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Mapping of growing stock and stand delineation for tropical forests using remote sensing

Zhengyang Hou
School of Forest Sciences
Faculty of Science and Forestry
University of Eastern Finland

Academic dissertation

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Author: Zhengyang Hou

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Thesis supervisors:
Prof. Timo Tokola
School of Forest Sciences, University of Eastern Finland, Joensuu, Finland
Prof. Tuula Packalen
Finnish Forest Research Institute (METLA), Joensuu Research Unit, Finland

Pre-examiners:
Prof. Markus Holopainen
Department of Forest Sciences, University of Helsinki, Finland
Dr. Sakari Tuominen
Finnish Forest Research Institute (METLA), Vantaa Research Unit, Finland

Opponent:
Dr. Mikko Vastaranta
Department of Forest Sciences, University of Helsinki, Finland

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ABSTRACT

This package aims to advance remote-sensing-based mapping of growing stock and stand delineation for tropical forests in an attempt to respond to the call for the methodological development of forest inventory by the collaborative initiatives on Reducing Emissions from Deforestation and forest Degradation (REDD) and on sustainable forest management by REDD +. Tropical forests in Laos were taken as the study area, and remote sensing materials were collected from ALOS AVNIR-2, airborne colour infrared (CIR) photography, and airborne laser scanning (ALS).

In Study I, the relative efficacy of these three types of remote sensing materials was evaluated for mapping stem volume and basal area based on established methodologies that were originally developed for boreal forests. The results showed that ALS data processed with the conventional area-based approach (ABA) outperformed optical data in mapping of the stem volume (RMSE 36.9%) and basal area (RMSE 47.3%). Airborne CIR was built, with models performing slightly better than models based on ALOS AVNIR-2, although both remained at a similar level of accuracy and fell considerably behind ALS. In general, boreal methodologies proved effective for tropical forests, but the efficacy was far lower than that achieved in boreal conditions.

In Study II, the focus was therefore put on how to adapt the conventional ABA to the tropics, where forest structures are much more diverse and complex. The adaptation relied on applying global or plot-adaptive cut-off thresholding to filter and denoise the raw normalized point cloud. By doing so, information on structural variability was enhanced. The results showed that the adapted ABA effectively improved to a new level the predictability of stem volume compared with the conventional ABA adopted in Study I. The thresholding height of the optimal global cut-off for filtering was detected at 3.6 m and the correspondingly extracted features helped to improve the RMSE by about 7% compared to the conventional ABA. The plot-adaptive cut-off thresholding further improved it by nearly another 2% compared to the optimal global cut-off height.

In Study III, an empirical model-based segmentation approach was developed to extract forest stands of tropical forests from remote sensing materials and empirical models derived in Study I. The results showed that the homogeneity of the delineated stands mostly conformed to the quality of the corresponding empirical models obtained in Study I. With the cost-effectiveness of the tested remote-sensing materials corresponding well to the three-tier standard of IPCC, forest attributes used for segmentation can be generalized to any variable retrievable from an empirical model, such as stem volume, net present value of economic returns, amount of biomass, or even carbon stock for REDD +.

Keywords: Airborne CIR, ALOS AVNIR-2, ALS, area-based approach, feature extraction, forest mapping, segmentation, stand delineation, tropical forest

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I must express my gratitude to my wife Qing Xu for her love and collaboration at home and at work, as well as to my daughter Muru Hou for her joining our little family. Muru, I hope that you will read this dedication one day, because you are literally the greatest piece of work that we have ever accomplished.

Zhengyang Hou
Joensuu, December 2014

LIST OF ORIGINAL ARTICLES

This thesis is based on the following articles, which are referred to by the Roman numerals I–III in the text. Articles I and III are reprinted with the kind permission of the publisher. Article II is the author's version of the submitted manuscript.

I Hou Z., Xu Q., Tokola T. (2011). 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 66: 776-786.
doi: 10.1016/j.isprsjprs.2011.09.005

II Hou Z., Xu Q., Tokola T. (2014). Improving the feature extraction from low-density ALS data in the area-based approach by applying global and plot-adaptive cut-off thresholds. Manuscript.

III Hou Z., Xu Q., Nuutinen T., Tokola T. (2013). Extraction of remote sensing based forest management units in tropical forest. Remote Sensing of Environment 130: 1-10.
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Zhengyang Hou was the first and corresponding author, responsible for the data analyses and writing of papers. Qing Xu inspired and helped progress these studies through continuous discussion of technical details. Professor Tuula Packalen provided her expertise in forest management and planning and made valuable comments on the manuscripts. Professor Timo Tokola contributed research ideas and mentored the corresponding author for the entire thesis.

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LIST OF ABBREVIATIONS

ABA	Area-based approach
AIC	Akaike information criterion
AIC_{var}	A non-supervised method for segmentation assessment
ALOS AVNIR-2	ALOS advanced visible and near-infrared radiometer-2
ALS	Airborne laser scanning
CDM	Canopy density metrics
CIR	Colour infrared
DTM	Digital terrain model
FCPF	Forest Carbon Partnership Facility
GPS	Global positioning system
IPCC	Intergovernmental Panel on Climate Change
ITD	Individual tree detection
LiDAR	Light detection and ranging
LR.max	Maximum height of last returns of a sample plot
NDVI	Normalized difference vegetation index
NIR	Near-infrared
RMSE	Root mean squared error
REDD	Reducing Emissions from Deforestation and forest Degradation
UNFCCC	United Nations Framework Convention on Climate Change
VHT	Vegetation height threshold

1 INTRODUCTION

1.1 Background

Deforestation and forest degradation in the tropics account for a large share of global greenhouse gas emissions (World Bank 2014). The mechanism of Reducing Emissions from Deforestation and forest Degradation (REDD) was then developed to constrain the impact of climate change through creating financial returns for the carbon stored in forests as incentives for developing countries to reduce emissions from the forested lands (UN-REDD 2014). REDD has recently evolved into REDD +, which goes even further by encouraging sustainable forest management, conservation, and enhancement of carbon stocks in tropical forests (UNFCCC 2009, FCPF 2014). At the operational level, the first and foremost prerequisite for achieving these objectives is to build baseline maps for forest attributes in the tropics. As for the mapping accuracy, the Intergovernmental Panel on Climate Change (IPCC) proposed a three-tier standard that could be satisfied by remote sensing materials collected from different platforms with a matching cost-effectiveness (IPCC 2006, GOFC-GOLD 2009).

1.2 Optical data

The optical data are obtainable from sensors embedded in spaceborne or airborne platforms. This type of sensing is passive because objects are illuminated by sunlight and sensors record the intensity of radiative energy of various frequency spectra. The spatial resolution of satellite images (or scenes) ranges from a few metres to a few hundred metres, while airborne photography is commonly of sub-metre resolution. Spatial coverage of one scene from the satellite is much larger, however. Cost-wise, satellite data are relatively cheap to purchase and archive, which partly explains why they are used so frequently in time series. Due to the varying atmospheric conditions such as shadows and bidirectional effects (Holopainen and Wang, 1998a, 1998b), optical images obtained from either type of platform often require a radiometric correction. Among the methods that can be used for a relative correction, a multivariate alteration detection transformation-based radiometric normalization proposed by Canty et al. (2004) and a local radiometric correction proposed by Tuominen and Pekkarinen (2004) appeared to be adequate for forestry applications (Xu et al. 2012).

Spectral and textural features are typically employed to explore the relationships between forest attributes and optical data. Optical data are raster graphics comprised of a rectangular grid of pixels whose size does not necessarily match that of sample plots used in a forest inventory. Therefore, optical features are commonly extracted from a group of neighbouring pixels rather than from a single one (e.g. Hyvönen et al. 2005, Packalén 2009). Haralick et al. (1973) developed 14 types of textural features based on the principle of the spatial dependence matrix of pixel values, and some extended versions were examined for mapping boreal forests by Tuominen and Pekkarinen (2005) and Packalén and Maltamo (2007). The textural features are independent of the spectral features in terms of the spatial variation, so using both together should contribute to a better mapping accuracy than just using one type alone.

