Norwegian University of Life Sciences
Faculty of Environmental Science and Technology
Department of Ecology
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Philosophiae Doctor (PhD)
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Methods for estimating volume, biomass and tree species diversity using field inventory and airborne laser scanning in the tropical forests of Tanzania

Metoder for estimering av volum, biomasse og treslagsdiversitet ved hjelp av feltinventering og flybåren laserskanning for tropiske skoger i Tanzania

Ernest William Mauya

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Ås, 28-08-2015.

Ernest William Mauya

Contents

Abstract

Deforestation and forest degradation in the tropical countries have reduced the extent of forest and woodlands, which conserve biodiversity, provide essential resources to people and help in mitigating climate change through carbon sequestration. Forest conservation projects need methods for estimating tree species diversity to effectively generate information necessary for implementing biodiversity management plans, while greenhouse gas reduction programmes such REDD+ (Reducing Emissions from Deforestation and Forest Degradation) require robust methods to estimate volume and aboveground biomass (AGB). Such methods are also needed in the context of general forest management planning. The four papers included in this thesis are aimed to test and evaluate methods for estimating volume, AGB, and tree species diversity using field and remotely sensed data in the tropical forests and woodlands of Tanzania. In paper I, tree models for estimating total, merchantable stem, and branch volume applicable for the entire miombo woodlands of Tanzania were developed. In Paper II, III, and IV the potential of airborne laser scanning (ALS) data for predicting AGB and measures of tree species diversity was tested and evaluated. The results have shown that ALS data can be used for predicting AGB with reasonable accuracy by using both parametric and non-parametric approaches. Effects of plot size on the AGB estimates were investigated and the results indicated that the prediction accuracy of AGB in ALS-assisted inventories improved as the plot size increased. Finally, the results showed that measures of tree species diversity and particularly tree species richness and Shannon diversity index, can potentially be predicted by using ALS data.

List of papers

This PhD thesis is based on the following papers which are referred to by their roman numerals (I-IV).

Paper I

Mauya, E.W., Mugasha, W.A., Zahabu, E., Bollandsås, O.M., Eid, T., 2014. Models for estimation of tree volume in the miombo woodlands of Tanzania. Southern Forests: a Journal of Forest Science 76, 209-219.

Paper II

Mauya, E.W., Ene, L., Bollandsås, O.M., Gobakken, T., Nasset, E., Malimbwi, R., Zahabu, E., 2015. Modelling aboveground forest biomass using airborne laser scanner data in miombo woodlands of Tanzania. Carbon Balance and Management (under review).

Paper III

Mauya, E.W., Hansen, E., Gobakken, T., Bollandsås, O.M., Malimbwi, R., Næsset, E., 2015. Effects of field plot size on prediction accuracy of aboveground biomass in airborne laser scanning-assisted inventories in tropical rain forests of Tanzania. Carbon Balance and Management 10, 1-14.

Paper IV

Mauya, E.W., Bollandsås, O.M., Eid, T., Gobakken, T., Næsset, E., 2015. Modelling and predicting measures of tree species diversity using airborne laser scanning data in miombo woodlands of Tanzania (manuscript).

1.0. Introduction

1.1. Tropical forests and REDD+

Tropical forests account for about 44% of the global forest area (McMahon, 2014). They encompass various forests types including rainforests, mangroves, montane forests, dry forests, and wooded savanna systems (woodlands) (Brandon, 2014; FAO, 2001; Lewis, 2006). Tropical forests are critical to local, regional, and global climate cycles principally through the moisture and carbon that they store, where approximately 271 ± 16 Pg C (Pg, 1Pg = 1.0^9 tons) (Grace et al., 2014) is stored in the tropical forests. Beyond carbon storage, tropical forests also contain higher levels of biodiversity than any other type of forests on the planet, holding 2/3 of land-based species (Brandon, 2014). Additionally, these forests provide a wide range of ecosystem services including timber, fuelwood, water purifications, and they have cultural and religious values as well. These benefits are crucial to the more than 50 million people who live in tropical forests and many millions of others who are indirectly dependent on the services from these forests (Hewson et al., 2014). Despite their potential, tropical forests are threatened by deforestation and forest degradation, mainly caused by human induced activities such as timber and fuelwood extraction, conversion of the forest to land uses for agriculture farmland, oil and gas production, mining, and infrastructure development (Lanly, 2003; Venter and Koh, 2012). Loss of biodiversity and increase in global carbon emissions are the major consequences of deforestation and forest degradation in the tropics, which in turn possess a threat to future global climate stabilization. It is estimated that between the years 1990 and 2010 land uses in the tropics including both deforestation and forest degradation, have emitted about 1.4 Pg C per year which is equivalent to 15% of the global human induced carbon emissions (Houghton, 2013).

To address the concerns over the conservation of tropical forest and to mitigate adverse effects of carbon emissions on global climate change, a compensation-based policy mechanism to reduce emission from deforestation (RED), was firstly introduced to United Nations Framework Convention on Climate Change (UNFCCC) in 2005, at the 11th Conference of Parties (COP) in Montreal (Wertz-Kanounnikoff and Kongphan-apirak, 2009). Later in 2007, at the 13th COP held in Bali, RED was expanded to include emissions from forest degradation and hence became REDD. In 2008, at the 14th COP in Poznan, REDD was finally expanded to REDD+ by including aspects related to forest conservation, sustainable management, and enhancement of forest carbon stock, thereby marking the addition of the “plus” to REDD, i.e. REDD+ (Birdsey et al., 2013).

Under the REDD+ mechanism, participating developing countries receive financial incentives (i.e. payments) for their verified success (i.e. performance) in reducing carbon emissions from forest-related activities as well as enhancing the removal of the carbon from the atmosphere (i.e. enhancing the carbon stock) (Goetz et al., 2015). This mechanism has been accepted as a low-cost and promising approach for mitigating climate change (Angelsen and Brockhaus, 2009) that also will secure many ecological functions of forests, including biodiversity conservation and provision of a number of ecosystem services. The interest among developing countries to prepare for hosting REDD+ projects, and in testing the potential mechanisms, has increased significantly since the initial discussions under UNFCCC in 2005.

In spite of the increasing attention drawn to the REDD+ policy, and the large number of pilot projects currently being implemented in the countries, several key aspects of the REDD+ policy have not yet been fully resolved in many tropical countries. They include, among others, development of baseline scenarios (i.e. reference levels against which the enhanced storage of carbon can be measured), and designing credible and efficient forest carbon Measuring, Reporting, and Verification (MRV) systems (Mattsson et al., 2012). Such aspects are fundamentally important because payments for carbon offsets (i.e. financial benefits) under the REDD+ mechanism rely heavily on the reliable estimates of forest carbon stocks and changes over time (Goetz et al., 2015).

Development of MRV systems for REDD+ implementation requires accurate methods for estimation of above ground biomass (AGB) as the primary variable for computing carbon stored in forests. According to Lu (2006), estimation of AGB can be done by using methods based on (1) field measurements, (2) geographical information systems (GIS), and (3) remote sensing. Field based approaches are the most accurate methods for estimation of AGB. However these methods are often time consuming, labor intensive, difficult to implement in the remote areas and they are impossible to apply for large geographical areas with reasonable cost and precisions (Lu et al., 2014; Saarela et al., 2015). GIS-based methods are also difficult because of problem in obtaining good quality ancillary data (Lu, 2006; Lu et al., 2014). On the other hand, remote sensing-assisted methods have gained a wide acceptance for AGB estimations, given their ability to account for limitations related to sample size, time lines, expenses, and accessibility. Moreover, remotely sensed data can provide a synoptic view over large areas and greatly increase the efficiency and usefulness of limited conventional field-based methods (Patenaude et al., 2005; Sinha et al., 2015). Remotely sensed data are therefore considered to play a fundamental role in the development of cost-efficient methods for AGB estimations needed in REDD+ MRV systems (Asner et al., 2012a;

GOFC-GOLD, 2011). Thus it is important to understand and quantify the contribution of different remotely sensed data on improving the estimates of AGB under different forest conditions. This may guide investment decisions in development of cost–efficient MRV systems in the tropical countries. Remotely sensed data have also been reported to be useful for monitoring and assessing different aspects of forests biodiversity, including tree species diversity (e.g. Leutner et al., 2012; Oldeland et al., 2010). In light of the current need for assessment of the impact of REDD+ on biodiversity conservation (Ehara et al., 2014; Vanderhaegen et al., 2015), remotely sensed data may provide valuable information for biodiversity assessment at spatial scales that hardly can be provided by conventional field-based methods at reasonable costs.

