Alternative remote sensing materials and inventory strategies in tropical forest inventory - Case Lao PDR

Materiais alternativos de sensoriamento remoto e estratégias de inventário no inventário de florestas tropicais – Caso Lao PDR

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Abstract

In this study, the potential of remote sensing in tropical forests is examined in relation to the diversification of sensors. We report here on the comparison of alternative methods that use multisource data from Airborne Laser Scanning (ALS), Airborne Color Infrared Photograph (CIR), Quickbird and ALOS AVNIR-2 to estimate stem volume and basal area, in Laos. The predictors of ALS metrics were calculated by means of the canopy height distribution approach, while predictors from both spectral and textual features. The correlation of remote sensing materials and field data were used to demonstrate needs for field inventory in different forest landscapes and varying tropical forest conditions. Variogram based analysis was used to derive optimal forest inventory procedure for different parts of case country.

Key words: large area forest inventory; sampling design; auxiliary data; costs.

Resumo

Neste estudo, o potencial do sensoriamento remoto em florestas tropicais é examinado em relação a diversidade de sensores. Registramos aqui a comparação de métodos alternativos que utilizam dados de fontes múltiplas do Airborne Laser Scanning (ALS), Airborne CIR, Quickbird e ALOS AVNIR-2 para estimar o volume do caule e a área basal em Laos. Os preditores dos dados ALS foram calculados pelo método da distribuição de altura do dossel enquanto preditores para características espectrais e textuais foram geradas, respectivamente, para os dados Airbone CIR e ALOS AVNIR-2. A correlação dos materiais de sensoriamento remoto e dados de campo foram usados para demonstrar a necessidade do inventário de campo em diferentes paisagens florestais e condições variáveis em floresta tropical. A análise baseada no variograma foi utilizada para gerar um

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procedimento otimizado para o inventário florestal de diferentes partes do país em estudo.

Palavras-chave: inventário florestal de larga escala; desenho amostral; dados auxiliares; custo.

Introduction

In the global context of Reducing Emissions from Deforestation and forest Degradation (REDD), many tropical countries are making efforts to develop remote sensing-aided carbon assessment methodologies. To achieve the accuracy requirements specified by Tier II and Tier III, as defined by the Intergovernmental Panel on Climate Change (IPCC, 2006), the approach that integrates a field plot inventory with satellite mapping and carbon modelling can be employed and validated so that the improved ecosystem protection and increased carbon sequestration can qualify for a corresponding increase in carbon credits (GIBBS et al., 2007). By means of remote sensing, many of the forest attributes of interest are retrievable at varying accuracy levels with due cost-effectiveness. Compared with traditional field inventory work, forest inventories assisted by remote sensing reap the benefits not only of lower cost and less time consumed, but also with respect to the feasibility of conducting inventories in unreachable forests located in remote or even sometimes life-threatening areas, such as in Laos, where 12 out of the 18 provinces are peppered with unexploded bombs or landmines as a legacy of past wars (TANSUBHAPOL, 1998).

National Forest Inventories are conducted in many countries for forest and carbon parameter reporting. Forest area, timber volume, biomass, health and productivity are considered key parameters of such assessments. In addition, to these core parameters, increasing attention is now paid to both the non-timber value of forests and also to isolated trees outside main forest areas. Ideally, the inventory methodology should follow a procedure which can be repeated as required at regular intervals. The information is used typically in strategic or provincial level planning.

When a national level forest data collection strategy is planned, typically the following steps are followed:

1. Study of the target population: Landscape patterns and forest structure.
2. Comparison of remote sensing materials for stratification.
3. Planning and design of suitable field work for different variables and forest types.
4. Comparison of the procedural alternatives for updating.

One of best examples of the National Forest Inventory (NFI) planning process is the Swedish NFI. As a basis for the statistical design of the survey, a geostatistical analysis is used to determine the variation within areas, the importance of the size of the sample plot, the time required and the economic practicability of the available resources. The analysis has resulted in a division of the country into 5 regions, the designing of survey tracts, a weighting between permanent and temporary survey tracts and a standard size of sample plot (MATERN, 1960; MATERN, 1981; RANNEBY, 1981a; RANNEBY, 1981b). Variograms have been used to describe variations in land use, forest volume and topography (MATERN, 1960; RANNEBY, 1981b), and these spatial functions have been used to define an effective layout of the survey tracts.

Forest inventory systems based on remote sensing and their implementations can be categorized in the following way:

- Remote sensing oriented systems; the main attention has been paid to the identification of different forest classes, including species classes and volume categories, meant for thematic map production purposes (e.g. HORLER; AHERN, 1986; BROCKHAUS; KHORRAM, 1992). Ground truth data is collected from subjectively chosen training areas with some field observations.
- Field data oriented systems; the calculation of inventory results is based on field sample plots and the inventory system has been established according to a pre-designed sampling frame. Remote sensing data have been used as auxiliary information mainly in two-phase sampling schema (e.g. POSO, 1984; KÖHL, 1990) or in calibration approach (e.g. BAUER et al., 1997).
- Updating oriented systems; the main interest is to fulfill the information needs of the database and control the quality of data. The base information has mostly been collected with more accurate inventory systems, and remote sensing data are used for monitoring purposes and to allocate field checking (VARJO, 1997). The existing data can be utilized as auxiliary data in the planning of a data collection procedure.

The accuracy of satellite image classification can be increased by using information from ancillary sources, such as topographical maps (eg. STRAHLER, 1980; HUTCHINSON, 1982; SKIDMORE, 1989), spatial characteristics of the image (PEDDLE; FRANKLIN, 1991; FRANKLIN; WILSON, 1992) and database information (VARJO, 1997). Ancillary data can be used before, during or after classification, through stratification, classifier operations or post-classification sorting (HUTCINSON, 1982). The optimized use of existing data and proper acquisition procedures of new information are the ways towards the combination of effective data service systems. For the first time field data can be collected, for example, by using a systematic field plot network or proportional field plot allocation to strata derived from an unsupervised satellite image interpretation. Simulation studies (TOKOLA; SHRESTHA, 1999) can be used after basic information has been collected on the target population, usually after the first inventory.

Remote sensing is the best approach to estimate biomass at a regional level where field data is difficult to collect and sampling is the only feasible alternative to cover entire areas. Almost two decades have passed since pioneers like Sader et al. (1989) related biomass to reflectance. Since then, several studies in different regions have found strong correlations between biomass and reflectance at different wavelengths: in India (ROY; RAVAN, 1996), in Bolivia and Brazil (STEININGER, 2000), in Malaysia (PHUA; SAITO, 2003), and in Eastern Brazil (LU et al., 2004).

