

Where s is the standard deviation of the sample and n is the sample size (number of observations).

Using the sample size as an indicator of the spatial scale (area) at which a mean estimate is produced, the scale-dependent mean error was calculated as:

$$ME(\theta)_n=\sqrt{\frac{s^2}{n}+bias(\theta)^2}\ , \qquad \text{Eq. 3}$$

Where s is the standard deviation of above-ground biomass in FRA plots which was considered the true standard deviation of biomass, and n is the number of FRA plots or LAMP estimates respectively for a certain area.

For the FRA approach, n was scaled according to forest area, adopting an ideal case of equal spatial distribution of field plots over the forest:

$$n_R=\frac{R}{A}*n_{FRA}\ ; \qquad \text{Eq. 4}$$

Where R is the forested area (in hectares) from which the mean estimate is produced, A is the total forested area (350,000 ha) according to the available vegetation map, and n $_{FRA}$ is the total number of FRA plots.

For the LAMP approach, n is equal to the area from which the estimate is produced. The LAMP method produces biomass estimates at 1-hectare resolution. That means LAMP produced 350,000 samples in 350,000 ha but field based FRA approach designed only 150 samples.

The FRA approach was considered an unbiased method because it is a design-based method that better follows to the laws of statistics, so that in this case the formula could be simplified to the formula for standard error of the mean (Equation 2). The bias of LAMP was calculated by comparing LAMP estimates at FRA-plot locations with the corresponding FRA-based AGB values. The accuracy of the LAMP approach was calculated using Equation 3.

3. Results

3.1 Cost comparison

3.1.1 Total and administrative costs

Deducting the cost of lidar indicated in the project document, total budget of FRA, Nepal project is US Dollar (USD) 7099973 allocated to conduct comprehensive national FRA. On the other hand, the LAMP was a sub approach under the project conducted at sub-national scale to estimate AGB. The total cost of LAMP was USD 728957 which includes USD 265320 allocated by the FRA Nepal project. Remaining budgets were contributed by WWF –USA/Nepal and Arbonaut, Finland. On the basis of total allocated budget, costs of field based FRA was USD 0.48/ha and 0. 31/ha of LAMP. The administrative cost of field-based FRA becomes USD 0.26/ha whereas such cost is only 0.03/ha in case of LAMP.

3.1. 2 Initial variable cost

3.1.2.1 LAMP approach

In the study area, the total variable cost of LAMP was USD 655037, which comprises USD0.28/ha. A break-down of the entire variable costs under each item and cost per hectare are presented in Table 2. The result reveals that LiDAR scanning is the most expensive comprising 44% of the total cost, followed by the field inventory which forms 31.6 % of the cost.

Table 2.Initial cost of LAMP over the entire study area.

Cost items	Total cost USD	Cost/ha USD
LiDAR scanning	290400	0.125
Procurement of satellite imagery	18480	0.0079
Field inventory	207240	0.089
ModellingLiDAR data with field plots	23232	0.0099
LAMP model building and data processing	115685	0.05
Total cost	655037	0.2818

3.1.2.2 Field based Multi-source FRA

In comparison to LAMP, the total variable expense for the multi-source FRA method amounts to USD522450 for the same study area, which comprises USD 0.22 per hectare. A break-down of the total cost under each item and cost per hectare are presented in Table 3.

Table 3. Baseline cost (US$) of the multi-source FRA method in TAL-Nepal

Cost items	Total cost	Cost/ha
Procurement of satellite Image	18480	0.0079
Procurement of ancillary data & maps	2500	0.0011
First phase sampling	3000	0.0013
Method development and testing	2000	0.001
Training cost	8000	0.0034
Cost for second phase field inventory	359219	0.15
Data entry, processing and analysis	129250	0.055
Total cost	522450	0.22

3.1. 3 Subsequent monitoring cost

For future monitoring, the costs for LAMP are only related to model updates and data analysis for each successive LAMP cycle. These costs equal about US$ 0.05/ ha which was integrated in a cumulative figure for each successive cycle. Table 4 below lists the cumulative cost for LAMP up to third consecutive series with US$ 0.43/ha. In comparison, in case of field based multi-source FRA almost the same variable costs are involved in every following inventory. Therefore, the initial cost of US$ 0.22 /ha was added for each inventory cycle. As a result, the cumulative cost per hectare (US$0.44) for the approach is higher than the cost of LAMP (USD 0.33) already from the second inventory cycle onwards. By the fourth cycle, the cost of the design-based FRA approach reaches a price of USD 0.88/ha which compares to USD 0.0.43/ha for the LAMP approach.