Despite the potential of the remote sensing-based methods for REDD+ related issues including sustainable forest management and biodiversity conservation, there has been scarcity of relevant studies in relation to tropical forests, particular in East Africa. Because of that, the Tier-3 approach to carbon inventory that was proposed by Intergovernmental Panel on Climate Change (IPCC) (Eggleston et al., 2006) and further elaborated by Gibbs et al. (2007) can be challenging to implement in many tropical contries in Africa. However, data from airborne laser scanning (ALS) - one among the most promising remote sensing techniques for precise estimation of AGB and other forest properties, have potentials for successful application to tropical forests.

1.2. Status of forest resources and REDD+ MRV system in Tanzania

Tanzania main land has a total land area of about 88.3 million ha (MNRT, 2015). Forests and woodlands occupy about 48.1 million ha, equivalent to 55% of the total land area. About 44.7 million ha, or 92% of the total forest area, is classified as woodlands, out of this miombo woodlands make up by far the largest part. The remaining forest areas are mainly occupied by tropical high (mountain) forests, lowland forests, mangrove, and plantation forests . Like in other tropical countries, deforestation and forest degradation are the major challenges for management of forest and woodland resources in Tanzania (Mbwambo et al., 2012). It is estimated that Tanzania lost an average of 403,350 ha or 0.97% of its forest cover per year from 1990 to 2010 (FAO, 2010a). This was mainly a result of heavy pressure from agricultural expansion, livestock grazing, wild fires, and general over-exploitation of wood resources due to different human activities (Blomley and Iddi, 2009; FAO, 2010b). The Tanzanian government has implemented several initiatives to address the challenges of deforestation and forest degradation through adoption of legal frameworks and implementation of participatory forest management regimes (Mbwambo et al., 2012; Treue et al., 2014). The main sources of finance for these initiatives have been obtained from charges levied on the major forest products and services, state budget allocation to the local forestry administrations, and grants obtained from development partners. However, in the recent decade limited financial resources are compelling the country to identify innovative financing mechanisms to support forest management activities outside these traditional channels (URT, 2012).

The emergence of REDD+ under UNFCCC has therefore been considered as an exceptional opportunity for the Tanzanian government to obtain financial resources that will help to improve the management of the forest resources by reducing deforestation, forest degradation, and loss of biodiversity (Araya and Hofstad, 2014; Zahabu et al., 2007). To date Tanzania has already participated in the REDD+ readiness mechanism of the United Nations Collaborative Program on Reducing Emissions from Deforestation and Forest Degradation in Developing Countries (UN REDD), which aimed to enhance government capacity to coordinate, implement, and monitor the REDD+ process (Chiesa et al., 2009). The Tanzanian government also in 2008 signed a letter of intent with the Norwegian government to establish a partnership to address climate change. This partnership intends to build capacity and create carbon accounting methodologies, as well as to support projects that directly seek to reduce deforestation and forest degradation. As a result, Tanzania has become a pioneer among the REDD+ countries with a larger number of sub-national REDD+ projects than any other African country (Lin et al., 2014).

Additionally, Tanzania, with financial support of the Government of Finland and the FAO-Finland Forestry Programme, between 2009 and 2014 established and conducted a national forest inventory, namely the National Forestry Resources Monitoring and Assessment (NAFORMA), with permanent sample plots distributed all over the country (MNRT, 2015). NAFORMA sample plots forms the backbone of a system for estimation of the current state of the forest resources needed for national forest policies and general forest management as well as inputs for monitoring changes in carbon stock needed for the development of national carbon MRV systems under REDD+ implementation. NAFORMA data may also be used for biodiversity monitoring since much information related to biodiversity have been collected as part of the field campaign. This may generate an important platform for assessment of the impact of REDD+ on enhancing biodiversity conservation and other related policies that are aimed towards conservation planning.

1.3. Rationale for the study

Irrespective of the well updated national forest inventory data (i.e. NAFORMA), reliable information on forest resources in Tanzania will in the future heavily depend on the availability of accurate methods for quantification of different forest attributes including volume, AGB, carbon stock, and tree species diversity. For volume, AGB, and carbon stock, relevant tree models covering different vegetation types of Tanzania are needed for computation of plot-based estimates, which is a fundamental part of any forest inventory. However, such models are often limited in Tanzania. Besides that, for development of cost-efficient forest monitoring system needed for REDD+MRV, conservation planning, and general forest management decision-making, methods based on remote sensing techniques are needed for enhancing the precisions of NAFORMA plot-based estimates (MNRT, 2015; Tomppo et al., 2014). Unfortunately, to date empirical evidence on the accuracy and performance of remote sensing-based methods for estimation of different forest attributes in Tanzania are limited. Most of the reported remote sensing-based studies have focused on mapping and quantification of forest cover changes using satellite-based remote sensing (Lupala et al., 2015; Swetnam et al., 2011; Tabor et al., 2010), with little attention on estimation of forest attributes, like those mentioned above. Furthermore, more recently developed techniques such as ALS, which has gained widespread application in forests in other parts of the world, has to date not been validated for forest attribute estimation purposes in Tanzania. The current thesis aims at filling some of this gap.

2.0. Research objectives

The main objective of this study was to test and evaluate methods for estimating forest resources as a basis for forest management decision-making and development of a REDD+ MRV system in Tanzania. The thesis is divided into the following sub-objectives addressed in four different papers;

1. To develop allometric models for estimating tree volume in miombo woodlands of Tanzania (Paper I).
2. To model the relationship between AGB and ALS data in miombo woodlands of Tanzania and assess the model performance (Paper II).
3. To assess effects of field plot size on prediction accuracy of AGB in ALS-assisted inventories in tropical rainforests of Tanzania (Paper III).
4. To model and predict measures of tree species diversity using ALS data in miombo woodlands of Tanzania (Paper IV).

3.0. Background

3.1. Analytical conceptual framework of the thesis

Accurate information on forest resources, needed for making informed decisions on forest management as well as for development of REDD+ MRV systems, requires application of reliable methods for estimation of different forest attributes. Field data and remotely sensed data are the primary data sources for development of such methods. In the conceptual framework presented in Figure 1, data on stem and branch volume of trees derived from destructive sampling are obtained from the field data. Such data are used as an input to develop allometric tree volume models using ordinary least square (OLS) and nonlinear least square (NLS) regression techniques. Field data also provided plot-based information on AGB in Mg per ha, AGB in Mg per ha on different field plot sizes, and measures of tree species diversity. The information is combined with ALS metrics (derived from ALS data) using different statistical methods including; OLS, linear mixed effects models (LMMs), and k-nearest neighbors (*k*-NN). The outputs are methods in terms of prediction models based on the ALS data for estimating AGB and measures of tree species diversity. These models in combination with allometric tree volume models form methods that can be used for estimation of forest resources needed for making informed decisions in forest management and for development of a REDD+ MRV system.