Biomass is a three-dimension feature of vegetation and has been estimated using popular optical sensors like Landsat or Spot. However, the ability of these sensors is limited to two dimensions only, i.e. the upper layers of vegetation. Steininger (2000) found that the canopy reflectance–biomass relationship saturated at around 150 Mg/ha. These drawbacks result in large uncertainties and the methods that are used may not be applicable in all conditions (FOODY et al., 2003). Houghton et al. (2001) found that AGB (above ground biomass), below ground biomass and necromass for large geographic extents like the Brazilian Amazon vary from the lowest estimates of 78 billion Mg up to the highest of 186 billion Mg. Another approach to biomass estimates using remote sensing applications is based on canopy density (SUGANUMA et al., 2006) which is represented by tree cover percentage maps. The main advantage of tree cover percentage maps over traditional maps of discrete classifications is the representation of the internal variability of vegetation distribution. This is also standard approach in visualising National Forest Inventory results in many countries (eg. REESE et al. 2002)

Despite much early promise, recent remote sensing analyses of Bornean forests have shown only weak correlations between data for one or two spectral bands and tree biomass (FOODY et al., 2001). Multiple regression involving combinations of many bands generally do a little better in the humid tropics (i.e., $r2 < 0.3$: FOODY et al., 2001; FOODY, 2003), Good correlations have been observed where neural network based estimation have been used (FOODY et al., 2001, 2003; FOODY; CUTLER, 2003) rather than multiple regressions. These models are, however, high order (i.e., have many parameters), estimation process is difficult to control and therefore, may have large uncertainties associated with their predictions.

Comparisons of remotely sensed data (Landsat-5 TM resolution is 0.09 ha) with measurements from individual plots 0.1–5 ha in area will be sensitive to: (i) small errors in the georeferencing, (ii) difficulties in sampling the complex forest resulting from selective felling, and (iii) for stand margin reflectance variation (PINARD; PUTZ, 1996; TOKOLA; KILPELAINEN 1999), weak correlations may be partly attributed to inadequacies in the handling of the 'ground truth' (i.e., the plot) data.

The state-of-the-art method for accurate biomass estimate uses remote sensing is LiDAR data (light detection and ranging), designed to allow the penetration of the signal through the canopy. During the last 10 years there is a growing interest for airborne and spaceborne LiDAR in order to estimate biomass (LEFSKY et al., 1999; DRAKE et al., 2002). Spaceborne LIDAR has been utilised using radargrammetric processing (KARJALAINEN et al. 2012), and it allow promising measurement of forest height and vertical structure with low precision. This active sensor is, by far, the best option to estimate biomass at a local scale. Radar data has also been used to estimate biomass, Luckman et al. (1998) has a well discussed of the JERS-1 bands to estimate AGB in the central Amazon.

Some studies (eg. ASNER et al., 2003) have combined a detailed field study of forest canopy damage with calibrated Landsat 7 Enhanced Thematic Mapper Plus (ETM+) reflectance data and texture analysis to assess the sensitivity of basic broadband optical remote sensing to selective logging in Amazonia. The field study encompassed measurement of ground damage and canopy gap fractions along a chronosequence of post-harvest regrowth of 0.5–3.5 years. It

Table 1. Comparison of coefficient of determination estimates for biomass in tropics

Sensors	Biomass, R2	Area and Sources
MODIS	0.55-0.82	Colombia (ANAYA et al., 2009)
Landsat TM	0.36-0.66 0.32-0.7 0.25-0.69 0.3-0.5 0.51 0.53	Amazon (LU et al., 2004) Brazil (FOODY, 2003) Malesiya (FOODY, 2003) Thailand (FOODY, 2003) Brazil (STEININGER, 2000) Bolivia (STEININGER, 2000)
Landsat ETM	0.01-0.57	Amazon (ASNER et al., 2003)
Ikonos	0.70-0.92	French Guiana (PROISY et al., 2007)
Quickbird	0.62-0.70	Bolivia (BROADBENT et al., 2008)
Lidar	0.87-0.94	Costa Rica (DRAKE et al., 2002)

was found that canopy damage and regrowth rates varied according to the logging method used (either conventional logging or reduced impact logging). Areas used to stage felled trees prior to transport, log decks, had the largest gap fractions immediately following cutting. Log decks were quickly colonized by early successional plant species, resulting in significant gap fraction decreases within 1.5 years after site abandonment. Although log decks were the most obvious damage areas on the ground and in satellite imagery, they accounted for only 1–2% of the total harvested area of the blocks studied. Other forest damage features such as tree-fall gaps, skid trails, and roads were difficult to recognize in Landsat reflectance data or through textural analysis. These landscape features could be only crudely resolved in the most intensively logged forests and within about 0.5 years following harvest. Forest damage within any of the landscape strata (decks, roads, skids, tree falls) could not be resolved with Landsat reflectance or texture data when the canopy gap fraction was < 50%. The basic Landsat ETM+ imagery lacks the resolution of forest structural features required for quantitative studies of logging damage. Landsat textural analyses may be useful for broad delineation of logged forests, but detailed ecological and biogeochemical studies will probably need to rely on other remote sensing approaches. Until spatial gradients of canopy damage and regrowth resulting from selective logging operations in tropical forests are resolved, the impacts of this land use on a continental scale will remain poorly understood.

Forest cover monitoring has a long history in Lao PDR. During 1985-89 the first and second phase of the SIDA supported Lao-Swedish Forestry Programme, and conducted the first nation-wide assessment of Forest and Land Use by aerial photo interpretation on sample plots based on 1: 30,000 scale aerial photos from 1982. The result of this initial assessment was then updated to the period 1989-1992 by interpretating these image plots on SPOT Satellite Image Maps. The final report of the Nationwide Reconnaissance Survey was published in December 1992. An additional third land cover project was implemented during 2002 to identify further changes in land use and forest/vegetation cover in the country and in the regions.

The first national forest inventory with field work of accessible forests was done during the period 1991-1999. The Swedish Forestry Programme also supported this activity. This work resulted in a complete field sample plot database and reliable statistics for the entire country.