Table 4. Cumulative cost of multiple inventory cycles of LAMP and field based FRA

Forest Monitoring approaches	Estimated cumulative cost (USD) for successive			
	Baseline cost	First cycle	Second cycle	Third cycle
Model based Lidar Assisted Multisource Program	0.28	0.33	0.38	0.43
Designed based Multisource FRA	0.22	0.44	0.66	0.88

*successive cycles = five year cycle)

3.2 Accuracy comparison

Table 5 and Figure 2 demonstrate the behavior of the mean error in mean biomass estimates produced by FRA and LAMP approach at different spatial scales. The larger the estimation area, the lower is the mean error of the estimate.

Table 5. Mean error of mean biomass estimates at different scales for FRA and LAMP method.

Resolution (hectares of forest)	Mean error in FRA-plot derived mean biomass estimate (tonnes/ha)	Mean error in LAMP-derived mean biomass estimate (tonnes/ha)
1	6243.95	129.29
10	1974.51	40.97
100	624.39	13.21
1,000	129.26	4.90
5,000	88.30	3.26
10,000	62.44	2.99
50,000	27.92	2.76
100,000	19.75	2.73
350,000	10.55	2.71

The results indicate that mean error of LAMP at 1 ha resolution is 129.29 tons/ha and after that it gradually decreases with increasing estimation area and reaches an asymptotic limit of 2.7 tons/ha at a 350,000 ha spatial resolution, which is the bias detected in the method. After that limit mean error of estimate remains the same, even when the estimation area is increased. In comparison, the mean error of the FRA estimate at 1 ha is 6243.95 tonnes/ha which is very high but afterward slowly decreasing with increasing forest areas and goes down to 10.6 tonnes/ha when estimation forest area reaches 350,000 ha.

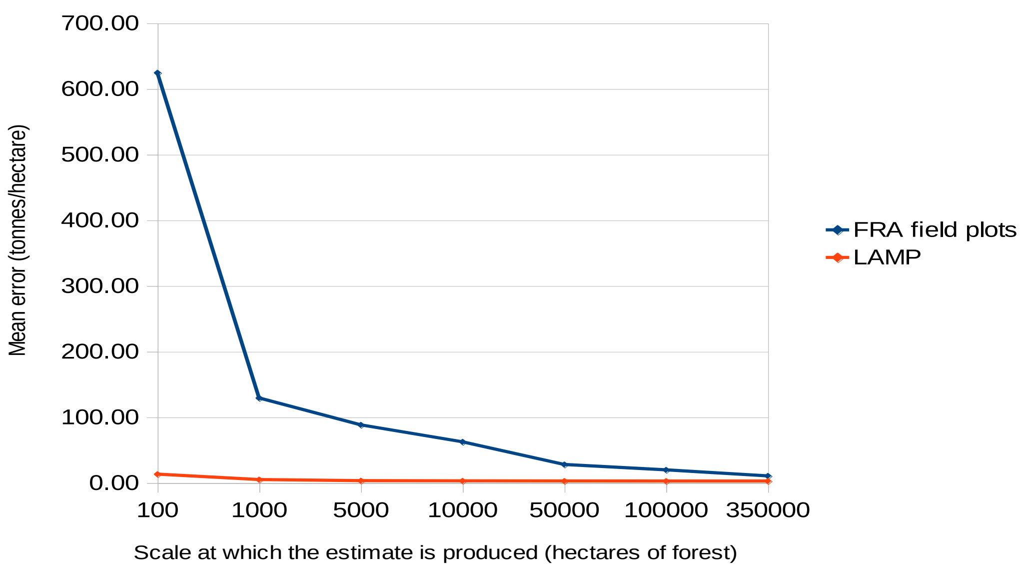

Figure 2. Mean error of the mean estimate of AGB at different spatial scales.