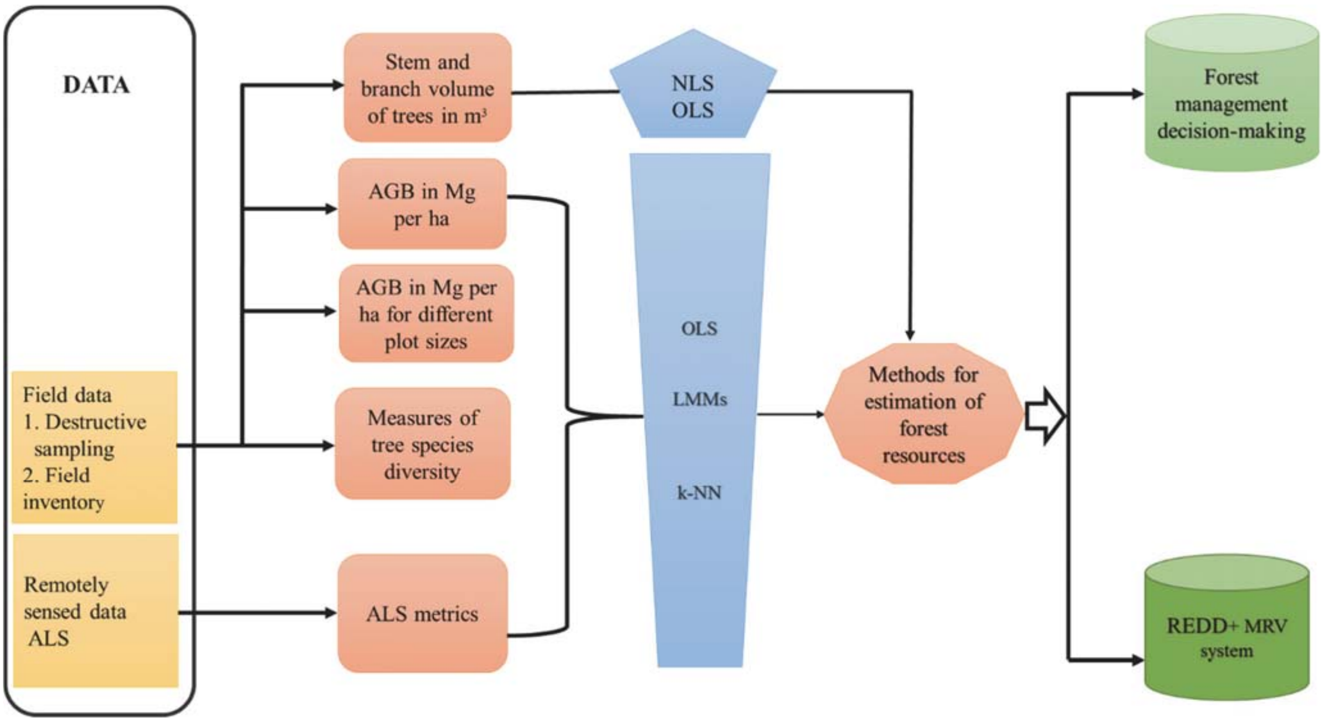

Figure 1. Analytical conceptual framework for the thesis.

3.2. Tree AGB and volume models

Allometric tree AGB and volume models (models for individual trees) are crucial for quantifying many forest products and services such as commercial timber volume, bioenergy volume, and carbon stock. Development of tree AGB models usually involves harvesting and weighing a sample of trees across a range of diameter and/or height classes, and then estimating the parameters of a model relating AGB to diameter at breast height (*dbh*) or a combination of *dbh* and total tree height (*ht*) using regression techniques. Such models can then be used to estimate AGB using *dbh* or combinations of *dbh* and *ht* measured in forest inventories. Another approach is to estimate AGB based on volume and subsequently use an expansion factor (Birdsey et al., 2013). The latter approach of using tree volume models and expansion factors has been used by most of the countries for reporting national forest biomass (FAO, 2010a), as compared to the direct use of tree AGB models.

The process of developing tree AGB and volume models is time consuming and expensive as it relies on destructive sampling as previously mentioned. In tropical forests, where there is a wide range of different tree species, development of allometric tree AGB and volume models valid for large geographical areas has always been a challenge. For dry tropical forests and woodlands, relatively few models for estimating tree AGB and volume have been developed as compared to moist and wet tropical forests (Henry et al., 2011). For the miombo woodlands of Tanzania, Malimbwi et al. (1994), Chamshama et al. (2004), and Mwakalukwa et al. (2014) have developed volume and AGB models. The applicability of these models is, however, limited by the sample size and tree size ranges of the data used for modelling. Furthermore, the models cover only limited geographical ranges of miombo woodlands and thus none of them can be regarded as general models covering the whole country. This is obviously a challenge for the development of a sustainable forest management and an effective forest monitoring system needed for implementation of a REDD+ policy, irrespective of the availability of more recently updated forest inventory data in the country. Thus, robust tree models in terms of geographical and tree size coverages are needed both for REDD+ reporting and for supporting the development of other decision-support tools for forest management (Mugasha, 2014). General tree AGB models for miombo woodlands covering the entire miombo woodlands of Tanzania have recently been developed by Mugasha et al. (2013), but no general tree volume models exist. The main objective of Paper I was therefore to develop tree volume models for miombo woodlands of Tanzania. The specific objectives were to (1) develop both general and site specific models, (2) develop models for total volume, merchantable stem volume, and branch volume, and (3) compare the performance of the general models with models developed previously by other researchers.

3.3. Remote sensing support for forest inventory

As part of the requirements for development of a cost effective REDD+ MRV system, the application of remote sensing techniques has been considered as a relevant option for improving the statistical precision of AGB estimates (GOFC-GOLD, 2011). Likewise, for deriving information needed for forest management at different spatial scales, ranging from local to national levels. Types of remote sensing data that have been used for estimation of AGB include optical, synthetic aperture radar (SAR), and ALS (De Sy et al., 2012). However, the performance of optical remote sensing, and to a lesser extent SAR, in tropical forests are affected by forest structure complexity, canopy density, and cloud coverage (Gibbs et al., 2007). As a result of this, both of the two remote sensing techniques saturate at lower AGB levels, say, around 20-250 Mg ha^{-1} of AGB (Kaasalainen et al., 2015; Patenaude et al., 2005), although SAR data have shown to saturate at higher values as compared to optical remote sensing (Lucas et al., 2007; Sinha et al., 2015).

ALS has proved to overcome some of the limitations of other remote sensing techniques, because of its ability to retrieve three-dimensional (3D) forest structures at high spatial resolution. Such information is more useful for forest inventories as well as for ecological applications than the information from any of the other remote sensing techniques (Coops et al., 2004; Lefsky et al., 2002; Vauhkonen et al., 2014). The strengths of ALS in estimating forest attributes have been investigated from both research perspective and operational perspective, and ALS is currently used in operational management inventories in the Nordic countries (Vauhkonen et al., 2014). Promising results from the tropical forests of Asia and south America have also been reported (e.g. Asner et al., 2012b; Hou et al., 2011; Mascaro et al., 2012). In the tropical forests of Africa, the application of ALS is at very early stages despite its wide acceptance as a potential tool for AGB estimations necessary for the development of a MRV system under REDD+ initiatives. In Tanzania, this thesis is one among the earlier works to test the potential of ALS for estimating AGB.

3.3.1. Modelling and predicting AGB using ALS data

Application of ALS for estimation of forest attributes including AGB has commonly been done by using two methods, namely; the individual tree-based approach and the area-based (ABA) approach (Hyyppä et al., 2008; Vauhkonen et al., 2014). When using the individual tree-based approach, individual trees are detected and tree-level attributes, such as AGB, height, and volume, are measured or predicted from the ALS data, i.e. the basic unit is an individual tree. The potential of the individual tree-based approach has been demonstrated in different studies (e.g. Hauglin et al., 2012; Maltamo et al., 2004; Vauhkonen et al., 2010) in which forest attributes such as tree position, AGB, tree height, and volume have been accurately predicted. However, the individual tree-based approach requires denser ALS data, which then increases the ALS acquisition cost (Hyyppä et al., 2008). Furthermore, with the individual tree-based approach, linking a tree crown delineated from ALS data to a field-measured tree, requires positions of the tree measured in field. This might be a limitation in a complex ecosystem such as tropical forests, where the number of trees per unit area usually is larger than in temperate forests (Lu et al., 2014). In such a situation, the ABA is the most favored alternative. With the ABA, various metrics are extracted from the ALS data recorded on the field plot, and statistical models relating the ALS metrics and plot level forest variables are constructed. The models are then used to predict for example AGB for all areas covered by ALS data (Næsset, 2014).