Material and Methods

Structure of Forest Areas

The relative spatial distribution of forests and trees varies, because of changing land use practices, differences in the terrain, relief, fertility of soil, and the hydrology, competition, and size distribution of trees. On a national level, both correlation and autocorrelation functions have been employed to interpret the larger structures of forest area, and forest volumes. The functions describe the similarity of forest characteristics in terms of distance and allow avoiding inefficient remeasurement of similar forest areas. For example, in Scandinavian forests there is a slightly increasing autocorrelation until a 200m interval distance is used. This information is used to estimate the optimal distance between inventory tracts, the overall shape of the tract, and the distance between sample plots within tracts. For example, to obtain a sufficient sampling set-up for the entire nation of Sweden, the country is divided into five regions with marginally diverse correlation functions for different variables. The final sampling design is based on their spatial characteristics and other practical considerations.

Variograms were used to estimate the standard error with regard to large areas and to describe spatial autocorrelation. Autocorrelation is indicated by similarity between locations. Distance between useful plots can best be done using autocorrelation. At a certain point, the optimum density of network plots is reached, and any further increases will not yield much more information. When sample of remote sensing images are used in measuring plots, the size of image is also critical, that we can cover different type of objects. If we have very high resolution image with small area coverage, it is very difficult to obtain good regional data in case of high

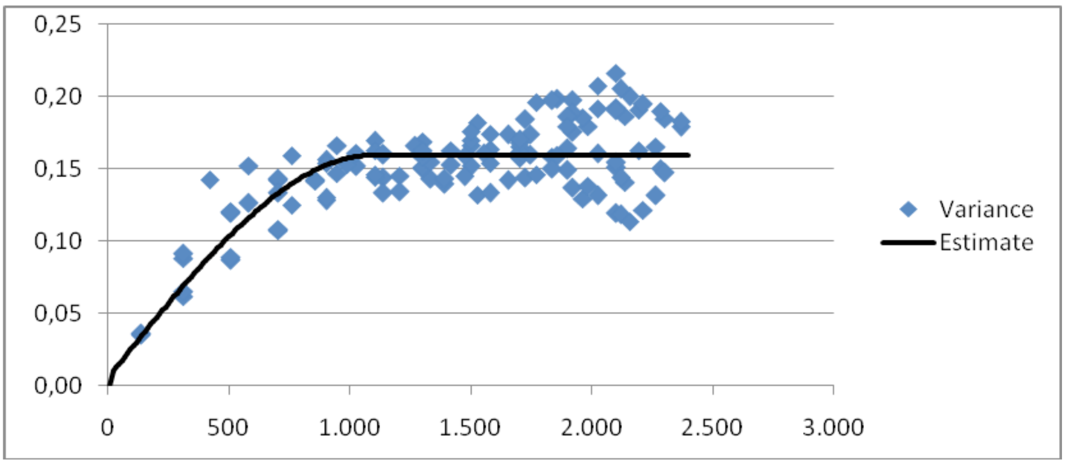

Figure 1. Sample of the estimated variogram for Huaphane Province (range 1090 m). X-axis refers to distance and Y-axis to co-variance. Similar variograms were estimated for each province.

autocorrelation of forest characteristics. So, we need to have good spatial accuracy and large enough coverage of different forest types inside remote sensing scene.

The standard errors of systematic cluster sampling can be estimated using model-based estimators, which utilize the parameters of correlation functions. This way, the information about spatial dependency can be utilized to estimate error while the spatial structure of forests is taken into account.

Variograms were estimated separately for each province of country. Capital area is a totally different area compared to other provinces. Land use is correlated until 2.3 km. Northern provinces have correlation until 0.78 km and form unique areas for similar inventory technique. Other major areas of the country have correlation up to 1-1.3 km. The southern forested districts have correlation up to 1.7 km. We can therefore divide the regions into four categories that need each a different inventory methodology: One for capital area, second for the north-western region, third for northern region and fourth for the southern region (Figure 2).

Structure of Forest Types

There are many forestry variables that are spatially sparse and scattered. This is often the case when one is assessing coarse woody debris in managed forests, or surveying threatened species. The spatial description of sparse populations can be problematic. On the landscape level, information about spatial distribution of different key habitats and areas with a high ecological value are used to assess the probability of existing rare species. Field data about indicator species and remote sensing data about landscape features are valuable as a priori

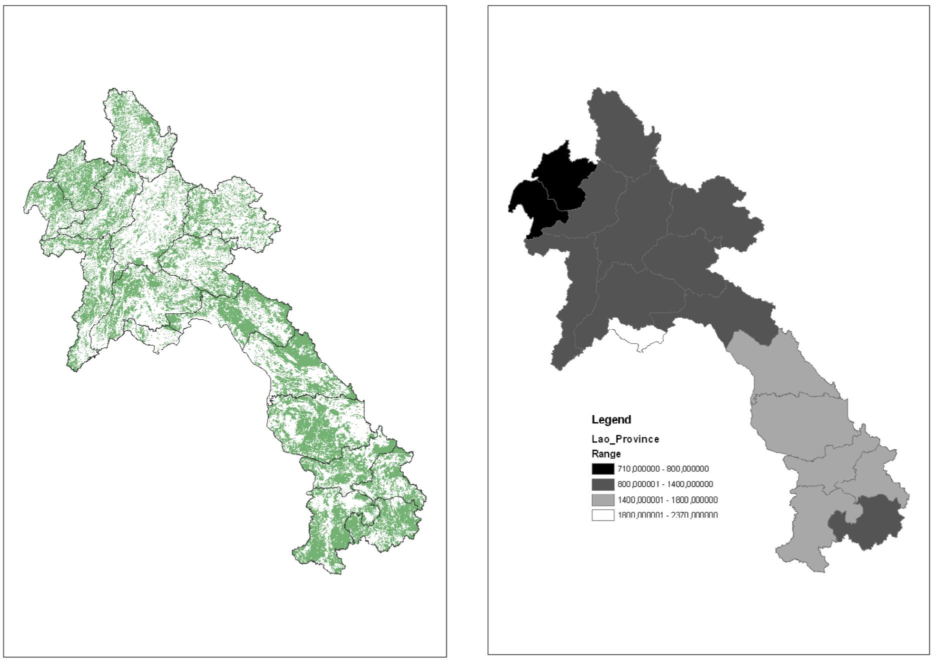

Figure 2. Areas for different forest inventory methods are defined using variogram parameters. Green color of left side figure indicates actual forest area and right side figure demonstrate four different categories for specific inventory methodology.

information for estimating such presence/absence probability and for stratifying areas of interest.