1.3 ALS data

Airborne laser scanning (ALS) is an application of a LiDAR sensor embedded into an airborne platform. Light detection and ranging (LiDAR) is active sensing in that the sensor system showers the target with laser pulses and then receives the reflected laser returns. Each received laser return is positioned with coordinates in the 3D space, and a large number of them form the spatially registered point cloud of ALS data. The immediate capability of providing height information for forest stands distinguishes ALS data from 2D passive data. However, although the spectrum used in a LiDAR system designed for land surveys is mostly near infrared (1064 nm), which is sensitive to vegetation and safe for human eyes, the energy intensity of laser returns reflected from the same type of object is too inconsistent to be applied properly. However, it should also be noted that although the intensity values of laser returns are not correlated to forest variables directly, there is still useful information in the intensity texture for estimating stem volume and biomass (Tuominen and Haapanne 2013). Multispectral LiDAR systems are also under development. In this context, multispectral optical data are naturally expected to complement some spectral information for ALS data.

The height information of ALS data forms the basis of two mainstream approaches developed for retrieving biophysical properties from boreal forests. One is known as the area-based approach (ABA) (Næsset 2002) and the other as individual tree detection (ITD) (Hyyppä and Inkinen 1999), which remains an area of active research due to the problem of identifying suppressed trees (Breidenbach et al. 2010, Kaartinen et al. 2012, Xu et al. 2014a, 2014b). Maltamo et al. (2006) concluded that estimates of ABA in boreal forests are as good as the traditional design-based inventories at the plot and stand levels. For instance, Packalén and Maltamo (2006, 2007) reported a root mean square error (RMSE) of 20.51 to 23.86% for stem volume and 17.15% for basal area by using hybrid models composed of ALS data and aerial photographs. Yu et al. (2010) mapped stem volume with an RMSE of 20.9%. ABA was established so well that it was widely used in operational forest inventory and management in Scandinavia.

1.4 Adapting ABA to tropical forests

An adaptation of ABA to tropical forests is not only adequate but necessary. The vast majority of ALS studies were conducted under boreal conditions and apparently the accordingly established ABA will be best suited to boreal forests. Tropical forests are typically comprised of many species of different ages, so forest structures in the tropics can be much more diverse and complex than the boreal forests. Therefore, the well-established ABA will not necessarily be as effective in the tropics. It is also necessary to adapt ABA to tropical forests especially for those who deal with the output of an ALS campaign as part of a sampling strategy (McRoberts 2014, Næsset et al. 2013a, 2013b). Considerable uncertainties are associated with the up-scaling of predictions from local and regional to state level. These uncertainties at different spatial scales impact the level of carbon compensation and policy making, thus impairing progress in mitigating global warming as a whole.

There is a niche in which the adaptation may take place in the low-level processing of the ALS point cloud. Since lasers can be reflected back from undesired objects such as boulders, shrubs, and other low-lying vegetation, these returns are noise and will thus affect the extraction of ALS features (or metrics) from the point cloud. Conventionally, a global cut-off threshold must be selected empirically in a typical range of 0.5 to 2 m for boreal forests, and then this threshold will filter out point entries of the normalized point-cloud whose heights are lower than the threshold height. ALS features which are intended to be used as predictors in modelling forest attributes for prediction will be extracted from the normalized point cloud only after filtration (e.g. Gobakken and Næsset 2008, Gobakken et al. 2012, Næsset et al. 2013a, 2013b). We will refer to this threshold below as the vegetation height threshold (VHT). The VHT controls the feature extraction. Because the application of a VHT will substantially modify the original point cloud, the selection of a different VHT will cause the content of an extracted feature (a vector of loadings) to alter; that is, the resulting features vary as a function of VHT. Therefore, in practice the selection of a VHT value must comply with the vertical structure of forests and will be optimized on a data-specific basis.

1.5 Stand delineation

Sustainable forest management relies on management units such as forest stands, which are typically formed on an operational or biological basis (Leppänen et al. 2008, Tokola et al. 2008). Traditionally, forest stands are delineated manually by expert foresters. Homogeneity is a primary criterion in delineation, so trees within a stand can be similar in terms of the size, age, species composition, and so on, which will facilitate the management and planning (Koivuniemi and Korhonen 2006, Leckie et al. 2003).

Segmentation is a numerical way to achieve an automatic delineation of forest stands. It, in a spatially continuous fashion, clusters neighbouring pixels into individual segments based on similarity criteria of the digital number and texture (Meinel and Neubert 2004); that is, it is a technique for subdividing imagery into spatially continuous and homogenous regions (Haralick and Shapiro 1992, Baatz and Schäpe 2000, Cheng et al. 2001). A successful segmentation will minimize the heterogeneity within a segment and maximize it between segments. Segmentation algorithms can be categorized as the edge-based or area-based approach (Muñoz et al. 2003). An edge-based approach detects abrupt changes and draws boundaries to form segments. An area-based approach forms a segment by allocating pixels according to similarity rules on intensity, spectral tone, neighbourhood texture, or other properties.

Remote-sensing materials have been commonly used for delineating forest stands. Satellite and airborne imageries have been widely evaluated in studies using various segmentation algorithms for delineating forest stands automatically (e.g. Tomppo 1988, Hagner 1990, Mäkelä and Pekkarinen 2001, Sell 2002, Leckie et al. 2003, Hay et al. 2005, Radoux and Defourny 2007). ALS data after rasterization were also tested for the same purpose (e.g. Diedershagen et al. 2004, Mustonen 2007, Leppänen et al. 2008, Tokola et al. 2008). Mustonen et al. (2008) also tried to combine a canopy height model derived from ALS data and airborne imaging together for segmentation.

1.6 Objectives

The overall goal of the package was to contribute to the methodological advancement of mapping of growing stock and sustainable forest management in the tropics using remote sensing. The specific aims of the respective studies were as follows:

I. To evaluate the relative efficacy of three types of remote sensing materials for mapping stem volume and basal area in the tropics using well-established methodologies developed in boreal studies. The materials were collected from the spaceborne ALOS AVNIR-2, airborne CIR, and ALS.
II. To adapt ABA, which was originally developed for boreal forests, to the structurally more complex tropical forests. The adaptation focused on exploring the pros and cons of global VHT and on developing a new filter based on plot-adaptive VHT so as to improve the feature extraction from ALS data.
III. To develop an empirical model-based segmentation approach to extract management units from tropical forests. The remote-sensing materials and the empirical models used for segmentation were derived from Study I.

2 MATERIALS

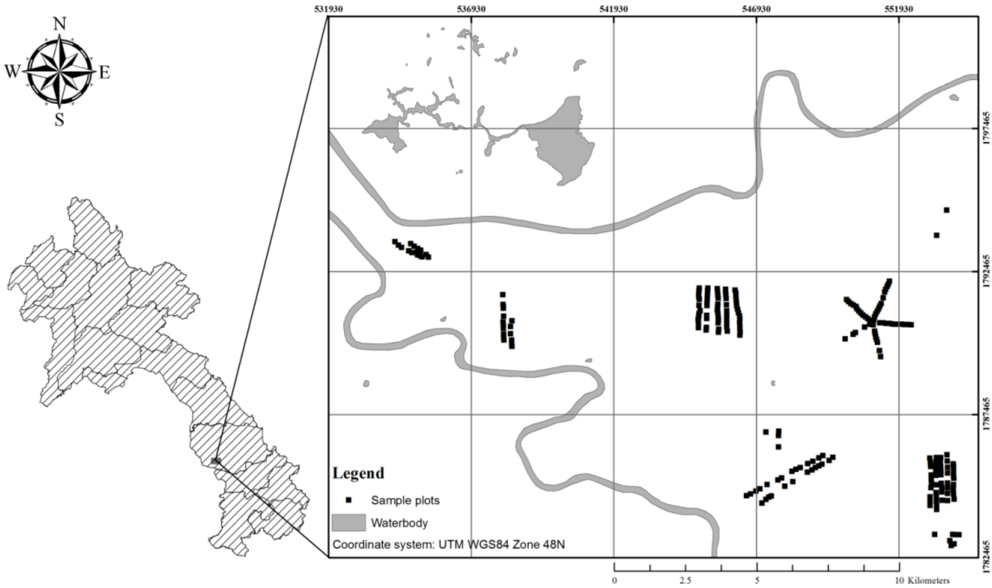
2.1 Study area and field data

For all studies, the study area was situated in the Dongsithouane production forest in the province of Savannakhet (latitude 16° 33' N, longitude 104° 45' E) in Laos (Fig. 1). The average elevation of the terrain is 128 m. The region experiences two seasons: wet from May to October and dry from November to April, where the dry season comprises a cool dry period from November to February and a hot dry period during March and April. Annual average precipitation is 1490 mm/year, with the least precipitation occurring in February.