A "wall-to-wall" ABA is commonly used in operational forest inventories in the Nordic countries (Næsset, 2014), mainly because of lower cost and maturity of the approach as compared to the individual tree-based approach. However, for larger territories such as entire regions (districts) or even nations, it is currently not economically feasible, and most likely not required from an accuracy perspective, to provide wall-to-wall data. It has therefore been proposed to use just a sample of ALS data collected along some selected flight lines over the territory of interest (McRoberts et al., 2014). These flight lines should primarily be distributed over existing ground plots according to sound statistical principles, allowing the development of models that tie the AGB on the ground to the ALS data. These models are then used to predict AGB over the entire area covered by ALS strips, and subsequently these predictions are used for final estimation of AGB for the area of interest using either design-based model-assisted or model-dependent inferential frameworks (e.g. Gobakken et al., 2012; Gregoire et al., 2010). Thus, the quality of the AGB estimates produced by ALS-based inventories relies heavily on the development and application of appropriate predictive AGB models.

Many statistical techniques have been tested for predicting AGB when using ALS data and they can be grouped into two broad categories: parametric and non-parametric. Each method has its own strengths and requirements for data inputs that have created challenges in identifying the optimal method for improving prediction accuracy of AGB when using ALS data (Lu et al., 2014). Because of that, comparative analysis of different methods such as OLS, random forests, and nearest neighbor techniques have been conducted in temperate and boreal forests (e.g. Bollandsås et al., 2013; Gagliasso et al., 2014; Gleason and Im, 2012). All these efforts were aimed at improving performance of ALS-aided inventories in terms of prediction accuracy of the models. Unfortunately, the majority of these studies have mainly focused on temperate and boreal forests as indicated above – forests that may differ quite much in structure, composition, and internal distribution of AGB between different tree and canopy elements compared to tropical forests. In the tropical forests, particular those of Africa, the reported studies have so far focused on the use of parametric methods (e.g. Asner et al., 2012b; Hansen et al., 2015), and neither of them has been conducted in the miombo woodlands of Tanzania. The main objective of Paper II was therefore to address this knowledge gap by assessing the performance of parametric and non-parametric methods for modeling and predicting AGB using ALS data in the miombo woodlands of Tanzania. The specific objectives were to (1) compare the performance of parametric and non-parametric methods in modelling and predicting AGB using ALS data, and (2) assess the effects of post-stratification on the prediction accuracy of the parametric models.

3.3.2. Effects of field plot size on prediction accuracy of AGB in ALS-assisted inventories

Previous studies in temperate, boreal, and tropical forests have indicated that field plot size is an important sampling parameter that should be taken into account when designing ALS-assisted inventories (e.g. Frazer et al., 2011; Mascaro et al., 2012; Næsset et al., 2015). Model prediction errors have been reported to decline with increase in plot size, although the ranges of the plot sizes were varying from one forest type to another. For example, plots sizes ranging from 0.02 ha (Næsset et al., 2011) to 0.3 ha (Yao et al., 2014) have been reported from temperate and boreal forests, while for tropical forests plot sizes up to 1 ha have often been recommended (e.g. Asner and Mascaro, 2014; Mascaro et al., 2011; Zolkos et al., 2013). In all cases the studies indicated that an increase in plot size resulted in better prediction accuracy because of reduction of the errors caused by the discrepancies between ground and ALS-based measurements (Zolkos et al., 2013).

Given the potential of ALS for development of REDD+ MRV systems, it is important to determine the plot size ranges that should be considered for designing future ALS-assisted inventories and to address MRV standards in different forest types in tropical forests. A field plot size equivalent to a radius of 15 m has commonly been used in field-based forest inventories in Tanzania (Tomppo et al., 2014). For ALS-assisted inventories, however, such a plot size may not result in sufficiently good prediction accuracy due to the challenges discussed above, and especially so in high forests where the potential for discrepancies between large trees measured on the ground (tree stems inside the plot) and ALS measurements of tree crowns (crowns rather than stems inside the vertical extension of a plot) are substantial. Therefore the main objective of Paper III was to assess the effects of field plot size on prediction accuracy of AGB in ALS-assisted inventories in tropical rainforests of Tanzania. The specific objectives were to (1) examine the effects of field plot size on AGB regression model quality, (2) assess plot boundary effect and its impact on model quality based on the field data, and (3) quantify the precision of ALS-assisted estimates of AGB relative to field-based estimates of AGB assuming the same design for different plot sizes.

3.3.3. Modelling and predicting measures of tree species diversity using ALS data

ALS has gained wide acceptance also in ecologically-based studies in the recent decades due to its ability to quantify the3D structure of forests, which is of particular interest in characterizing species diversity of different taxonomic groups in the forest (Müller and Vierling, 2014). Several studies have explored the potential of ALS to model the assemblage, compositions and diversity of insects, spiders, and birds (e.g. Muller et al., 2009; Vierling et al., 2011; Vogeler et al., 2014). Measures of tree species diversity, including Shannon diversity index and tree species richness have also been reported to be successfully predicted and classified using ALS data (Leutner et al., 2012). Despite the encouraging results from this body of work, few studies have estimated or analyzed the relationship between measures of tree species diversity and ALS data in tropical forests. Lack of ALS data and complexity of the structure, due to the high diversity of tree species in tropical forests, are among the possible reasons for the low number of such studies in tropical forests. In Tanzania, no previous studies have attempted to use ALS data for modelling and predicting measures of tree species diversity. As stated above, remotely sensed data may provide valuable information for biodiversity assessment at spatial scales that hardly can be provided by conventional field-based methods at reasonable costs. The main objective of Paper IV was therefore to assess if ALS data can be used to predict measures of tree species diversity in the miombo woodlands of Tanzania. The specific objectives were to (1) examine the performance of parametric and non-parametric methods for predicting measures of tree species diversity using ALS data, and (2) assess the prediction accuracy of measures of tree species diversity across different vegetation types.

4.0. Materials and methods

4.1. Study sites

The study sites were located in five different administrative regions in Tanzania (Figure 2) in order to cover the different objectives of the thesis. Out of the five sites, four were mainly dominated by miombo woodlands (i.e. Manyara, Tabora, Katavi, and Lindi) and one (i.e. Tanga) was mainly dominated by tropical rainforest.

Miombo woodlands

Miombo woodlands make up a significant proportion of the forested land in Tanzania. The largest concentration of the miombo woodlands in Tanzania is found in the western and southern part of the country (Abdallah and Monela, 2007). Miombo woodlands also extend to other African countries including Angola, Democratic Republic of the Congo, Mozambique, Malawi, Zambia, and Zimbabwe (Dewees et al., 2010). According to White (1983), miombo woodlands may be divided into two major distinct groups; dry and wet miombo woodlands. Dry miombo woodlands occur in areas receiving less than 1000 mm rainfall annually while wet miombo woodlands occur in areas receiving more than 1000 mm. The vegetation of the miombo woodlands is floristically rich characterized by the overwhelming dominance of *Brachystegia*, *Julbernardia*, and *Isoberlinia* tree species belonging to the Fabaceae (legume) family (Backéus et al., 2006). In mature miombo, these species comprise an upper canopy layer made of 10-20 m high trees and a scattered layer of sub-canopy trees. The understory layer is discontinuous and is composed of broadleaved shrubs and suppressed saplings of canopy trees. A sparse, but continuous herbaceous layer of grasses, forbs, and sedges dominate the ground-layer (Campbell et al., 2007). Miombo woodlands soils are typically acidic, highly leached and low in organic matter (Frost, 1996).