The structure of forest types was studied using National Forest Inventory (NFI) plots, where the length of specific type was recorded. There was no large difference between provinces in terms of mean size of forest type stand. When 66 % probability distance is applied (mean+std) it can be concluded that different types should appear after 250 m. When 99 % probability distance is applied (mean+2*std) it can be concluded that different types should appear after 400 m. However, normally two observations from each forest type should be sufficient and therefore the distance between plots should be c. 250 m for effective field work.

Comparison of Mapping and Sampling Alternatives

There are many alternative remote sensing materials available for this feasibility study. Unfortunately the selection of satellite imagery data is not a very easy task. Traditionally 20-30 m ground resolution imageries have been used in national level inventories. However, it has been found in many studies that separation between scrub and woody vegetation is quite difficult at this resolution. Higher resolutions are required (eg. 2.5-10 m multispectral IRS LISS-4 MX or SPOT) High resolution imagery allows the use of texture analysis needed for separation of trees and other green vegetation. Limited imagery availability probably requires that a combination of different sensors is employed. Three QuickBird satellite images with 0.6 meter ground resolution and three Kompsat-2 images with approximately one meter resolution were also used (Figure 3).

In the traditional national inventory, biomass estimates are based on field measurements of the number of trees per hectare combined with diameter and height of each tree. To update such measurements is both time consuming and expensive. Costs may be reduced by updating only a fraction of total area each year, but this will obviously lead to global estimates always being somewhat outdated. New technology is being introduced for this purpose. By measuring the time of laser light emitted from equipment (Lidar, ALS) mounted on aircraft to be reflected from the ground and the canopy of vegetation, one may directly estimate biomass density.

Two phase sampling with regression estimators (combining data from field samples and samples in remote sensing material by means of regression techniques) provides a systematic approach to compare

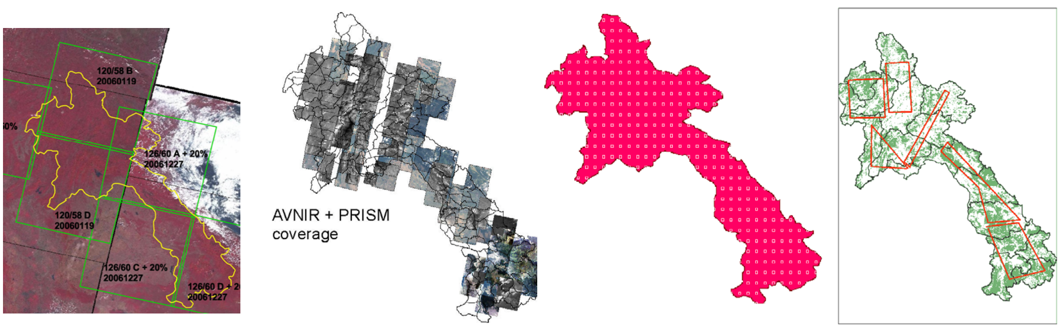

Figure 3. Alternative remote sensing materials showing IRS, ALOS, Quickbird, and Laserscanning material used in forest inventory methodologies

alternatives with varying coefficient of determination (R^2). Pilot tests are normally implemented in those conditions where the estimated performance of specific remote sensing material (R^2) is not very well known. The coefficient of determination (R^2) is used in the context of statistical models wherein the main purpose is the prediction of future outcomes on the basis of other related information. It is the proportion of variability in a data set that is accounted for by the statistical model. It provides a measure of how well future outcomes are likely to be predicted by the model. In this paper, analysis is made for different R^2 levels and remote sensing material specific coefficients have been estimated using literature and best knowledge gained in other countries. The capacity of very high resolution images has been assumed to be close to aerial photographs.

Time Studies

The effectiveness of the sampling desigThe effectiveness of the sampling design was estimated analysing multiple relations between direct and indirect work operations carried out in the sample plot and tract. The time required for carrying out different operations was ascertained. According to the time input required for carrying out different operations in a single tract and sample plot, the time required for a full tract for different numbers of sample plots was estimated. Average Time required for field work was evaluated in previous inventory. Workload for each cluster/tract is based on camping, travelling by car and walking to the tract. Plot level work is separated and depends on the amount of plots within each tract.

Typically, one inventory team consists of 4-8 persons. The size of crew needed and the amount of vehicles are the most important costs. Average time estimates from teams in Saravane province test are presented in decimal hours. Walking time between plots (250 m in the new design) was also estimated. Optimal times for each cluster were calculated using the formula of Zeide (1980). This formula is intuitively quite clear: the greater the distance between plots the larger they must be. It is not worthwhile to spend a lot of time travelling to establish a small plot.

The cost of field measurements can be compared to detailed remote sensing plots. The VHR (Very High Resolution) and Laser scanning plots are as expensive as field plots without vehicle leasing costs. If an organisation already has a vehicle in use, the additional costs are small. However, if cars need to be hired around 2-5 VHR/ALS remote sensing plots can be measured for the same price as a field plot.

Results

Quality of ALS & Quickbird Data

The reliability of ALS is very good in estimation of biomass properties (Figure 4). These results were calculated using field plots, ALS variables and regression analysis.

First pulse variables include first-of-many and only echoes. Last pulse variables include last-of-many and only echoes. Intermediate echoes were ignored. The height percentile variables contain 11 bands with the height at given percentiles: 5%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% and 95%. Ground hits were excluded. The proportional density variables contain 11 bands with the density for: 5%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% and

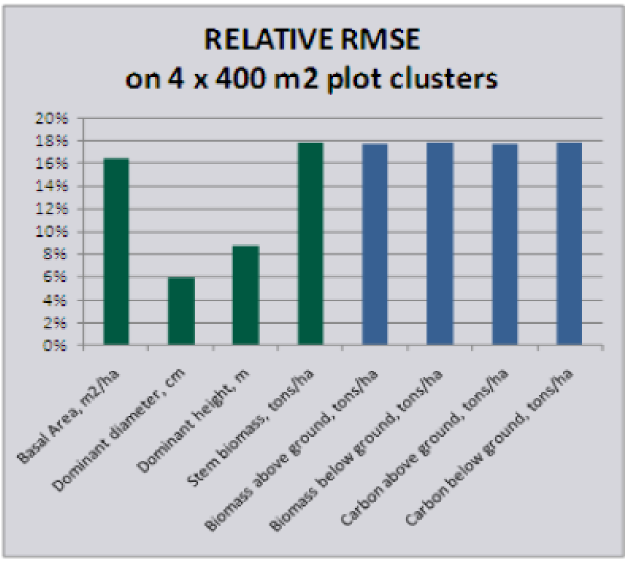

Figure 4. Major ALS Pilot reliability statistics

95%. The other statistics variables include, in this order: mean elevation, elevation standard deviation, elevation coefficient of variation, density. Ground hits were excluded for elevation mean, standard deviation and coefficient of variation. Coefficient of variation was set to zero where mean elevation was zero. Density was calculated as the ratio of number of vegetation hits (any vegetation excluding ground) to the number of total hits.