A field campaign was undertaken in February 2009. The sampling design for the field plots was a mixture of random sampling and stratified sampling for the purpose of covering the distribution of growing stock as completely as possible. The aim of this design was to reduce error and variation inside one forest class. A total of 233 sample plots were surveyed (Table 1), with the coordinates of their centres being measured using a handheld GPS device.

Table 1. Characteristics of the sample plots. Stem volume was based on a model by Pukkala (2005).

Characteristics	Mean	Max	Min	SD
Number of stems per hectare	1405.9	20575.0	25.0	2372.8
Basal area median diameter (cm)	31.1	109.7	14.3	10.1
Height of the basal area median tree (m)	12.1	23.5	5.0	3.9
Stem volume (m^3/ha)	110.1	1512.4	6.4	124.6



The Dongsithouane Production Forest
Left: Administrative map of Laos marked with the study area
Right: Enlarged study area with the location of the sample plots

Figure 1. The Dongsithouane production forest area with its sample plots.

2.2 Remote sensing data

The remote sensing materials for this area were collected from ALOS AVNIR-2, airborne high-resolution digital infrared orthophotos (airborne CIR), and ALS (Table 2), with their cost-effectiveness expected to correspond well to the three-tier standard recommended by the IPCC. The ALS and airborne CIR data were obtained synchronously from a Piper PA-31 Navajo aircraft over a period of three days: 6 to 8 February 2009. The cruising speed was 120 knots and the altitude 2000 m. The air route consisted of 20 optimal trajectories planned beforehand with Leica Flight Planning and Evaluation Software (Leica FPES 2014). One flightline was acquired on a trajectory perpendicular to the rest and used for calibration. Ground control points were employed for the registration of ALS data with optical data. All the remote-sensing data and field measurements were projected into the WGS84/UTM zone N48 geo-reference system.

Table 2. Origins of the multisource data

Data type	Scenes	Spatial resolution	Acquisition time	Supplier
ALS	n/a	1 pulse/m^2	6-8 February 2009	Finnmap and Arbonaut
Airborne CIR	989	0.25m	6-8 February 2009	Finnmap
ALOS AVNIR-2	1	10m	13 September 2006	Savannakhet

For all studies, a Leica ALS 40 LiDAR scanner was used for collecting ALS data. The scanner was set at a field of view of 30° and a sidelap of 20%. A nominal sampling density of 1 pulse/m^2 was acquired with up to 4 returns/pulse recorded. A digital terrain model (DTM) with a spatial resolution of 5 m derived from the ALS data was supplied by the data vendor (Finnmap 2014). The normalized point cloud representing the height above ground level was generated by subtracting the DTM height from each above-ground return.

For Studies I and III, a Leica MP 39 digital camera was used for taking the aerial photos. A total of 989 images were photographed with a resolution of 0.25 m. Only the green, red, and near-infrared bands were used. All the images were orthorectified using DTM and geo-referenced according to Finnmap commercial photogrammetric mapping standards (Finnmap 2014). Because an obvious colour difference between the days was found to be caused by bidirectional reflectance effects (Pellikka 1998), a relative radiometric correction was considered necessary.

For Studies I and III, the AVNIR-2 sensor of the Japanese satellite ALOS was used for collecting multispectral optical imagery in four wavebands (blue, green, red, and near-infrared) with a 10 m spatial resolution. Due to its sun-synchronous orbit at a height of 692 km above the ground, the swath width of the image was 70 km at the nadir, so that one scene was sufficient to cover the entire region on a scale of 1:25,000. The quality of the image was satisfactory for direct application and did not need the radiometric calibration.

3 METHODS

3.1 Feature extraction from the optical data

In Study I, a relative radiometric calibration for the airborne CIR data was implemented using the method introduced by Tuominen and Pekkarinen (2004), whose main idea lies in correction of the anomalies in airborne CIR by means of local adjustment with third-party imagery as a reference, given that the latter is less prone to the bi-directional reflectance effect. The only scene from ALOS AVNIR-2 was taken as the reference. Due to the different spatial resolutions of airborne CIR and ALOS AVNIR-2, local adjustment of the correction was based on a unit of the focal window representing one satellite pixel and several pixels in the aerial photo. In this instance, the focal window was set at 10 × 10 m so as to represent one ALOS AVNIR-2 pixel and 400 airborne CIR pixels, whose resolution was resampled to 0.5 m. The local adjustment was carried out separately for each corresponding band, green to green, red to red, and NIR to NIR. The advantage of this method is that it keeps the shape of the histogram unchanged within the focal window and only shifts its location.

Table 3. Spectral and textural features extracted from the optical data.

Optical data	Spectral bands	First principal component of spectral bands	NDVI
Airborne CIR	Green/red/NIR	Eight textual features	Eight textual features
ALOS AVNIR-2	Blue/green/red/NIR	Eight textual features	Eight textual features

Spectral and textural features were extracted from the optical data and were produced as wall-to-wall predictors for mapping the stem volume and the basal area (Table 3). Since vegetation characteristics are of more concern than other land-cover types in forestry applications, the normalized difference vegetation index (NDVI) and the first principal component were used instead of the original spectral bands for extracting the textural features. NDVI serves well to distinguish vegetation from other land-cover types, and the first principal component accounts for the most information contained in the original spectral bands and achieves the purpose of dimension reduction. Out of Haralick's 14 textural features, seven were used according to their higher correlations with forest attributes than others shown in previous studies (Holopainen and Wang 1998a, Tuominen and Pekkarinen 2005), and the maximum probability of the matrix was also extracted as the eighth textural feature. The extraction took the size of the plot and that of an image pixel into account, so that the extracted digital number could properly represent the forest information at the plot level.

3.2 Feature extraction from the ALS data

3.2.1 Conventional ABA examined in tropical forests

In Study I, the area-based approach (ABA), which has been conventionally applied in boreal studies for processing ALS data (Næsset 2002), was examined in a tropical context for mapping the stem volume and the basal area. The last returns were classified into ground and aboveground returns. The ground returns were then employed to produce a triangulated irregular network that was later linearly interpolated for each point in order to produce the DTM for the area (Axelsson 1999). The normalized point cloud representing the height above ground level was generated by subtracting the DTM height from each above-ground return. An empirical global VHT of 2 m referred from works in the literature (see Næsset 2002, Næsset et al. 2013b) was then applied to the normalized point cloud so as to further exclude ground returns and other returns from stones, shrubs, and so on.

Features of the ALS data were extracted from the normalized point cloud for a grid size of 5 × 5 m and stored as wall-to-wall maps. These features were height percentiles, canopy density metrics (CDMs), and other descriptive statistics. The height percentiles included quantiles corresponding to 5, 10, 20, 30, 40, 50, 60, 70, 80, 90, and 95% of the height distribution. CDMs were also calculated for these quantiles as a ratio of the count of first returns above a given height percentile to the count of all first returns above the global VHT. Other descriptive statistics referred to the mean, standard deviation, coefficients of variation of elevation and density.