Tropical rainforest

Most of the Tanzanian tropical rainforests occurs primarily on mountain slopes and are confined to the Eastern Arc Mountains (EAM) system, which is a chain of mountains that stretches from Makambako, southwest of the Udzungwa Mountains in southern Tanzania, to the Taita Hills in south-coastal Kenya. The most important parts of EAM with rainforests are Southern Pare, West Usambara, East Usambara, Nguu, Nguru, Ukaguru, Uluguru, Rubeho, Malundwe, Uduzungwa, Mahenge, and Matengo (Bjørndalen, 1992). Since these forests are spatially isolated from each other, they have more diverse flora and fauna than many other ecosystems. The most important functions of this type of forests are to serve as watershed catchments areas and soil protection areas. Rainfall in most of these rainforests is heavy, with a short dry season. In this thesis, Amani Nature Reserve (ANR), located in East Usambara, was selected as a site representing the typical tropical rainforest existing in Tanzania. ANR is dominated by trees of genera *Afrosersalisia*, *Allanblackia*, *Celtis*, *Drypetes*, *Ficus*, *Isoberlinia*, *Leptonychia*, *Macaranga*, *Myrianthus*, *Newtonia*, *Parinari*, *Sorindeia*, *Strombosia*, *Syzygium*, and *Tabernaemontana* (Hamilton and Bensted-Smith, 1989). Generally, the forest is denser and is often regarded as one among the tropical rainforests with highest values of AGB (e.g. Marshall et al., 2012; Munishi and Shear, 2004), ranging from 43.2 to 1147.1 Mg ha^{-1} (Hansen et al., 2015) in ANR in particular. Thus, the selection of this site was aimed to demonstrate the typical challenges that would be expected when using ALS in tropical rainforests with high AGB densities.

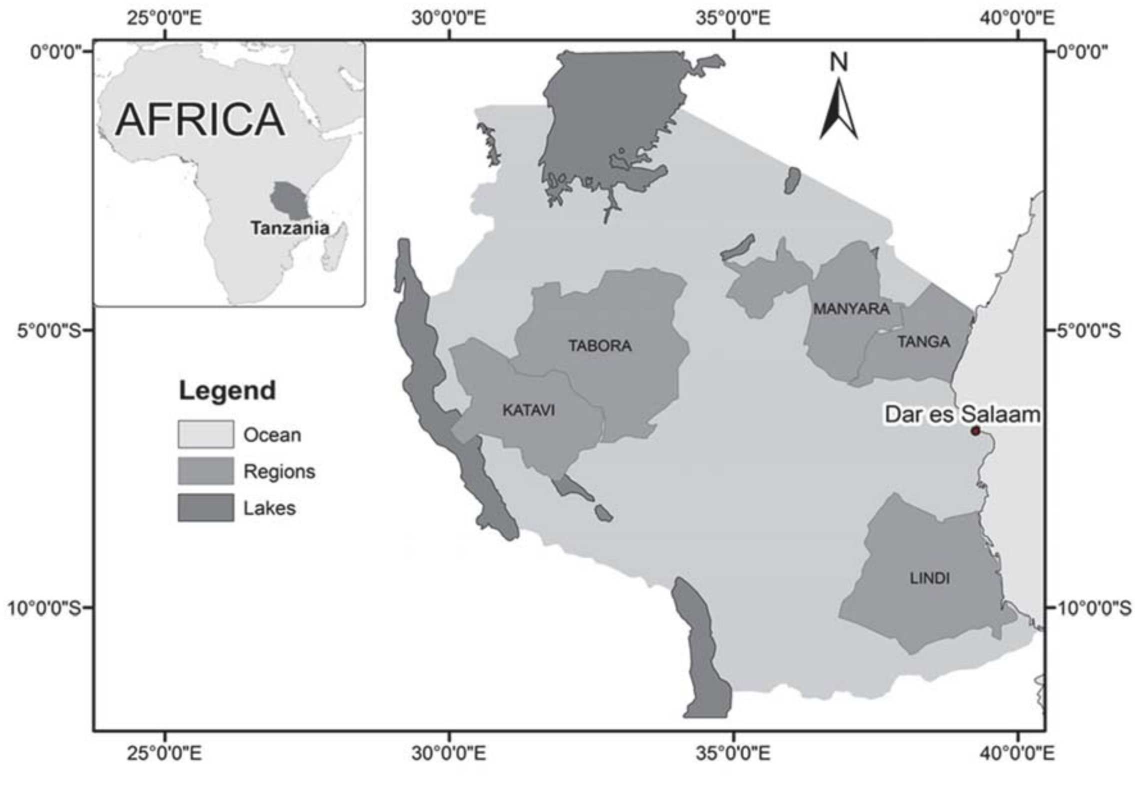

Figure 2. Location of the study sites in five administrative regions of Tanzania.

4.2. Data collection

Three types of data, comprising a total of five different datasets, were used in this study, i.e. one dataset based on destructive sampling of trees, two field inventory datasets, and two remotely sensed datasets. Details regarding these datasets are described below.

4.2.1. Destructive sampling data

The dataset based on destructive sampling of trees was used in Paper I. The data were collected from one site in each of the following regions: Manyara, Tabora, Babati, and Lindi (Figure 2) and the selected trees have previously been used to develop general allometric above- and belowground biomass models for miombo woodlands of Tanzania (Mugasha et al., 2013). The sites covered a wide range of growing conditions in the miombo woodlands of Tanzania. To secure an appropriate distribution of sample trees with regard to tree sizes and tree species, information from previous systematic sample plot inventories carried out for each of the four sites was used as guidance when selecting the trees. For each site, sample plots with 15 m radius were established on a systematic grid, and from these plots one or two trees were selected purposely for destructive sampling. Prior to tree felling, all sample trees were identified for species name (local and scientific name), and *dbh* was measured with calipers and diameter tapes while *ht* was measured with Suunto and Vertex hypsometers. A total of 158 trees, including 55 different tree species distributed in the four sites were sampled; Manyara (39), Tabora (40), Lindi (39) and Katavi (40). As part of the destructive sampling procedure, all sample trees were separated into merchantable stem (tree section suitable for timber) and branches including top (to minimum diameter of 2.5 cm).

The volume of each log was calculated by multiplying the cross sectional area at the midpoint of each log with its length. Volume of merchantable stem and branches for a tree was obtained by summing the volumes of the logs of the respective sections for that specific tree. Total tree volume was finally obtained through summation of merchantable stem and branches volumes.

4.2.2. Field inventory data

Two datasets consisting of field inventory data (sample survey plots) were collected. Field inventory dataset 1 was used in Papers II and IV. This dataset was based on the plot locations of the sample plots that were initially established and measured by NAFORMA crews as part of the national forest inventory in Liwale district, Lindi-region, in June 2011. The field work for dataset 1 was conducted eight months later after the completion the initial measurement done by NAFORMA. The aim of the field work was to accurately record the positions of the field plots using high precision positioning equipment and to re-measure the NAFORMA field sample plots in order to have temporal consistence with the time of the ALS data acquisition. Measurements on the plots followed the same protocol as used by NAFORMA in 2011. Field measurements were collected for 65 NAFORMA clusters, each having a total of ten sample plots per cluster (MNRT, 2011). However, in this field work two sample plots for each cluster were omitted because they were outside the corridors (swaths) designated for the ALS data acquisition. Therefore eight plots per cluster were re-measured for the current analysis. On each plot, the (x, y) center coordinates were determined using differential post-processing of dual-frequency Global Positioning System (GPS) and Global Navigation Satellite System (GLONASS) measurements. On each plot, tree species name and *dbh* were recorded following the concentric plot design for the 15 m radius plots described in MNRT (2011). Height measurements were acquired for every fifth tree in the cluster.

AGB for each tree was estimated using allometric models developed by Mugasha et al. (2013). The AGB of the individual trees were then summed to obtain estimates for each plot, which were used in Paper II. The same dataset was used in paper IV to compute measures of tree species diversity, i.e. tree species richness and Shannon diversity index based on the information collected from the tree species names.

Field inventory dataset 2 was used in Paper III. A total of 30 circular field plots were established in ANR and distributed along elevation ranges from 200 to 1000 m above sea level. On each of the 30 plots, all trees with *dbh* ≥ 5 cm were callipered and registered for botanic names, local names, and the horizontal distance to the plot center. The horizontal distance was measured from plot center to the front of each tree using a Vertex hypsometer, and half of the tree diameter was added to get the total horizontal distance (i.e. radius). The distance measures were used to generate different plot sizes within the limit of the maximum radius. The maximum radius varied among the 30 plots due to the somewhat unequal performance of the Vertex hypsometer in the different plots (different tree densities etc); 31 m (22 plots), 28 m (2 plots), 26 (1 plot), and 25 m (5 plots). For this study, a minimum radius of 7.98 m and a maximum of radius 30.90 m was used, which is equivalent to the plot sizes 200 m^2 and 3000 m^2, respectively. Three trees (largest, medium, and smallest) per plot were measured for height using a Vertex hypsometer. Precise field coordinate positions for each plot center were determined by means of the GPS+GLONASS receivers and procedures describe above. AGB was calculated for individual trees within each plot using an allometric model developed from destructively sampled trees in ANR by Masota et al. (2015). The values were finally scaled to per ha basis for each of the plot sizes.