Field plots were used by combining the four most similar plots, because small plots didn't give reliable response. However, regression models resulted in about 16% RMSE for basal area, 6% RMSE for dominant diameter, 8% RMSE for height and 18% RMSE for biomass and carbon.

Google Earth was used for geometric referencing and the Globcover satellite based land cover map was used to test the sampling designs. A digital elevation model from the Shuttle Radar Topography Mission (SRTM) was used to remove the topographic effects from radar data. AVNIR optical satellite data with 10 meter resolution and ALOS PalSAR radar data with approximately 30 meter resolution for the whole Savannakhet was obtained from the European Space Agency. However, optical data from the western part of Savannakhet arrived too late to be included in the analyses.

Stratified sampling was compared with non-stratified sampling. Visual and numerical interpretation of satellite images was applied (Figure 5) using Quickbird data. In the visual interpretation Lao and Finnish experts analyzed land cover class proportions within 50 m by 50 m squares that were placed at 800 m distances within the VHR images. Crown closure within the forest class and degree of degradation were also evaluated. A land cover and biomass map was then made of Savannakhet using both the radar data and the optical AVNIR data.

The results indicated that a relatively high resolution is required when scrub and forest needs to be separated. However, observation was based on visual verification and no field data was used to compile this result.

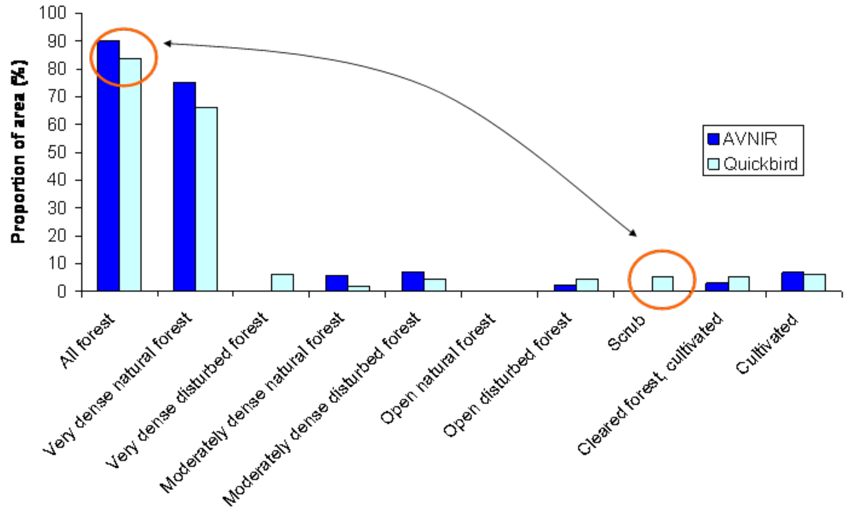

Figure 5. QuickBird image area of 10 km by 10 km - Class proportions from the maps produced. (VTT2009)

The empirical evaluation of the AVNIR map showed high overall accuracies in land cover classification. Forest and non-forest areas could be separated very well in AVNIR classification. In some cases the VHR image classification to the target classes was not completely plausible and the classified AVNIR map may have been more reliable than the plot evaluation. The coefficient of determination R^2 in the growing stock volume estimation was in the order of 0.6 (several ground test set of ground plots were merged to one test unit).

Comparison of ALS, Airborne CIR and ALOS AVNIR-2 Data

The potential of remote sensing in tropical forests is examined in relation to the diversification of sensors in related study (HOU et al., 2011). We compared alternative methods that use multisource data from Airborne Laser Scanning (ALS), Airborne CIR and ALOS AVNIR-2 to estimate stem volume and basal area, in Laos. Multivariate linear regression analyses with stepwise selection of predictors were implemented for modelling. The predictors of ALS metrics were calculated by means of the canopy height distribution approach, while predictors from both spectral and textual features were respectively generated for Airborne CIR and ALOS AVNIR-2 data. With respect to the estimation capacity from individual data sources after leave-one-out cross-validation, the ALS data proved superior, with the lowest RMSE of 36.92% for stem volume and 47.35% for basal area, whereas Airborne CIR and ALOS AVNIR-2 remained at similar accuracy levels, but fell well behind the ALS data. By integrating ALS metrics with other predictors from Airborne CIR or ALOS AVNIR-2, hybrid modelling was further tested respectively. The results showed that only the hybrid model for stem volume involving ALS and Airborne CIR improved the accuracy of 1.9% in terms of relative RMSE than that of using ALS alone (HOU et al., 2011).

Comparison of Populations and Remote Sensing Alternatives

The needed number of plots in each province is highly dependent on correlation with remote sensing data. Provincial variation also varies quite a lot, which is visualised in figure 6.

The total cost of field work required for measurements were estimated during test inventories in Saravane. The decreasing trend and importance of accurate remote sensing information is visualised in figure 6. When the R^2 value between field data and remote sensing data is increasing the need for field work is decreasing rapidly. The size of field sample plot is also important. If we have too small field sample plots, the variation between plots is very high. The inclusion probability for small areas of large trees is so low that relatively large plots are required. However, it is recommended that where possible whole plots should fall in the same forest type, so that remote sensing procedures can utilise plot information directly as ground truth training area. Figure 6 shows that almost double the amount of small field plots are required compared to large plots, when there is low correlation between field and remote sensing data.