3.2.2 Adapted ABA developed for tropical forests

3.2.2.1 Optimal global VHT method

As shown in Study I, a global VHT has been conventionally applied for the purpose of denoising the raw point cloud in the ABA procedure. This is appropriate in structurally simple stands such as uniform plantations with a short, even understorey, and an empirically derived global VHT should be adequate to reduce the interference from ground objects in boreal forests, but it is questionable whether it is suitable in heterogeneous forests under varying growing conditions, as is the case in the tropics. A global VHT may over- or under-denoise the returns in stands with different types of understoreys, and either situation will result in height distributions deviating from the overstorey response.

In Study II, the optimum global VHT was sought by conducting a sensitivity analysis of the predicted stem volume to this parameter. A height range of 0 to 5 m was tested at 0.1 m intervals, resulting in 51 global VHT values and 51 sets of point clouds, from which the ALS features were extracted and used for modelling the stem volume. After thresholding, the ALS features (Table 4) were extracted at the plot level from the normalized first returns (Hosking 1990, Magnussen and Boudewyn 1998, Næsset 2002, Parker and Russ 2004).

3.2.2.2 Plot-adaptive VHT method

The global VHT is principally the outcome of a compromise between sample plots; that is, it neglects the structural diversity between plots and reduces the structural variability within each plot. Such a global VHT seems to suffice to describe all the data characteristics other than the vegetation structure.

In Study II, a plot-adaptive VHT method was developed to maintain the structural variation between plots so as to tackle this problem. A floating VHT setup that corresponded to the specific vertical structure of each sample plot was adopted in which the VHT was determined by the maximum height of the last returns from each plot (LR.max). As the vast majority of last returns are reflected from the ground or understorey, these are best able to indicate the structural complexity of the sample plot. However, LR.max may occasionally be a reflection from the overstorey canopy and if this is used to determine the VHT for the plot, many of the canopy returns will be removed and some structural information on this plot will be lost. Therefore, two versions of the plot-adaptive VHT method were examined by considering whether or not LR.max came from the overstorey. ALS features extracted afterwards were in accordance with Table 4.

Table 4. ALS features extracted from the normalized first returns.

Type of features		Metrics
Height percentiles		P(1st, 5th, 10th, 20th, 25th, 30th, 40th, 50th, 60th, 70th, 75th, 80th, 90th, 95th, 99th)
Order statistics		Max, Median, Min
Moment statistics	Central tendency	Mean, Mode
	Skewness and kurtosis	Skewness, Kurtosis
	Dispersion	SD, CV, IQR, AAD
Robust statistics	L-moments	L1, L2, L3, L4
	L-ratios	L.skewness, L.kurtosis, L.CV
Canopy density metrics	Proportional returns	CDM.ratio at respective height percentiles
	Count of first returns	CDM.count.above respective height percentiles
		CDM.count.below respective height percentiles

3.3 Modelling for predictive mapping

Features extracted from remote sensing data were used as predictors for predicting the stem volume (m^3/ha) and the basal area (m^2/ha) in Study I and for predicting the stem volume in Study II. The stem volume and the basal area are two basic biophysical attributes required for evaluating present and future conditions in a forest. The stem volume is also a key variable relevant to mapping the biomass and the carbon stock by indirect methods that employ expansion factors. The basal area represents the structural condition of forests and provides an understanding of the variation of density.

In Studies I and II, multiple linear regression was used for modelling. Although other popular alternative estimation approaches would be classification and non-parametric methods, these were rejected here due to difficulties in defining the classification categories and the insufficient number of sample plots for non-parametric methods. The estimated coefficients obtained in a parametric regression are useful for comparing models with identical predictors in Study II. The Akaike Information Criterion (AIC) evaluates the goodness of fit of a model and includes a penalty for model complexity so that the model with the smallest AIC score is preferred (Akaike 1974, Burnham and Anderson 1998, Venables and Ripley 2002). In practice, AIC was applied to the stepwise selection of predictors and the model with the lowest score was adopted. Parsimony in modelling was maintained, which made it possible to build a common basis for comparing models of different remote-sensing materials (Study I) and different feature extraction methods (Study II). This general rule also prevents the achievement of a subjective improvement by increasing the number of predictors.

3.4 Segmentation for stand delineation

Study III focused on extracting forest management units from remote-sensing materials for tropical forests. The segmentation approach differed from many others, because the input layers were output maps of the stem volume and the basal area which were predicted with various remote-sensing materials in Study I. The algorithm of multi-scale region merging developed by Baatz and Schäpe (2000) was used for delineating forest stands in the software environment of eCognition (eCognition 2014). This algorithm starts with objects or regions at the single-pixel level and then merges them pairwise with objects in the vicinity to generate larger objects, following local spectral or textural homogeneity criteria.

3.5 Assessment methods

In Studies I and II, the prediction accuracy was assessed by RMSE and its relative form. The regression model is normally unbiased, but a bias may be introduced by applying transformation to the response. This bias and its relative form were therefore calculated. In order to prevent over-fitting and to check the stability of the models, all error metrics were calculated on the basis of leave-one-out cross-validation.

In Study III, a non-supervised method denoted by AIC_{var} was developed for assessing the homogeneity of delineated forest stands in the form of segments. For each set of segmentation, AIC_{var} quantified the overall homogeneity of delineated segments by evaluating the variance of field measurements contained in the corresponding segment. The smaller the value of AIC_{var}, the more homogenous this set of segmentation.

4 RESULTS

4.1 Summary of models

The models obtained in Studies I and II are summarized in Table 5. In Study I, ALS processed with the conventional ABA outperformed optical data in mapping the stem volume and the basal area in a tropical context. Airborne CIR was built with models performing slightly better than models based on ALOS AVNIR-2, although both remained at a similar accuracy level and fell considerably behind ALS. Although the hybrid stem volume model based on ALS and airborne CIR improved the $RMSE_{\%}$, this improvement of 1.9% was not considered cost-effective.

Study II shows that the adapted ABA developed for tropical forests effectively improved the ALS predictability to a new level compared with the conventional ABA. The optimal global VHT was found to be located at a height of 3.6 m and the correspondingly extracted ALS features helped to improve the $RMSE_{\%}$ by about 7% compared to the conventional ABA method. But both versions of the plot-adaptive VHT method further improved the $RMSE_{\%}$ by almost another 2% compared to the optimal global VHT method.

4.2 Adapted ABA

In the optimum global VHT method, a total of 51 models were established for mapping the stem volume, each corresponding to a global VHT in the range of 0 to 5 m at 0.1 m intervals. It was found that the way in which the global VHT denoises the raw point cloud had a significant effect on the final models, whose accuracy was very sensitive to the selection of the global VHT. The global VHT of 3.6 m led to the lowest $RMSE_{\%}$, which was about 30% and was accepted as the optimum with respect to the raw ALS data.

In the plot-adaptive ABA method, both versions of this method provided similar accuracies, with an $RMSE_{\%}$ of about 28%. Both models outperformed that based on the optimum global VHT because of the improved explanatory power of the ALS predictors, which reflected the structural diversity between plots and restored the structural variability within each plot.

Table 5. Accuracy of models used for mapping stem volume (SV, m^3/ha) and basal area (BA, m^2/ha).