4.2.3. Remotely sensed data

Two remotely sensed datasets based on ALS were used in this thesis: Remotely sensed dataset 1 was used in Papers II and IV, while remotely sensed dataset 2 was used in Paper III. Acquisition of the ALS measurements for dataset 1 was done by using a strip sampling approach covering about 26% of the study area in Liwale district. For dataset 2, the ALS measurements were acquired over the entire study area of ANR (i.e. wall to wall). Characteristics of the two remotely sensed datasets are shown in Table 1.

The initial processing of all the ALS data was accomplished by the contractor (TerraTec AS, Norway). Then several ALS metrics consisting of both height and canopy density variables were computed from the ALS data following the procedures described by Næsset (2004) and Gobakken et al. (2012).

Table 1. Characteristic of the remotely sensed datasets.

Remotely sensed dataset	ALS data characteristics	
1	**Acquisition settings**	
	Acquisition date	10 February to 07 March 2012.
	Platform	Cessna 404
	Canopy conditions	Leaf-on conditions
	Flying altitude	1200 m
	Flying speed	77.2 ms^{-1}
	Sensor settings	
	Sensor	Leica ALS-70
	Pulse repetition frequency	193 kHz
	Scan frequency	36.5 Hz
	Pulse density	1.8 points m^{-2}
2	**Acquisition settings**	
	Acquisition date	19 to 25 January and 2-18 February 2012
	Platform	Cessna 404
	Canopy conditions	Leaf-on conditions
	Flying altitude	800 m
	Flying speed	70 ms^{-1}
	Sensor settings	
	Sensor	Leica ALS70
	Pulse repetition frequency	339 kHz
	Scan frequency	58.6 Hz
	Pulse density	10.6 points m^{-2}

4.3. Data analyses

Different statistical techniques and analyses were employed in order to address the objectives of the individual papers.

Paper I

OLS and NLS regression techniques were used for fitting the tree volume models. Four model forms were selected and tested based on previous studies and, two of the model forms included *dbh* only as independent variable while the other two included both *dbh* and *ht*. Leave-one-out cross–validation (LOOCV) was used to evaluate the performance of the models. For each model, relative root mean square error (RMSE) and mean prediction error (MPE) were calculated based on the values from the LOOCV. Additionally, pseudo-R^2 was computed as an indicator of model fit. Previously developed tree volume models, which have been applied in Tanzania and in the neighboring countries, were also evaluated on our dataset and compared with the developed general model for total tree volume. Site-specific and tree sectional models (i.e. branch and merchantable stem) were also developed and evaluated using the same procedure as for the general model.

Papers II and IV

Parametric and non-parametric methods were used to develop statistical models for prediction of AGB and measures of tree diversity using ALS-derived metrics. Specifically LMMs and *k*-NN were used to account for the cluster structure. LOOCV was applied to compare the methods and asses accuracy of the predictions. LOOCV was performed at the cluster level to ensure that the hierarchical data structure was preserved during re-sampling (i.e. leave-one-cluster-out). Effects of post stratification were assessed by fitting separate models for different vegetation and land use types as defined in MNRT (2011).

Paper III

Multiple linear regression analysis with OLS was used to develop the statistical models relating the field reference AGB and the predictor variables from the ALS data for each of the plot sizes. In order to assess the performance of the models for each plot size, LOOCV was conducted. RMSE and MPE were used to assess the prediction accuracy across different plot sizes. In addition, the relative efficiency (RE) between ALS-assisted inventory and pure field-based inventory for different plot sizes was calculated as the ratio of the variance estimates of the field-based inventory relative to ALS-assisted inventory. Design-based and model-assisted variance estimators were used. RE values were then used to assess the efficiency gain by using ALS to assist in the estimation for different plot sizes.

5.0. Main findings and discussion

5.1. Tree volume models for miombo woodlands

In Paper I, tree volume models with *dbh* as independent variable and those that incorporate both *dbh* and *ht* were developed. The pseudo-R^2 of the general model with *dbh* only was 0.87 while for the model with both *dbh* and *ht* it was 0.88. Results from the LOOCV indicated that the RMSE value for the model with *dbh* and *ht* was lower as compared to the model with *dbh* only. Based on the results from the LOOCV, the model with both *dbh* and *ht* was considered as the best general tree volume model for miombo woodlands. The RMSE value of this model was 47.6% of the mean value and the MPE value was -0.6%. Both the pseudo-R^2 and the RMSE values were in line with most previous studies in the miombo woodlands and related vegetation types in Tanzania and nearby countries (e.g. Abbot et al., 1997; Chamshama et al., 2004; Malimbwi et al., 1994; Mwakalukwa et al., 2014). Site-specific models were also developed with pseudo-R^2 ranging from 0.77 to 0.95. The MPE values for the site-specific models were relatively small as compared to the values obtained when the general model was applied for the individual sites. Since the site-specific models performed best for their respective sites, it would be more meaningful to apply the site-specific models for local inventories at the respective sites as recommended by Abbot et al. (1997) and Mugasha et al. (2013). For large-scale inventories, such as national forest inventories (e.g. NAFORMA), the general models should be considered. Assessment of the performance of the previously developed models on the current dataset used for modelling, showed that the model with *dbh* only as the independent variable developed by Malimbwi et al. (1994) significantly under-predicted volume by 8.5%, while the models with *dbh* and *ht* as independent variables developed by Malimbwi et al. (1994) and Chamshama et al. (2004) significantly under-predicted volume by 20.8% and 31.2%, respectively. The model developed by Abbot et al. (1997) significantly over-predicted the volume by 30.6%. The trends of over- and under-prediction are also seen in Figure 3. The observed trends of over- and under-prediction illustrate the importance of being cautious when applying the models beyond geographical and size ranges used to construct the model.

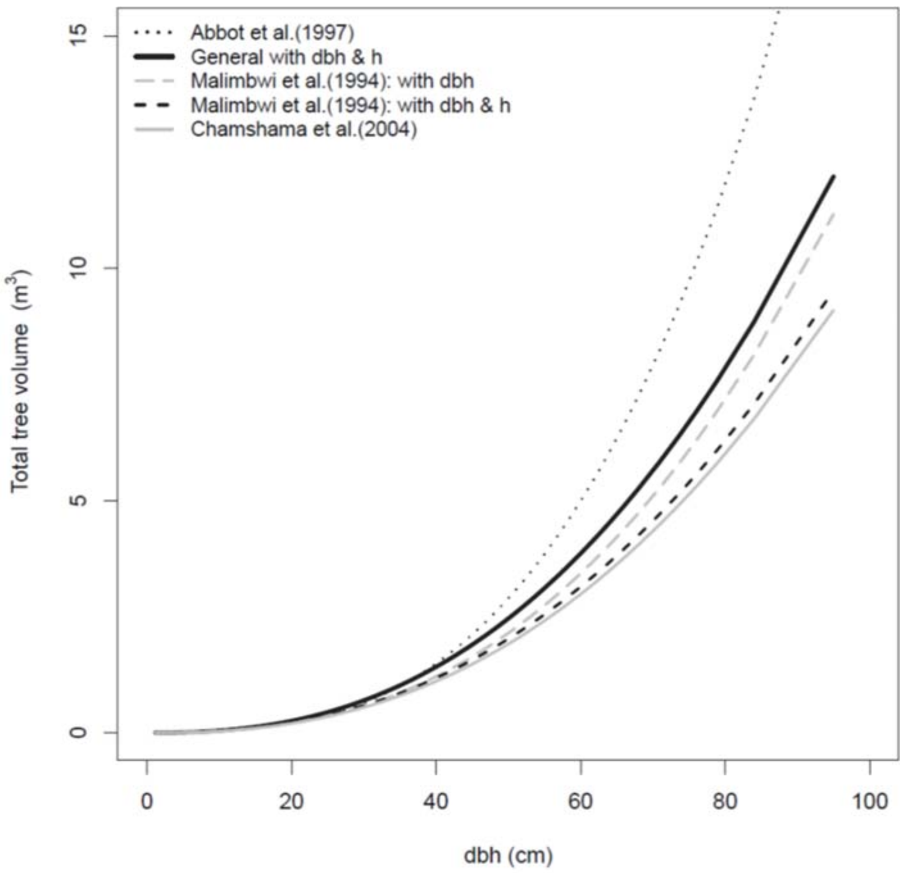

Figure 3. Display of predicted total tree volume over *dbh* based on the general model with *dbh* and *ht* as independent variables developed in this study and based on the models developed by Abbot et al. (1997), Malimbwi et al. (1994), and Chamshama et al. (2004).