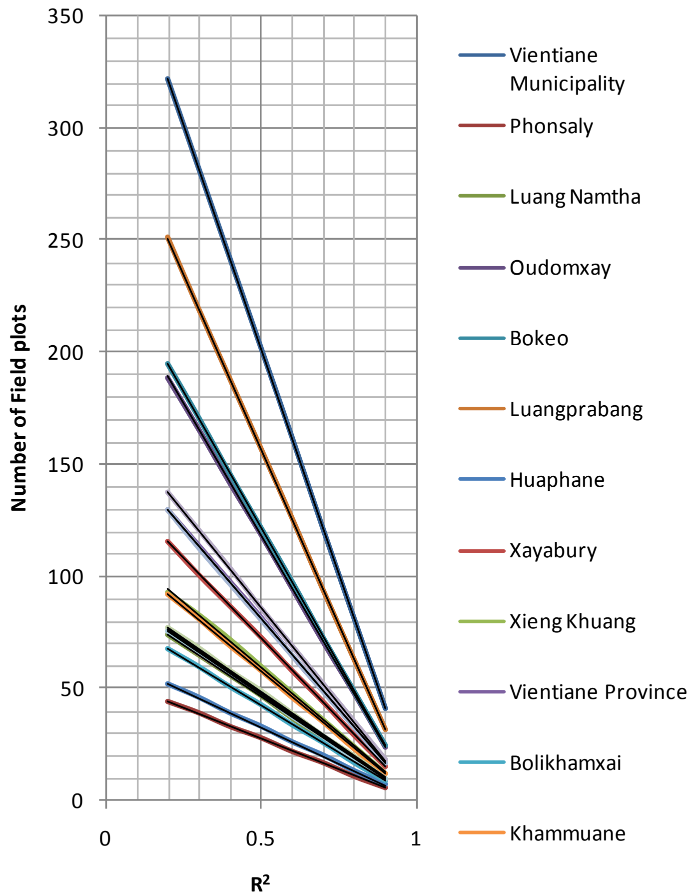

Figure 6. Comparison of field data needs in different provinces and in different R^2 levels. When large correlation between remote sensing and field data exists, there is small need for field data even in the provinces with large variation.

The cost and quality of remote sensing are normally connected to each other. Medium resolution satellite data is quite cheap per area unit and we can easily cover the entire country with low cost. VHR satellite data and ALS data are normally utilised on a sample basis. Depending on the autocorrelation of the forest population, certain types of information can be collected from a single sample unit. For comparison of different material, cost estimates for different scenarios were prepared (Table 2). The required sampling based number of image plots in a 25 km^2 area were determined using autocorrelation values of Lao PDR. The degrees of determination (R^2) for different material for landuse and biomass estimation were estimated. The value for biomass of ALS data were based on the pilot test.

When the cost of field measurements are considered, the difference between small and large plots is quite small when different remote sensing materials are compared (Table 2). The field data cost can be added to image data costs and total cost of the inventory system can be estimated (Table 2). Normally, we need a medium resolution whole country coverage image mosaic and additional VHR/ALS imagery for proper field sampling. Thus, the final system is a combination of full coverage, remote sensing sampling and field plots. So, according to current price assumptions, the most efficient price way is to use ALOS data, laser-scanning and field data. In this case, field plots are planned for the forest areas only. Additional cost figures and plots are needed for other land use strata (forest, non-forest, uncertain).

Table 2. Total cost of materials (image data and field plots) required for specific material, when given R^2 values are applied and 10 % reliability criteria is required for provinces. Field plots are planned for forest area only.

Image material	Purpose	Price of Images	Landuse R^2	Biomass R^2	Price of B Plots Eur	Total Price
ALOS AVNIR 10 m + Prism 2.5 m	Full coverage	120 000	0.7	0.3	126297	246 297
Spot, pan 2.5 + color 5 m	Full coverage	1 393 200	0.8	0.3	126297	1 519 497
Spot, pan 5 + color 10 m	Full coverage	696 600	0.7	0.3	126297	822 897
Spot, 20 m	Full/Monitoring	245 100	0.6	0.3	126297	371 397
IRS LISS 15 m + pan 5m	Full coverage	504 000	0.7	0.3	126297	630 297
IRS Awifs, 60 m	Monitoring	12 800	0.5	0.1		
Ikonos Pan 1 m + Color 4m	Sample, unit 25 km2	550 000	0.9	0.5	93330	643 330
GeoEye I, 0.5 m + 2 m	Sample, unit 25 km2	687 500	0.9	0.5	93330	780 830
Quickbird, 1 m + 4 m	Sample, unit 25 km2	990 000	0.9	0.5	93330	1 083 330
Kompsat-2, 1m + 4 m	Sample, 25 km2	440 000	0.9	0.5	93330	533 330
Ikonos Pan 1 m + Color 4m	Sample, unit 25 km2	250 000	0.9	0.5	93330	343 330
Quickbird, 1 m + 4 m	Sample, unit 25 km2	450 000	0.9	0.5	93330	543 330
Kompsat-2, 1m + 4 m	Sample, 25 km2	200 000	0.9	0.5	93330	293 330
Spot, 2.5	Sample, 25 km2	243 000	0.9	0.5	93330	336 330
Laser scannnig	Sample line	250 000	0.9	0.82	37692	287 692

Discussion

Among the remote sensing approaches employed here it was ALS that provided the most promising performance when estimating stem volume and basal area in a mixed-species tropical forest. ALOS AVNIR-2 and Airborne CIR data performed less well. Though, the ALS estimates of basal area did not attain the same accuracy level as that of stem volume after cross-validation. By contrast, optical data were found to be more accurate at estimating basal area than stem volume, although still with a less appealing performance than ALS. (HOU et al., 2011). Quickbird imageries have similar response that airborne CIR and are feasible solution for small scale mapping. The availability and price balance of different data sources can vary significantly between areas.

Methodology wise, it was feasible to transplant popular Scandinavian approaches from estimating boreal forest attributes (eg. TOKOLA et al., 1996) to that of tropical context. Among the data sources tested, it was ALS that proved to be the most accurate and competent in Laos, Southeast Asia, thus complement other investigations focused on different tropical areas (DRAKE et al., 2002; HURT et al., 2004; CHAMBERS et al., 2007). There has been several studies which have demonstrated rough monitoring in tropics (eg. ASNER, 2009; ASNER et al., 2009). However, inaccurate ALS measurements are still prone to occur in hilly or mountainous regions with errors extending up to several metres (MCKEAN; ROERING, 2004). Furthermore, the awareness concerning the effectiveness of hybrid models coincides with another study conducted by Nelson et al. (2007) who compared the ALS-only and joint ALS–RaDAR models and concluded that there was little gain brought by combination of sensors (HOU et al., 2011).

With respect to the cost of data procurement, ALS was the most costly despite its low pulse density at 1 pulse/m^2, and the second most expensive was Airborne CIR. ALOS AVNIR-2 was, in relative terms, ten times cheaper than ALS. If taking the cost-effectiveness under tropical context into consideration, ALOS AVNIR-2 data is of potential to be used for obtaining rough but economic estimates, while ALS data is an alternative to satisfy needs demanding better accuracy (HOU et al., 2011).