Source	Feature extraction	Models	Response	Predictors	Model SE	R^2	R^2_{adj}	RMSE	$RMSE_{\%}$	Bias	$Bias_{\%}$
Study I	Conventional ABA	ALS	SV	2	0.4	0.9	0.9	42.2	36.9	0.1	0.1
			BA	7	6.3	0.8	0.8	8.0	47.3	0.0	0.1
	Optical	ALOS AVNIR-2	SV	7	0.4	0.8	0.8	78.3	68.6	0.3	0.3
			BA	7	9.2	0.6	0.6	11.2	66.1	0.0	0.3
		Airborne CIR	SV	6	0.4	0.8	0.8	75.2	65.8	0.2	0.2
			BA	6	8.0	0.7	0.7	9.7	57.1	0.1	0.4
	Hybrid	ALS + ALOS AVNIR-2	SV	5	0.4	0.9	0.9	55.0	48.1	-0.2	-0.2
			BA	4	7.1	0.8	0.8	8.5	50.0	0.0	0.3
		ALS + Airborne CIR	SV	3	0.4	0.9	0.9	40.0	35.0	0.0	0.0
			BA	4	7.0	0.8	0.8	8.8	52.1	0.0	0.1
Study II	Adapted ABA	Optimal global VHT 3.6 m	SV	2	0.4	0.9	0.9	34.4	30.1	0.1	0.1
		Plot-adaptive VHT: version 1	SV	2	0.4	0.9	0.9	32.4	28.4	0.2	0.2
		Plot-adaptive VHT: version 2	SV	5	0.3	0.9	0.9	32.9	28.8	0.1	0.1

4.3 Residual analysis

The two best models, which were based on the optimal global VHT 3.6 m and the plot-adaptive VHT version 1, were used in the following analysis. Thirty sample plots, comprising the 10 most over-estimated ones, the 10 most under-estimated ones, and the 10 with the most accurate estimates, were selected and categorized into three groups according to their residuals. The non-parametric Kruskal-Wallis test was used to examine whether the predictors of the respective models were able to distinguish between these three groups, showing that only the CDM.ratio.P80 adopted in the optimal global VHT 3.6 m model failed to discriminate between these drastically different groups. This illustrates a need for novel types of CDMs to be extracted from the ALS data.

Figure 2 shows the size and the number of all trees in an example plot from each group and the plot falls into an identical group in all the respective models. A plot with a large number of stems tends to be underestimated and these stems have a large variety of sizes, whereas a plot with a few giant stems tends to be overestimated. Valid tree-density information is difficult to obtain from ALS data in tropical forests, which again emphasizes the need to develop novel CDMs to capture the horizontal variation in vegetation structures.

4.4 Assessment of delineated stands

Based on models derived in Study I, a total of 96 sets of segmentations were generated and indexed with AIC_{var}. The larger the segment, the more field measurements will be included in it, so a greater variance will result, causing a larger AIC_{var} reading. As a grouping criterion, the mean area of the delineated segments was employed to categorize the AIC_{var} indices for comparison purposes, amounting to six groups of approximately 5, 8, 10, 15, 20 and 25 hectares, respectively.

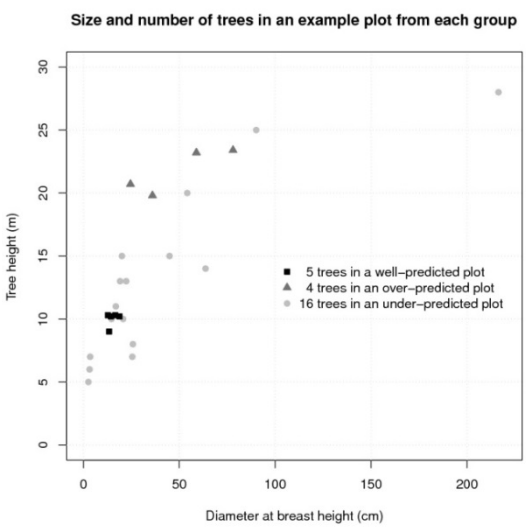


Figure 2. Trees in example plots from the three groups.

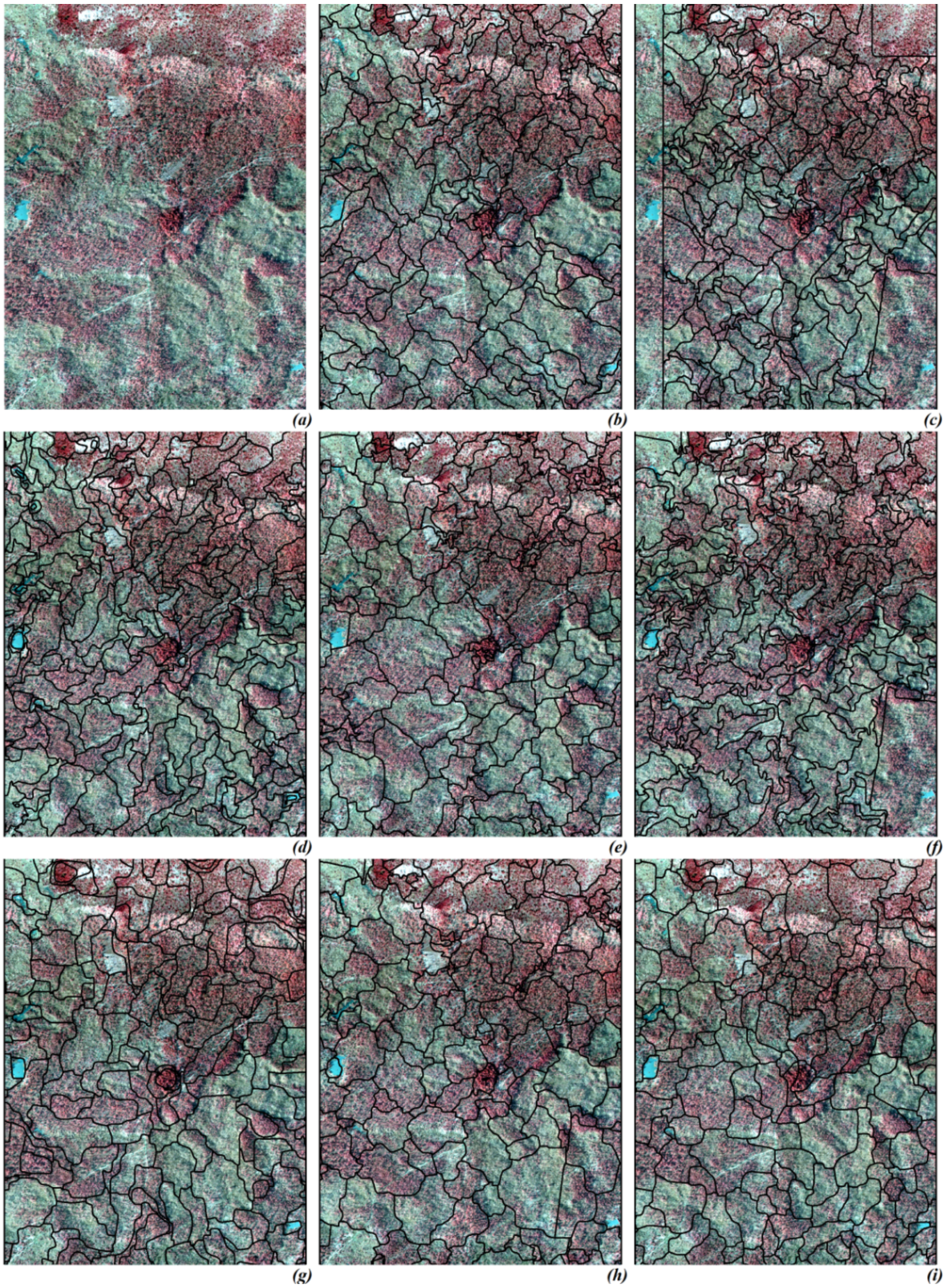


Figure 3. Samples at a mean segment size of about 5 ha for visual verification: (a) sample area; (b) ALS segmentation based on basal area; (c) airborne CIR segmentation based on basal area; (d) ALOS AVNIR-2 segmentation based on basal area; (e) ALS segmentation based on stem volume; (f) airborne CIR segmentation based on stem volume; (g) ALOS AVNIR-2 segmentation based on stem volume; (h) hybrid segmentation of ALS and airborne CIR based on stem volume; (i) hybrid segmentation of ALS and ALOS AVNIR-2 based on stem volume.