5.2. Modelling AGB using ALS data

In Paper II, the use of ALS data for modelling and predicting AGB using parametric and non-parametric methods was demonstrated. The results showed that the LMM, with a variance function that accounts for the cluster effects, resulted in the best prediction model ($R^2 = 0.68$, RMSE= 46.8%). The *k*-NN imputation method was also tested with different *k* values. The imputation with a *k value* of 10 turned out to be the best with an RMSE value of 55.9%. Even though the results suggest that there were only small differences in prediction accuracy for the two methods, they can both be considered for AGB prediction and estimation using ALS data in the miombo woodlands. The accuracy of the methods in terms of the reported R^2 and RMSE from the LOOCV were in line with most of the previous studies reported from tropical forests (e.g. Asner and Mascaro, 2014; Asner et al., 2012b; Hansen et al., 2015). Post-strata models fitted using LMMs performed well with relatively smaller RMSE values as compared to the RMSE values obtained when the non-post-stratified model was applied to different post strata. However, use of post-strata models for operational prediction purposes would require thematic maps for the land use classes and vegetation types in order to know where to apply different stratum-specific models. Such maps were not available at the time when the analyses were conducted. Thus, since the difference between the non-post-stratified model and the post-strata models were modest, the non-post-stratified model (which disregards the land use and vegetation types) is considered to be more adequate for most applications that will involve large-scale AGB estimation supported by ALS data, at least until high-quality thematic maps are made available. Despite the fact that both of the non -post-stratified and post-stratified models resulted in reasonable prediction accuracies, there were some limitations that may have reduced the prediction accuracy of the models. The plot size used in this study was relatively small as compared to the most widely used field plot sizes in ALS-based studies from the tropical forests (e.g. Asner and Mascaro, 2014; Asner et al., 2012b; Mascaro et al., 2011). Smaller plots are considered as a source of poor prediction accuracy because of the increase in the errors associated with the mismatch between the ground field measurements and ALS measurements (Frazer et al., 2011; Zolkos et al., 2013). The effects of plot size on ALS based inventories are further discussed in Paper III.

5.3. Effects of field plot size on prediction accuracy of AGB in ALS-assisted inventories

In Paper III, increasingly stronger relationships were found between field reference AGB and the ALS-derived metrics as the plot sizes increased from 200 m^2 to 3000 m^2. The adjusted R^2 increased from 0.35 to 0.74, while the relative RMSE decreased from 63.6 to 29.2%, indicating that the prediction accuracy improved with increasing plot size (Figure 3). The quality of the model fit as indicated by adjusted R^2 and RMSE (Figures 3 and 4) are in line with most of the previous studies reported from the tropical forests (e.g. Asner et al., 2012b; Hansen et al., 2015), although direct comparison should be done with caution due to the differences in factors such sample sizes, forest structure, and geographical range of the data used in the reporting. Results from the variance estimations further indicated that the relative efficiency of the ALS-assisted estimates was improved when the plot sizes increased compared to field based estimates. The relative efficiency values were all larger than one with a maximum value of 7.7 for a plot size of 3000 m^2, indicating that ALS-assisted estimates is about seven times more efficient than field-based estimates when using a plot size of 3000 m^2 in this forest type. Under simple random sampling a relative efficiency of, say, 7, translates to a need for seven times as many field plots for pure field-based estimation to provide the same precision of the AGB estimates as an ALS-assisted estimation. The gain in relative efficiency was more pronounced as plot size increased, suggesting that from a pure technically perspective larger plots are more favorable when ALS-data are used to assist in the estimation. It should be noted though that differences in costs associated with different plot sizes - and thus cost effectivity - were not considered in this study. Numerous causes for the seemingly higher relative efficiency of ALS-assisted estimates with larger plots can be given; reduced circumference to area ratio, spatial averaging, and smaller effects of positioning errors are among the possible causes (e.g. Frazer et al., 2011; Næsset et al., 2015; Zolkos et al., 2013).

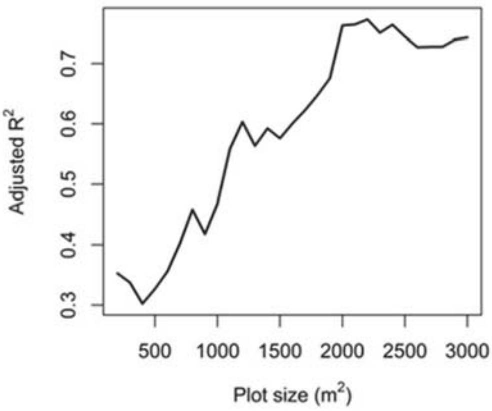

Figure 4. Adjusted R^2 versus plot size.

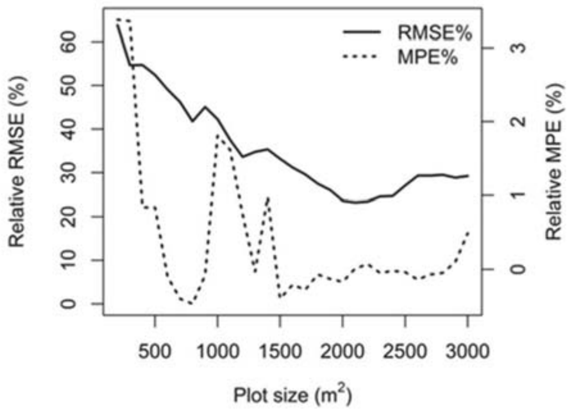

Figure 5. Relative mean prediction error (MPE%) and relative root mean square error (RMSE%) as percentage of field reference AGB versus plot size.

5.4. Modelling measures of tree species diversity using ALS data

In Paper IV, tree species richness and Shannon diversity index were modeled using ALS data. The explained variations (i.e. R^2) of LMM for tree species richness were relatively high as compared to Shannon diversity index. This indicates that the ALS metrics explain more of the variation in tree species richness as compared to Shannon diversity index. Results from the LOOCV showed that the RMSE values for both tree species richness and Shannon diversity index were slightly higher when using *k*-NN as compared LMMs (Table 2). However, both methods could be considered for prediction and estimation of measures of tree species diversity using ALS data. Prediction accuracy of both methods varied across different vegetation types.

The major findings in terms of model quality criteria, such as R^2 and RMSE%, are in accordance with previously published studies (e.g. Fricker et al., 2015; Wolf et al., 2012) that have attempted to use ALS data for predicting measures of tree species diversity in tropical forests. For example, Wolf et al. (2012) reported an R^2 of 0.48 when predicting tree species richness in the Neotropical forests of Panama. There are also deviations from other studies that have reported relatively better prediction accuracy in terms R^2 and RMSE (Hernández-Stefanoni et al., 2014; Laurin et al., 2014). Such deviations are not surprising, however, since in most cases the predictive ability of the remotely sensed data varies with the ecosystem and biogeographical context (Camathias et al., 2013). Furthermore, the differences in factors such as number of species, field design, data characteristics, and topography may influence the prediction accuracy. Generally, Paper IV provided an insight into how measures of tree species diversity potentially can be predicted by using ALS data in the miombo woodlands.