References

ANAYA, J. A.; CHUVIECO, E.; PALACIOS-ORUETA, A. Aboveground biomass assessment in Colombia: a remote sensing approach. **Forest Ecology and Management**, v.257, p.1237–1246, 2009.

ASNER, G. P.; BUSTAMANTE, M. M. C.; TOWNSEND, A. R. Scale dependence of biophysical structure in deforested areas bordering the Tapajos National Forest, Central Amazon. **Remote Sensing of Environment**, v.87, n.4, p.507–520, 2003 .

ASNER, G. P. Tropical forest carbon assessment: integrating satellite and airborne mapping approaches. **Environmental Research Letters,** v.4, n.3, 034009, 2009

ASNER, G. P.; KNAPP, D. E.; BALAJI, A.; PAEZ-ACOSTA, G. Automated mapping of tropical deforestation and forest degradation: CLASlite. **Journal of Applied Remote Sensing**, v.3, n.1, 033543, 2009.

BAUER, M. E.; BURK, T. E.; EK, A. R.; COPPIN, P. R.; LIME, S. D.; WALSH, T. A.; WALTERS, D. K.; BEFORT, W.; HEINZEN, D. F. Satellite Inventory of Minnesota Forest Resources. **Photogrammetric Engineering and Remote Sensing**, v.60, p.287-298. 1994.

CHAMBERS, J. Q.; ASNER, G. P.; MORTON, D. C.; ANDERSON, L. O.; SAATCHI, S. S.; ESPIRITO-SANTO, F. D.; PALACE, M.; SOUZA, C. JR. Regional ecosystem structure and function: ecological insights from remote sensing of tropical forests. **Trends in Ecology and Evolution**, v.22, n.8, p.414–423.2007.

BROCKHAUS, J. A.; KHORRAM, S. A comparison of Spot and Landsat-TM data for use in conducting inventories of forest resources. **International Journal of Remote Sensing**, v.13, n.16, p.3035-3043, 1992.

GIBBS, H. K.; BROWN, S.; NILES, J. O.; FOLEY, J. A. Monitoring and estimatingtropical forest carbon stocks: making REDD a reality. **Environmental Research Letters**, v.2, n.4, p.1–13. 2007.

ASNER, G. P.; KELLERC, M.; PEREIRA, R.; ZWEEDED, J. C. Remote sensing of selective logging in Amazonia Assessing limitations based on detailed field observations, Landsat ETM+, and textural analysis. **Remote Sensing of Environment**, v.80, p.483–496, 2002.

BROADBENT, E. N.; ASNER G. P.; PEÑA-CLAROS, M.; PALACE, M.; SORIANO, M. Spatial partitioning of biomass and diversity in a lowland Bolivian forest: Linking field and remote sensing measurements. **Forest Ecology and Management**, v.255, n.7, p.2602–2616, 2008

DRAKE, J.B.; DUBAYAH, R.O.; KNOX, R.G.; CLARK, D.B.; BLAIR, J.B. Sensitivity of large-footprint LIDAR to canopy structure and biomass in a neotropical rainforest. **Remote Sensing of Environment**, v.81, p.378-392. 2002

FOODY, G. M.; CUTLER, M. E.; MCMORROW, J.; PELZ, D.; TANGKI, H.; BOYD, D. S., ; DOUGLAS, I. Mapping the biomass of Bornean tropical rain forest from remotely sensed data. **Global Ecology and Biogeography,** v.10, p.379–387, 2001

FOODY G. M. ; CUTLER M. E. J. Tree diversity in protected and logged Bornean tropical rain forests and is measurement by satellite remote sensing J. **Biogeogr.** v.30, p.1053–66. 2003

FOODY, G. M.; BOYD, D. S.; CUTLER, M. E. J. Predictive relations of tropical forestbiomass from Landsat TM data and their transferability between regions. Remote Sensing of Environment, v.85, p.463–474. 2003.

FRANKLIN, S. E.; WILSON, B. A. A Three-Stage Classifier for Remote Sensing of Mountain Environments. P**hotogrammetric Engineering & Remote Sensing**, v.58, p.449-454. 1992.

HÄME, T.; KILPI, J.; AHOLA, H.; RAUSTE, Y.; SIRRO, L.; BOUNPONE, S. Monitoring of tropical forest cover and biomass by combining VHR image sample and wall to wall optical and SAR data. **ESA Living Planet Symposium**. Bergen, Norway, 28.6. - 2.7.2010. Proceedings of the ESA Living Planet Symposium. European Space Agency . Noordwijk, The Neatherlands, 2010.

HORLER, D. N. H.; AHERN, F. J. Forestry information content of Thematic Mapper data. **International Journal of Remote Sensing**, v.7, n.3, p.405-428. 1986.

HOU, Z.; XU, Q.; TOKOLA, T. Use of ALS, Airborne CIR and ALOS AVNIR-2 data for estimating tropical forest attributes in Lao PDR. **ISPRS Journal of Photogrammetry and Remote Sensing**, v.66, n.6, p.776–786. 2011.

HOUGHTON R. A.; LAWRENCE K. T.; HACKLER J. L.; BROWN S. The spatial distribution of forest biomass in the Brazilian Amazon: a comparison of estimates. **Global Change Biology**. v.7, p.731–46. 2001.

HURTT, G. C.; DUBAYAH, R.; DRAKE, J.; MOORCROFT, P.; PACALA, S. W.; BLAIR, J. B.; FEARON, M. G. Beyond potential vegetation: combining LiDAR data and a height structured model for carbon studies. **Ecological Applications**, v.14, n.3, p.873–883. 2004

HUTCHINSON, C. F. Techniques for Combining Landsat and Ancillary Data for Digital Classification Improvement. **Photogrammetric Engineering & Remote Sensing**, v.48, p.123-130. 1982

IPCC. 2006. **IPCC Guidelines for National Greenhouse Gas Inventories**. Available from: <http://www.ipcc-nggip.iges.or.jp/public/2006gl/index.html> Accessed: 21. jan.12.

KARJALAINEN, M.; KANKARE, V.; VASTARANTA, M.; HOLOPAINEN, M.; HYYPPÄ, J. Prediction of plot-level forest variables using TerraSAR-X stereo SAR data. **Remote Sensing of Environment**, v.117, p.338–347. 2012.