These results show that the homogeneity of the delineated stands mostly conforms to the quality of the corresponding empirical models obtained in Study I. Delineations based on maps of basal area conformed to the accuracies of the models, especially for mean segment sizes below 10 ha. Most delineations based on maps of stem volume also conformed to the performance of the corresponding model. A visual verification coincided well with the assessment of AIC_{var} (Figure 3).

5 DISCUSSION

This work package shows that the experience gained in boreal forests in mapping forest attributes and extracting forest stands from remote sensing data is also applicable in a tropical context, but it is still highly desirable to adapt these methods to tropical forests which are structurally more complex. Among the remote-sensing materials employed here, ALS turned out to be the most competent for the applications presented so far.

5.1 Mapping growing stock

ALS outperformed the passive optical sensors for mapping the stem volume and the basal area in a mixed-species tropical forest. ALOS AVNIR-2 and airborne CIR data performed less well. Optical data were found to be more accurate for estimating basal area than stem volume, although they still fell behind ALS. Tropical forests have a more complicated vertical structure and a greater variety of tree species, and this presents challenges when the aim is to obtain such good results as under boreal conditions. Especially, tropical forests may pose a challenge to the successful detection of tree crowns due to the density and the overlay of neighbouring tree crowns. The systematic underestimation of tree numbers and forest attributes mentioned by Gonzalez et al. (2010) would be even worse with tropical forests. Despite this, the greatest limitation on using optical data to estimate tropical forest attributes arises from the fact that optical sensors record mainly the tree crown surface, while the suppressed understorey often remains undetectable. This also helps to explain the relatively large estimation error of passive optical sensors.

ALS point clouds are products of a sampling process and contain two sources of sampling error in forest areas. One error arises from the low sampling intensity, resulting in incomplete variation in the trees sampled, while the second is introduced by noise, mainly from objects above the bare ground but also from the canopy. As a way to enhance the sampling intensity, increasing the pulse density must help to capture the diversity of forest structure in more detail. Selecting pulse density should depend on the general complexity of the vegetation. For boreal forests, low-density ALS data have been proved suitable for providing satisfactory mappings (e.g. Næsset 2006, 2007), whereas higher-density data should be adequate for tropical forests which are structurally more complex. However, increasing the pulse density is not always effective for especially young and dense stands, due to the saturation problem, which means that the information regarding the structural variability cannot be enriched any further (Jakubowski et al. 2013).

VHT thresholding is a simple way to remove noises from above the bare ground by finding a threshold that clearly distinguishes understorey objects from the canopy layers. A global VHT which has been used in Scandinavia is determined on the basis of foresters' knowledge and experience, but it is impractical to do this in the tropics where a forest can be over-heterogeneous or simply peppered with land mines as a legacy of past wars. Objective measurements must be made of the ground vegetation and understorey, which can be used as proper indicators. The last returns from the ALS pulses serve the purpose just in time. These are usually deemed to be mainly reflected from the ground and are therefore used for producing DTMs. This further explains why the last returns were used here to determine the plot-adaptive VHT.

The plot-adaptive VHT is a function of vegetation structures other than data characteristics as is the case of the global VHT. A unified global VHT for all sample plots is at best a compromise between plots and serves to adjust the statistical relationship between the response and the ALS predictors. If the global VHT is employed, there is still some doubt as to whether the optimal global VHT for predicting the stem volume will result in the most accurate estimates of basal area or other forest attributes. As a result this concern poses another question as to how one can adequately impute several responses simultaneously by a non-parametric multiple-imputation method. Conversely, the plot-adaptive VHT is customized for each sample plot and thus by nature is able to portray the variability between plots and within plots, making features extracted in this way suitable for the multiple imputation.

In short, the global VHT method is more suitable for forests that have a simple, consistent vertical structure, while the plot-adaptive VHT method should be favoured for forests characterized by large variation of forest structures. However, this difference should not prevent the plot-adaptive VHT method from performing well even in situations where a global VHT would also be applicable.

5.2 Stand delineation

The potential of ALS, airborne CIR, and ALOS AVNIR-2 was examined for their performance in delineating forest stands in the tropics. The distinguishing feature of an empirical model-based segmentation method is that the delineation is fully automated, homogeneous, and adjustable in size. The areas produced by such segmentation can serve as managerial units in forest management and planning.

A common concern relates to the randomness of the segments produced by the multi-scale region merging. It has been observed that even with identical parameter settings, minor discrepancies may appear between segments that represent the same cartographic location but are generated in different runs. The reason for these discrepancies is ascribed to the random positions at which the initial seeding was planted. Alternatively, recent segmentation algorithms on the basis of “level sets” or “graph cuts” (Szeliski 2010) can also be examined for the present purpose.

In forestry, automatically extracted stands are usually evaluated by a reference delineated by an expert (Hyppänen et al. 1996, Radoux and Defourny 2007, Mustonen et al. 2008). Although the difference can be assessed quantitatively as a local measure, methods of this type are qualitative, because the outcome is fully contingent on the reference, which is subjective. The use of the AIC_{var} index as an objective, unsupervised measurement is adequate for quantitative comparisons of both diverse parameterizations of a particular segmentation method and fundamentally different segmentation methods.

The process of segmentation duly reflected the performance of empirical models based on ALS, airborne CIR, and ALOS AVNIR-2 data. The resulting spatially homogeneous and disjunct segments would correspond reasonably well to forest stands (Mäkelä and Pekkarinen 2001, Leppänen et al. 2008). In addition to homogeneity, delineations are expected to meet the required size and shape for the forest management, which in turn must comply with the clearly defined goal of forest planning.

The empirical model-based segmentation is compatible with planning from the operational to the strategic level subject to the goal in question, which often entails a management unit based on cutting or other silvicultural operations (Tokola et al. 2008). Depending on this goal, forest attributes used for segmentation can be generalized to any variable retrieved from an empirical model, such as stem volume as a biological indicator, net present value of economic returns, amount of biomass, or even carbon stock for REDD +.

Apart from delineating forest stands, the segmentation of remote sensing data has been previously tested for applications to many other aspects of forestry such as tree-crown delineation (Kaartinen et al. 2012, Vauhkonen et al. 2012) and change detection (Clark and Pellikka 2009, Maeda et al. 2010). In an ITD system, the crown delineation allows the extraction of information regarding the dimensions and shapes of tree crowns, which favours the modelling of tree-level attributes. This work typically involves two sequential steps: the detection of individual trees and then the delineation of respective trees. While the algorithm of multi-scale region merging used in this study is admittedly also applicable to delineating individual tree crowns, Vauhkonen et al. (2012), after comparing six sets of detection and delineation algorithms, concluded that the structure and spatial pattern of trees rule the efficacy much more than the algorithm itself.

Proceeding one step further from the change detection, the empirical model-based segmentation approach could be interesting for quantifying deforestation and forest degradation in connection with REDD +, as it allows a level of cost-effectiveness that corresponds to the remote-sensing data. Having established the initial forest stands by validated segmentation, one can conduct all future detection and quantification steps using the same material and based directly on the initial segments and zonal statistics. Deforestation or forest degradation, in the sense of either stem volume or basal area, is therefore reflected in the magnitude of the variations between the situations before and after such events. If accurate expansion factors are introduced into the stem volume statistics, both aboveground and belowground biomass can be expressed, thus facilitating carbon monitoring.

REFERENCES

Akaike H. (1974). A new look at the statistical model identification. IEEE Transactions on Automatic Control 19: 716–723.
http://dx.doi.org/10.1109/TAC.1974.1100705

Axelsson P.E. (1999). Processing of laser scanner data - algorithms and applications. ISPRS Journal of Photogrammetry and Remote Sensing 54: 138-147.
http://dx.doi.org/10.1016/S0924-2716(99)00008-8

Baatz M., Schäpe A. (2000). Multiresolution segmentation - an optimization approach for high quality multi-scale image segmentation. In: Angewandte Geographische

Informationsverarbeitung XII (Eds.), Beiträge zum AGIT-Symposium Salzburg 2000 (pp.12-23). Karlsruhe: Herbert Wichmann Verlag.