4. Discussion

Nepal is in a REDD+ readiness/demonstration phase and needs to pay special consideration to the cost-efficiency and accuracy of the proposed REDD monitoring concepts. It is good practice to appraise alternative FRA methods under the criteria of cost-efficiency and accuracy which eventfully facilitates to determine accurate and reliable methods required to meet higher tiers approach for the estimation of carbon stock changes in cost effective way (IPCC 2006). This study evaluated and compared the cost-efficiency and accuracy between LAMP approach and filed based FRA method applied in Nepal's TAL area for the same purposes.

Hardcastle and Baird (2008) argued that the cost of forest inventory would be the total budget of the project and in such case variable and administrative costs assumed to be equal. However, this study reveals that administrative cost (USD 0.26/ha) of field based FRA is higher than the variable cost (USD 0.22/ha). The reason behind is that about 46% project cost goes to the salary of experts; international 39%, regional 7% and about 16% is under operating cost(GoN/GoF 2010).It indicates that forest monitoring system has not been institutionalized and capacity of operating agency is poor. The cost analysis explains that administrative cost of FRA project appears significantly higher than the LAMP. Because FRA project is for five years to conduct national level FRA, however LAMP was applied within three months period for estimating only AGB in the targeted area.

The results presented in this study reveal that model based LAMP was more expensive in per hectare variable cost by USD0.06than the design based FRA for collecting the base line data. Although the cost difference between two approaches seems insignificant, field-based FRA process has collected data on more attributes than LAMP approach. It is obvious that multisource FRA is more cost efficient than the LAMP in baseline data collection for the whole TAL area.

The IPCC estimates £0.025 – £0.30/ ha cost of national forest carbon inventories (Hardcastle and Baird 2008). LiDAR based forest inventory has been recently applied in different parts of the world to estimate forest carbon stock. Carnegie Institution for Science, USA operated LAMP in Peru, Madagascar and Colombia to estimate forest carbon stocks and emission by using 2.8-12% LiDAR sampling, freely available Landsat Thematic Mapper (TM) image, limited field measurement and automated noncommercial CLASlite software at cost range from $0.20 to $0.06 ha^{-1} (Asner *et al.* 2010, 2011; Asner 2009). For the 4.3 million ha Peruvian Amazon forest 12% LiDAR sampling was used and only 131 large field plots (radius 30 m, area per plot 0.2827 ha, total area 37 ha), and 37 small field plots (radius 3 m, area per plot 28.27 m^2, total area 1,046 m^2) were measured in the study area to calibrate LiDAR metrics of aboveground carbon at a cost less than USD 0.08/ha (Asner *et al.* 2010). This study discloses that the cost of LAMP in Nepal is higher than in those countries indicated. One of the reasons for this is that the intensity of field sampling was significantly higher (radius 12. 62 m, area per plot 500 $m^{2,}$ plot measured 792 and total area 39.6 ha) in Nepal to represent the vegetation types and regional variation. Field inventory did cost second highest amount (USD 0.089/ha) after LiDAR scanning. Moreover, employing international experts for data processing and model building increased the cost.

Analyzing of variable cost of multisource FRA (Table 3)shows that the field inventory forms the most expensive component. Average per plot cost was USD 531.5 and total estimated cost to measure 676 CCP was USD359219 (71%).Data entry and processing consists of approximately 23% of the all cost. Expenditure under remaining items seems insignificant.

The results of subsequent variable cost comparison (Table 4) show that the minimum cumulative cost of field based FRA is significantly increasing from the first cycle of inventory and reaches more than double the cost of LAMP up to the 3rd cycle. The reason for this is that all the variable cost items involved in every successive cycle for multisource FRA processes, whereas in the case of LAMP, cost only involves for model updating through new satellite image interpretation. As a result, the LAMP approach appears to be more cost efficient in subsequent forest carbon monitoring.

Multisource FRA is a design--based method, whereas LAMP is a model-based approach. The key difference between the two approaches lies in source of randomness they utilize (Särndal 1978**)**. In designed based sampling theory the source of randomness is the probability introduced by sampling design to the various subsets of population. However, in a model-based approach, all the randomness in the inference is due to the population, not to the sampling method as in a design-based approach (Kangas and Maltamo 2006, Kangas 1993).