KÖHL, M. Double sampling in the Swiss National Forest Inventory. Results of a Pilot Study. In Proceedings from **SNS/IUFRO workshop** in Umeå 26-28 Feb. 1990. Remote Sensing Laboratory, Swedish University of Agricultural Sciences, Report, v.4, p.76-83. 1990.

LEFSKY, M. A.; HARDING, D.; COHEN, W. B.; PARKER, G.; SHUGART, H. H. Surface Lidar remote sensing of basal area and biomass in deciduous forests of Eastern Maryland, USA. **Remote Sensing of Environment**, v.67, n.1, 83–98.1999.

LU, D.; MAUSEL, P.; BRONDÍZIO, E.; MORAN, E.. Relationships between forest stand parameters and Landsat TM spectral responses in the Brazilian Amazon Basin. **Forest Ecology and Management**, v.198, p.149–167. 2004.

LUCKMAN, A.; BAKER, J.; HONZAK, M.; LUCAS, R. Tropical Forest Biomass Density Estimation Using JERS-1 SAR: Seasonal Variation, Confidence Limits, and Application to Image Mosaics - Active and Passive. **Remote Sensing of Environment**, v.63, n.2, p.126-139. 1998.

MATERN, B. Spatial variation. Medd. Statens Skogsf. Inst. 49(5). Also appeared as number 36 of Lecture Notes in Statistics. **Springer-Verlag**, New York, 1986. original edition, 1960.

MATERN, B. Funderingar om provträd I riksskogstaxeringen. Inst. f. Skogstaxering, SLU, Umeå. **NUTAX-Rapport,** n.8, 1981.

MCKEANA, J.; ROERING, J. Objective landslide detection and surface morphology mapping using high-resolution airborne laser altimetry. **Geomorphology**, 1412 (2003) p.1 –21. 2004.

NELSON, R.F.; HYDE, P.; JOHNSON, P.; EMESSIENE, B.; IMHOFF, M.L.; CAMPBELL, R. ; EDWARDS, W. Investigating RaDARLiDAR synergy in a North Carolina pine forest, **Remote Sensing of Environment**, v.110, n.1, p.98-108. 2007.

PEDDLE, D. ; FRANKLIN, S. E. Image texture processing and data integration for surface pattern discrimination. **Photogrammetric Engineering & Remote Sensing**, v.57, n.4, p.413-420. 1991.

PHUA, M-H. ; SAITO, H. Estimation of biomass of a mountainous tropical forest using Landsat TM data. **Canadian Journal of Remote Sensing**, v.29, n.4, p.429-440, 2003.

PINARD, M. A.; PUTZ, F. E. Retaining Forest Biomass by Reducing Logging Damage. **Biotropica**, v.28, n.3, p.278-295. 1996.

POSO, S.; HÄME, T. ; PAANANEN, R. A method of estimating the stand characteristics of a forest compartment using satellite imagery. **Silva Fennica.** v.18, n.3, p.261-292. 1984.

PROISY, C.; COUTERON, P.; FROMARD, F. Predicting and mapping mangrove biomass from canopy grain analysis using Fourier-based textural ordination of IKONOS images. **Remote Sensing of Environment**, v.109, p.379–392. 2007.

RANNEBY, B. Provytestorlekens betydelse vid skogsinventeringar. Inst. f. Skogstaxering, SLU, Umeå. **NUTAX-Rapport,** n.4. 1981a.

RANNEBY, B. Den topograpfiska variationen inom olika områden. En redovisning av skattade korrelationfunktioner. Inst. f. Skogstaxering, SLU, Umeå. **NUTAX-Rapport,** n.5. 1981b.

REESE, H.; NILSSON, M.; SANDSTRÖM, P. ; OLSSON, H. Applications using estimates of forest parameters derived from satellite and forest inventory data. **Computers and Electronics in Agriculture**. v.37, n.1, p.37-55. 2002.

ROY P, S. ; RAVAN, S. A. Biomass estimation using satellite remote sensing data - an investigation on possible approaches for natural forest. **Journal of Biosciences**, v. 21, n.4, p.535-561. 1996.

SADER, S. A.; WAIDE, R. B.; LAWRENCE, W. T.; JOYCE, A. T. Tropical forest biomass and successional age class relationships to a vegetation index derived from Landsat TM data. **Remote Sensing of Environmen** v.28, p.143-156. 1989.

SKIDMORE, A. K. An expert system classifies Eucalypt forest types using Thematic Mapper data and a digital terrain model. **Photogrammetric Engineering and Remote Sensing**, v.55, p.1449-1464. 1989.

STEININGER, M. K. Satellite estimation of tropical secondary forest above-ground biomass: data from Brazil and Bolivia. **International Journal of Remote Sensing**. v.21, p.1139–1157. 2000.

STRAHLER, A. H. The Use of prior probabilities in maximum likelihood classification of remotely sensed data. **Remote Sensing of Environment**, v.10, p.135-63. 1980.

SUGANUMA, H.; ABE, Y.; TANIGUCHI, M.; TANOUCHI, H.; UTSUGI, H.; KOJIMA, T.; YAMADA, K. Stand biomass estimation method by canopy coverage for application to remote sensing in an arid area of Western Australia. **Forest Ecology and Management,** v.222, p.75–87. 2006.

TANSUBHAPOL, B. **Logistics prevent Laos from signing mine pact. Bangkok Post**, Thailand. Available from:<http://www.hartford-hwp.com/archives/27a/075.html> Accessed: 2 sep. 2011. 1998.

TOKOLA, T.; PITKÄNEN, J.; PARTINEN, S.; MUINONEN, E. Point Accuracy of a Non-Parametric Method in Estimation of Forest Characteristics with Different Satellite Materials. **International Journal of Remote Sensing**, v.17, n.12, p.2333-2351. 1996.

TOKOLA, T.; KILPELÄINEN, P. The forest stand margin area in the interpretation of growing stock using Landsat TM imagery. **Canadian Journal of Forest Research**, v.29, p.303-309. 1999.

TOKOLA, T.; SHRESTHA S. M. Comparison of cluster-sampling techniques for forest inventory in southern Nepal. **Forest Ecology and Management**, v.116, n.13, p.219-231. 1999.

VARJO, J. Change Detection and Controlling Forest Information Using Multi-temporal Landsat TM Imagery. **Acta Forestalia Fennica**, v.258, p.1-64. 1997.

ZEIDE, B. Plot size optimization. **Forest Science**, v.26, p.251-257. 1980.