Breidenbach J., Næsset E., Lien V., Gobakken T., Solberg S. (2010). Prediction of species specific forest inventory attributes using a nonparametric semi-individual tree crown approach based on fused airborne laser scanning and multispectral data. Remote Sensing of Environment 114: 911-924. http://dx.doi.org/10.1016/j.rse.2009.12.004

Burnham K.P., Anderson D.R. (1998). Model selection and inference: a practical information-theoretic approach. Springer. http://dx.doi.org/10.1007/978-1-4757-2917-7

Canty M.J., Nielsen A.A., Schmidt M. (2004). Automatic radiometric normalization of multitemporal satellite imagery. Remote Sensing of Environment 91: 441–451. http://dx.doi.org/10.1016/j.rse.2003.10.024

Cheng H.D., Jiang X.H., Sun Y., Wang J. (2001). Colour image segmentation: Advances and prospects. Pattern Recognition 34: 2259-2281. http://dx.doi.org/10.1016/S0031-3203(00)00149-7

Clark B.J.F., Pellikka P.K.E. (2009). Landscape analysis using multiscale segmentation and object orientated classification. In: Röder, A. & Hill, J. (Eds.), Recent Advances in Remote Sensing and Geoinformation Processing for Land Degradation Assessment. London: Taylor & Francis Group.

Diedershagen O., Koch B., Weinacker H. (2004). Automatic segmentation and characterization of forest stand parameters using Airborne LIDAR data multispectral and FOGIS data. In: International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 36(8/W2).

eCognition (2014). Definiens developer version 7. http://www.ecognition.com/sites/default/files/difference_to_definiens_professional%5D.pdf [cited October 9, 2014].

FCPF (2014). What is REDD +? http://www.forestcarbonpartnership.org/what-redd [cited October 9, 2014].

Finnmap (2014). Study on Options for Monitoring Changes in Forest-Based Carbon Stock in Lao PDR. http://wp.finnmap.com/wp-content/uploads/2013/09/FM_REFERENCES_International_5_2013.pdf [cited October 9, 2014].

Gobakken T., Næsset E. (2008). Assessing effects of laser point density, ground sampling intensity, and field sample plot size on biophysical stand properties derived from airborne laser scanner data. Canadian Journal of Forest Research 38: 1095-1109.

http://dx.doi.org/10.1139/X07-219

Gobakken T., Næsset E., Nelson R., Bollandsås O. M., Gregoire T. G., Ståhl G., Holm S., Ørka H. O., Astrup R. (2012). Estimating biomass in Hedmark County, Norway using national forest inventory field plots and airborne laser scanning. Remote Sensing of Environment 123: 443-456.
http://dx.doi.org/10.1016/j.rse.2012.01.025

GOFC-GOLD (2009). A sourcebook of methods and procedures for monitoring and reporting anthropogenic greenhouse gas emissions and removals caused by deforestation, gains and losses of carbon stocks in forests remaining forests and forestation. GOFC-GOLD Report version COP15-1. GOFC-GOLD Project Office. Alberta: Natural Resources Canada.

Gonzalez P., Asner G.P., Battles J.J., Lefsky M.A., Waring K.M., Palace, M. (2010). Forest carbon densities and uncertainties from Lidar, Quickbird, and field measurements in California. Remote Sensing of Environment 114: 1561-1575.
http://dx.doi.org/10.1016/j.rse.2010.02.011

Hagner O. (1990). Computer aided forest stand delineation and inventory based on satellite remote sensing. In: The Usability of Remote Sensing for Forest Inventory and Planning. Umeå: SNS/IUFRO Workshop.

Haralick R.M., Shanmugam K., Dinsteein J. (1973). Textural features for image classification. IEEE Transactions on Systems, Man, and Cybernetics 3: 610-621.
http://dx.doi.org/10.1109/TSMC.1973.4309314

Haralick R.M., Shapiro L.G. (1992). Computer and robot vision, volume 1. Boston: Addison-Wesley Longman Publishing Co., Inc.

Hay G. J., Castilla G., Wulder M.A., Ruiz J.R. (2005). An automated object-based approach for the multiscale image segmentation of forest scenes. International Journal of Applied Earth Observation and Geoinformation 7: 339-359.
http://dx.doi.org/10.1016/j.jag.2005.06.005

Holopainen M., Wang G. (1998a). The calibration of digitized aerial photographs for forest stratification. International Journal of Remote Sensing 19: 677-696.
http://dx.doi.org/10.1080/014311698215928

Holopainen M., Wang G. (1998b). Accuracy of digitized aerial photographs for assessing forest habitats at plot level. Scandinavian Journal of Forest Research, 13: 499-508.
http://dx.doi.org/10.1080/02827589809383011

Hosking J.R.M. (1990). L-Moments: analysis and estimation of distributions using linear combinations of order statistics. Journal of the Royal Statistical Society, Series B (Methodological) 52: 105-124.

Hyppänen H., Pasanen K., Saramäki J. (1996). The updating accuracy of boundaries of clear cutting stands. Folia Forestalia 4: 321-335.

Hyvönen P., Pekkarinen A., Tuominen S. (2005). Segment-level stand inventory for forest management. Scandinavian Journal of Forest Research 20: 75-84. http://dx.doi.org/10.1080/02827580510008220

Hyyppä J., Inkinen M. (1999). Detecting and estimating attributes for single trees using laser scanner. The photogrammetric Journal of Finland 16: 27-42.

IPCC (2006). 2006 IPCC guidelines for national greenhouse gas inventories. http://www.ipcc-nggip.iges.or.jp/public/2006gl/index.html [cited October 9, 2014].

Jakubowski M.K., Guo Q., Kelly M. (2013). Tradeoffs between lidar pulse density and forest measurement accuracy. Remote Sensing of Environment 130: 245-253. http://dx.doi.org/10.1016/j.rse.2012.11.024

Kaartinen H., Hyyppä J., Yu X., Vastaranta M., Hyyppä H., Kukko A., Holopainen M., Heipke C., Hirschmugl M., Morsdorf F., Næsset E., Pitkänen J., Popescu S., Solberg S., Wolf B.M., Wu, J.C. (2012). An international comparison of individual tree detection and extraction using airborne laser scanning. Remote Sensing 4: 950-974. http://dx.doi.org/10.3390/rs4040950

Koivuniemi J., Korhonen K.T. (2006). Inventory by compartments. In: Kangas, A. Maltamo, M. (Eds.). Forest Inventory - Methodology and Applications. Netherlands: Springer.

Leckie D., Gougeon F., Walsworth N., Paradine D. (2003). Stand delineation and composition estimation using semi-automated individual tree crown analysis. Remote Sensing of Environment 85: 355-369. http://dx.doi.org/10.1016/S0034-4257(03)00013-0

Leica FPES (2014). Leica flight planning and evaluation software. http://www.leica-geosystems.com/en/Leica-FPES_86824.htm [cited October 9, 2014].

Leppänen V. J., Tokola T., Maltamo M., Mehtätalo L., Pusa T., Mustonen J. (2008). Automatic delineation of forest stands from LiDAR data. GEOBIA 2008 - Pixels, Objects, Intelligence. In: International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences 38(4/C1).

Maeda E.E., Clark B.J.F., Pellikka P., Siljander M. (2010). Modelling agricultural expansion in Kenya's Eastern Arc Mountains biodiversity hotspot. Agricultural Systems 103: 609-620. http://dx.doi.org/10.1016/j.agsy.2010.07.004

Magnussen S., Boudewyn P. (1998). Derivations of stand heights from airborne laser scanner data with canopy-based quantile estimators. Canadian Journal of Forest Research 28: 1016-1031.

http://dx.doi.org/10.1139/x98-078

Mäkelä H., Pekkarinen A. (2001). Estimation of timber volume at the sample plot level by means of image segmentation and Landsat TM imagery. Remote Sensing of Environment 77: 66-75.
http://dx.doi.org/10.1016/S0034-4257(01)00194-8

Maltamo M., Eerikäinen K., Packalén P., Hyyppä J. (2006). Estimation of stem volume using laser scanning-based canopy height metrics. Forestry 79: 217-229.
http://dx.doi.org/10.1093/forestry/cpl007

McRoberts R.E. (2014). Post-classification approaches to estimating change in forest area using remotely sensed auxiliary data. Remote Sensing of Environment 151:149-156.
http://dx.doi.org/10.1016/j.rse.2013.03.036

Meinel G., Neubert M. (2004). A comparison of segmentation programs for high resolution remote sensing data. In: International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences 35(B4).