To attain Tier 3 in REDD+, spatially explicit estimates are required to evident reliable forest carbon stock difference. LiDAR assisted inventory is the most accurate method to provide higher resolution biomass estimates and carbon stock (Asner *et al.* 2012, Arbonaut 2010, IPCC 2006, Næsset 2002a-b). Accuracy refers to the size of deviation from the true mean which directly relates the Mean Square Error (MSE) or ME of an estimate. The ME (θ) is a useful criterion to compare two estimators, the one with smaller ME (θ) is said to be a more accurate approach than the other (Kohl *et al.* 2011). For the purpose of this study data set generated by LAMP and multisource FRA approaches were used to estimate mean AGB. Comparison of accuracy was done by calculating ME (θ).

Table 5 and figure 2 present the ME of mean biomass estimates at different scales ranging from 1 ha to 350,000 ha forest for both inventory approaches. The results clearly disclose that the biggest difference between two approaches is spatial resolution. ME in LAMP-derived mean biomass estimate are significantly smaller at all spatial resolutions than ME in FRA-plot derived mean biomass estimate. ME at 1000 ha scale of field based FRA becomes nearly equal (129.26 tonnes/ha) with ME at 1000 ha spatial resolution of LAMP estimate (4.9 tonnes/ha). Thus, accuracy of LAMP is enough to estimate AGB up to management regimes.

Community Forestry (CF) is one of the key strategies of forest management in Nepal, where national forests have been handed over to the local Forest Users Group (CFUG) for their autonomous management and use. CFUGs are authorized local organization have right to claim for carbon credit gained due to the protection and management of handed over forest. To date 17,808 CFUGs managing about 1.7 million ha forest over the country, which comprise 22% of the forest area of the country (DoF 2012). In TAL area there are more than 1600 CFUGs managing nearly 240000 ha forest (DoF 2012, Joshi and Bhatta 2010). The statistics show that average size of community forests is 150 ha in TAL region. The result (table 4) illustrate that mean error in LAMP derives mean biomass is 13.21 tonnes/ha at 100 ha of forest. However, same accuracy is not possible through field based FRA up to the 100000 ha spatial extent. As a result, the accuracy of LAMP is good enough to estimate biomass stock of community forests.

5 Conclusions and Recommendations

Selection of the most cost efficient and accurate forest monitoring method is matter of optimization which demands comparative study between the approaches. This study tried to compare the costs and accuracy of filed-based FRA and lidar assisted LAMP methods applied in TAL Nepal. The administrative cost of field-based FRA is higher than the variable costs due to the setting of project based organization and involvement of international and regional experts. This study concludes that the cost of forest monitoring greatly depends upon national capacity. National FRA in Nepal has been conducted in project basis; organizational capacity of executing agency is very poor. It is recommended that forest monitoring system in Nepal should be periodic and mandatory ensured by policy instruments and national forestry program.

Within the stipulated forest inventory schemes, variable expenses of LAMP were more costly in baseline data collection than the field based FRA. Contrary to baseline costs, model based LAMP is more cost efficient in subsequent forest monitoring. This study infers that LAMP is cost efficient to monitor forest carbon stocks in short period of time which involves less administrative cost and need not repeat the whole processes up to certain inventory cycles. But the cost of Nepal's LAMP is higher than that reported in other countries. Hence, it is recommended that intensities of LiDAR sampling and field plot measurement are the matter of further analysis.

Theoretically, the smaller the mean error of the estimate the higher the accuracy. The result reveals that mean errors of LAMP-derived estimates are significantly smaller than the mean error of FRA-plot derived estimate at different spatial scales ranging from 1-350000 ha forest area. For this reason, the study concludes that the LAMP approach is highly accurate to estimate AGB in the small spatial scale even in the management level forest regime like community forests of Nepal.

The choice of inventory method should always be made depending on the expected outcomes and forest variables to be measured. Through field based multisource FRA method, information about a vast number of target variables can be collected, ranging from tree-level characteristics to biodiversity and soil. The LAMP method covers much less forest variables and cannot replace a multisource inventory. However, LAMP produces biomass and carbon stock estimates at high spatial resolution suitable for IPCC Tier 3 level, which is difficult to achieve with field based multisource inventory**.** Finally, this study recommends REDD countries to apply LAMP approach according to their context to estimate high resolution base line biomass and forest carbon stock rapidly in more cost efficient and accurate ways.

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