Table 2. Pseudo-R^2, absolute root mean square error (RMSE), and relative root mean square error (RMSE%) for predicted tree species richness and Shannon diversity index

Measures of tree species diversity	Vegetation type [a]	n [b]	LMMs			*k*-NN	
			R^2	RMSE	RMSE (%)	RMSE	RMSE (%)
Tree species richness	Woodlands	387	0.41	2.08	38.9	2.84	53.0
	Forest	40	0.34	2.79	41.8	2.99	44.8
	Other cover types	57	0.36	1.84	57.0	2.93	90.7
	All	484	0.46	2.12	40.7	2.15	41.2
Shannon diversity index	Woodlands	387	0.32	0.42	35.0	0.59	49.2
	Forest	40	0.47	0.35	27.0	0.50	39.0
	Other cover types	57	0.39	0.53	73.0	0.72	99.0
	All	484	0.39	0.45	39.1	0.46	40.0

[a] Vegetation types according to MNRT (2011).
[b] Number of field plots.

6.0. Conclusions and future studies

The studies conducted within this thesis have provided information which may be useful for improving the current methods for assessment and quantification of forest resources in Tanzania. This is needed for forest management decision-making and for development of a REDD+ MRV system (Figure 2). More specifically, in Paper I models for estimating volume of miombo woodland trees, including total, merchantable stem, and branches volumes were developed. For each of these categories general and site-specific models were also constructed. The models are considered to be valuable for deriving information that can support management and utilization of miombo woodland resources by providing more accurate estimates of forest resources in terms of growing stock volumes. Volume models may also be used as an input in developing simulation tools that can be used to predict future conditions of forests under different management scenarios. Such a tool has recently been developed by Mugasha (2014) and the tree volume model with *dbh* and *ht* developed in Paper I has successfully been used to generate reliable information on volume stock.

Additionally, the volume models, when combined with expansion factors, may also be used in conjunction with NAFORMA data for estimation of forest AGB and national greenhouse gas emissions. Thus, at least two viable approaches for estimation of carbon stocks exist currently for the miombo woodlands of Tanzania, since there is already a more direct approach of using allometric AGB models developed by Mugasha et al. (2013). Although the models have been developed for miombo woodlands of Tanzania, they may potentially be used in the miombo woodlands of nearby countries, such as Malawi and Mozambique in the same context as described above. However, it is important to validate the models before use, and caution should be exercised when applying the models beyond the ranges of the data used for model development.

Papers II and III of the thesis have provided empirical evidence that ALS can potentially be used for prediction and estimation of AGB in the tropical forests and woodlands of Tanzania, despite a wide range of variation in forest structure and composition. Moreover, the findings have shown that selection of statistical modeling methods in ALS-based studies should be guided by the design used to determine the sample locations (e.g. nested/clustered designs) of the field inventory. In other words, the design of the field inventory should not be ignored when selecting the statistical method as this may have consequences for the accuracy of the models and finally for the precision of the estimates. NAFORMA data will in the future possibly be used in combination with various types of auxiliary data from remote sensing for monitoring of forest carbon. The statistical procedures described in Paper II may offer baseline information for such studies. Likewise, the experiences gained from the methodological part of this thesis may inform future decisions on the design of a REDD+ MRV system, including the modeling part of relationships between carbon stocks and auxiliary data. Furthermore, the findings in Paper III have shown that field plot size is an important survey parameter that must be considered when designing a field inventory to be used for estimation purposes in combination with auxiliary data from remote sensing. The analyses of the effects of plot size on ALS-assisted AGB estimates have clearly shown that both the model fit and the precision of the ALS-assisted AGB estimates increased with plot size. A firm and well justified recommendation for plot size in future surveys can hardly be given on the basis of this very limited study – limited in sample size (30 plots) and geographical extent (one study site), but the results do show a declining utility of increasing plot size beyond around 1200 m^2 in rainforest. This finding is nevertheless fairly well in line with findings from similar forests on other continents.

Lastly, the findings in Paper IV demonstrated that irrespective of the large number of tree species in the miombo woodlands of Tanzania, ALS holds potential for assessment of measures of tree species diversity. This paper was the first attempt to use remotely sensed data for predicting measures of tree species diversity in Tanzania, thus the results open an avenue for using ALS data when monitoring forest biodiversity, in particular tree species diversity.

Even though the four studies presented in this thesis have provided information that may be useful for improving the current methods for assessment and quantification of forest resources in Tanzania, there are still many research gaps that should be further addressed.

In Paper I, NLS was used for development of volume models. Compared to the commonly used OLS with log transformation this approach is considered to be more robust for development of tree allometric models (Sileshi, 2014). However, recently hierarchal Bayesian framework and mixed effects models have been preferred for development of tree allometric models (e.g. Cohen et al., 2013; Xiao et al., 2011). Future studies should therefore compare these approaches to OLS and NLS.

In Paper II, the *k*-NN was used as a non-parametric method for prediction of AGB using ALS data. Other non-parametric methods such as random forest have shown promising results in many of the previously studies (e.g. Hudak et al., 2008; Li et al., 2013; Mascaro et al., 2014). However, in this study random forest was not applied because the impact of dealing with clustered data in random forest is not well understood. With the recent development of a mixed effects approach for random forest by Hajjem et al. (2014), future studies may consider this as an alternative to improve the prediction accuracy. Furthermore, in this thesis ALS was the only source of auxiliary data from remote sensing. Fusing ALS data with other remotely sensed information, for example complementary data types such as optical and even hyperspectral (e.g. Dalponte et al., 2014) that may capture other properties of the trees and tree canopies than just 3D information, may improve estimates and could be considered in future studies. This may also help improving the quality in construction of continuous AGB maps and local small-area estimates of AGB, which may be useful for forest management planning at local scales (i.e. district to village level) and also for local REDD+ projects. This would be equivalent to products that are produced routinely with great success by ALS for forest management purposes in boreal forests (e.g. Næsset, 2014).

In Paper III, the maximum plot size of 3000 m^2 used to evaluate effects of plot size on the prediction accuracy and estimated precision of ALS-assisted AGB estimates leaves an open question as to whether there are any additional gains in precision beyond this size. Although, as stated above, there seems to be a declining utility of increasing plot size beyond a size of around 1200 m^2, future studies to confirm this finding should include plot sizes above 3000 m^2 to increase confidence in the results. Further studies of this important design property are clearly required also in other forest types than the rainforest. An obvious forest type to be considered in a Tanzanian context is the miombo woodlands. Likewise, other factors that may aid choice of an “optimal” plot size such as sample sizes, on-plot costs, traveling costs, and overall field inventory design should be considered. Furthermore, future studies should take terrain and topographical variables into account since for example traveling costs and on-plot costs as well as plot position accuracy may be influenced by these factors.

In Paper IV, an indirect modelling approach was used when developing predictive models for measures of tree species diversity. For future studies, use of more integrated statistical analyses, which directly relate tree species community information to ALS metrics without use of the estimators of tree species diversity, should be considered. Moreover, instead of focusing on the use of ALS alone, future studies could attempt to combine ALS with other remotely sensed data, such as hyperspectral images mentioned above. This will likely improve the prediction accuracy of the models, since the two types of sensor data will complement each other, especially when modelling multi-layered forests (e.g. Dalponte et al., 2008; Laurin et al., 2014).

Finally, we want to point out that this thesis had a purely technical approach, with the aim of providing empirical evidence of performance of ALS used for assisting in prediction of essential properties for management and carbon reporting in a broad sense. As a technology evolves from being a source of data for research purposes to a tool for operational data collection, economical aspects become essential, which also include choices between alternatives. ALS has become a great success for operational purposes in boreal forest inventory due to low acquisition costs relative to e.g. labor costs (Næsset, 2014). Higher accuracy of the produced information compared to alternative methodologies is also an important aspect. Thus, in the boreal context ALS-assisted methods have simply turned out to be more cost-effective compared to other methods (Bergseng et al., 2015; Eid et al., 2004). In developing countries in general and in Tanzania in particular, labor costs are lower and ALS acquisition costs are higher – even in absolute terms, than in many developed countries. Therefore, the economical aspects of the ALS-based applications compared to alternatives involving for example more extensive use of field campaigns, must accompany further research aiming at confirming and expanding the technical knowledge gained by this thesis – the first comprehensive study on use of ALS in forests in Tanzania.

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