Muñoz X., Freixenet J., Cufi X., Marti J. (2003). Strategies for image segmentation combining region and boundary information. Pattern Recognition Letters 24: 375–392.
http://dx.doi.org/10.1016/S0167-8655(02)00262-3

Mustonen J. (2007). Metsikkökuvioiden automaattinen segmentointi puuston latvustoa kuvaavan laserpintamallin ja ilmakuvan avulla. Pro Gradu, University of Helsinki. Department of Forest Research Management.

Mustonen J., Packalén P., Kangas A. (2008). Automatic segmentation of forest stands using a canopy height model and aerial photography. Scandinavian Journal of Forest Research 23: 534-545.
http://dx.doi.org/10.1080/02827580802552446

Næsset E. (2002). Predicting forest stand characteristics with airborne scanning laser using a practical two-stage procedure and field data. Remote Sensing of Environment 80: 88-99.
http://dx.doi.org/10.1016/S0034-4257(01)00290-5

Næsset E. (2006). Accuracy of forest inventory using airborne laser scanning: evaluating the first nordic full-scale operational project. Scandinavian Journal of Forest Research 19: 554-557.
http://dx.doi.org/10.1080/02827580410019544

Næsset E. (2007). Airborne laser scanning as a method in operational forest inventory: Status of accuracy assessments accomplished in Scandinavia. Scandinavian Journal of Forest Research 22: 433-442.
http://dx.doi.org/10.1080/02827580701672147

Næsset E., Bollandsås O.M., Gobakken T., Gregoire T.G., Ståhl G. (2013a). Model-assisted estimation of change in forest biomass over an 11 year period in a sample survey supported by airborne LiDAR: A case study with post-stratification to provide activity data. Remote Sensing of Environment 128: 299-314. http://dx.doi.org/10.1016/j.rse.2012.10.008

Næsset E., Gobakken T., Bollandsås O.M., Gregoire T.G., Nelson R., Ståhl, G. (2013b). Comparison of precision of biomass estimates in regional field sample surveys and airborne LiDAR-assisted surveys in Hedmark County, Norway. Remote Sensing of Environment 130: 108-120. http://dx.doi.org/10.1016/j.rse.2012.11.010

Packalén P., Maltamo M. (2006). Predicting the plot volume by tree species using airborne laser scanning and aerial photographs. Forest Science 52: 611-622.

Packalén P., Maltamo M. (2007). The k-MSN method for the prediction of species-specific stand attributes using airborne laser scanning and aerial photographs. Remote Sensing of Environment 109: 328-341. http://dx.doi.org/10.1016/j.rse.2007.01.005

Packalén P. (2009). Using airborne laser scanning data and digital aerial photographs to estimate growing stock by tree species. Dissertationes Forestales 77. Doctoral thesis, University of Joensuu, Faculty of Forest Sciences, Joensuu, Finland.

Parker G.G., Russ E.M. (2004). The canopy surface and stand development: assessing forest canopy structure and complexity with near-surface altimetry. Forest Ecology and Management 189: 307-315.

Pellikka P. (1998). Development of correction chain for multispectral airborne video camera data for natural resource assessment. Fennia 176: 1-110.

Pukkala T. (2005). Volume and taper models for forest trees in Lao PDR. Sustainable Forestry and Rural Development Project - Lao PDR. Technical Report.

Radoux J., Defourny, P. (2007). A quantitative assessment of boundaries in automated forest stand delineation using very high resolution imagery. Remote Sensing of Environment 110: 468-475. http://dx.doi.org/10.1016/j.rse.2007.02.031

Sell R. (2002). Segmentointimenetelmien käyttökelpoisuus ennakkokuvioinnissa. Metsätieteellinen aikakauskirja, 3: 499-507.

Szeliski R. (2010). Computer Vision: Algorithms and Applications. London: Springer.

Tokola T., Vauhkonen J., Leppänen V. J., Pusa T., Mehtätalo L., Pitkänen J. (2008). Applied 3D texture features in ALS-based tree species segmentation. GEOBIA 2008 - Pixels, Objects, Intelligence. In: International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences 38(4/C1).

Tomppo E. (1988). Standwise forest variate estimation by means of satellite images. University of Helsinki, Department of Forest Mensuration and Management. Research Notes 21: 103-111.

Tuominen S., Pekkarinen A. (2004). Local radiometric correction of digital aerial photographs for multi-source forest inventory. Remote Sensing of Environment 89: 72-78.
http://dx.doi.org/10.1016/j.rse.2003.10.005

Tuominen S., Pekkarinen A. (2005). Performance of different spectral and textural aerial photograph features in multi-source forest inventory. Remote Sensing of Environment 94: 256-268.
http://dx.doi.org/10.1016/j.rse.2004.10.001

Tuominen S., Haapanen R. (2013). Estimation of forest biomass by means of genetic algorithm-based optimization of airborne laser scanning and digital aerial photograph features. Silva Fennica 47: 1-20.
http://dx.doi.org/10.14214/sf.902

UN-REDD (2014). About REDD +.
http://www.un-redd.org/AboutREDD/tabid/582/language/en-US/Default.aspx [cited October 9, 2014].

UNFCCC (2009). Addendum, Part Two: Action taken by the Conference of the Parties at its fifteenth session (Copenhagen Accord). In: Report of the Conference of the Parties on its fifteenth session, Copenhagen, December 7-19, 2009. Geneva: United Nations Office at Geneva.

Vauhkonen J., Ene L., Gupta S., Heinzel J., Holmgren J., Pitkänen J., Solberg S., Wang Y., Weinacker H., Hauglin K.M., Lien V., Packalén P., Gobakken T., Koch B., Næsset E., Tokola T., Maltamo, M. (2012) Comparative testing of single-tree detection algorithms under different types of forest. Forestry, 85: 27-40.
http://dx.doi.org/10.1093/forestry/cpr051

World Bank (2014). Forests.
http://www.worldbank.org/en/topic/forests [cited October 9, 2014].

Venables W.N., Ripley, B.D. (2002). Modern applied statistics with S. Fourth edition. Springer.
http://dx.doi.org/10.1007/978-0-387-21706-2

Xu Q., Hou Z., Tokola T. (2012). Relative radiometric correction of multi-temporal ALOS AVNIR-2 data for the estimation of forest attributes. ISPRS Journal of Photogrammetry and Remote Sensing 68: 69-78.
http://dx.doi.org/10.1016/j.isprsjprs.2011.12.008

Xu Q., Hou Z., Maltamo M., Tokola T. (2014a). Calibration of area based diameter distribution with individual tree based diameter estimates using airborne laser scanning data. ISPRS Journal of Photogrammetry and Remote Sensing 93: 65-75. http://dx.doi.org/10.1016/j.isprsjprs.2014.03.005

Xu Q., Hou Z., Maltamo M., Tokola T. (2014b). Retrieving suppressed trees from model-based height distribution by combining high and low density airborne laser scanning data. Canadian Journal of Remote Sensing 40: 233-242. http://dx.doi.org/10.1080/07038992.2014.935933

Yu X., Hyyppä J., Holopainen M., Vastaranta M. (2010). Comparison of area-based and individual tree-based methods for predicting plot-level forest attributes. Remote Sensing 2: 1481-1495. http://dx.doi.org/10.3390/rs2061481