Norwegian University of Life Sciences
Department of Ecology
and Natural Resource Management

Philosophiae Doctor (PhD)
Thesis 2016:92

Biomass estimation models and methods for miombo woodlands of Malawi using field and remotely sensed data

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Ås, 10.10.2016

Daud Jones Kachamba

Contents

Abstract

Dry tropical forests, such as the miombo woodlands, play an important role in the global carbon budget as well as in contributing towards the sustainable development of countries such as Malawi. To ensure sustainability of these forests, availability of models and methods for assisting forest managers in quantifying volume and biomass are indispensable. This thesis therefore sought to develop volume and biomass prediction models as well as to test the potential of applying unmanned aerial vehicles (UAVs) in biomass prediction and estimation in miombo woodlands. In Paper 1 and 2, we developed models for predicting tree sectional (twigs, merchantable stem and branches) volume and biomass, total tree volume as well as tree above-and belowground biomass. The performances and evaluations suggested that the models can be used over a wide range of geographical and ecological conditions in Malawi with an appropriate accuracy in predictions. Application of UAVs for biomass prediction and estimation were tested and the results are presented in Papers 3 and 4. In Paper 3, we tested methods to derive digital terrain models (DTMs) while Paper 4 focused on the assessment of the efficiency of UAV-assisted inventories as well as the influence of sample plot sizes and number of sample plots on the precision of biomass estimates. The results, presented in Paper 3, show that among the tested DTMs, the model developed from unsupervised ground filtering based on a grid search approach performed best. Furthermore, the observed prediction errors for the biomass predictions are similar to results from previous studies using airborne laser scanning (ALS) data, thus showing the potential of applying this technology in miombo woodlands. Finally, Paper 4 demonstrated that UAV-assisted inventories produce more precise estimates compared to those based on purely field-based inventories. The results also indicated that large sample plot sizes and sample sizes favour UAV-assisted inventories and that UAV-assisted inventories are more efficient than purely field-based inventories. The developed models and the results from the tested methods presented in the thesis have taken us some steps forward that are expected to support and improve forest management decision-making in general as well as the implementation of a REDD+ MRV system covering the miombo woodlands of Malawi.

List of papers

Paper 1: Kachamba, D.J. and Eid, T. (2016). Total tree, merchantable stem and branch volume models for miombo woodlands of Malawi. *Southern Forests, 78, 41-51*.

Paper 2: Kachamba, D.J., Eid, T. and Gobakken, T. (2016). Above- and belowground biomass models for trees in miombo woodlands of Malawi. *Forests 7(2):38*

Paper 3: Kachamba, D.J., Ørka, H.O., Gobakken, T., Eid, T. and Mwase W. (2016). Biomass prediction using an unmanned aerial vehicle in a tropical woodland. Under revision.

Paper 4: Kachamba, D.J., Ørka, H.O., Gobakken, T., Eid, T. and Næsset, E. (2016). Influence of plot size and sample size on efficiency of biomass estimates in inventories of dry tropical forests assisted by photogrammetric data from an unmanned aerial vehicle. Manuscript.

1.0 Introduction

Dry tropical forests cover central and south America, Africa, India, south-east Asia and northern Australia (Miles et al. 2006). In southern Africa, dry forests are mainly dominated by miombo woodlands. These woodlands were estimated to cover an area of approximately 2.7 million km^2 (Frost 1996), but this area is most likely lower today due to deforestation and forest degradation. Miombo woodlands are presently spanning 11 countries in Africa, including Malawi (Chidumayo & Gumbo 2010; Ryan et al. 2011). The miombo ecoregion occurs in a climate with a dry season of three months or more and has mean annual precipitations and temperatures of 710 – 1365 mm and 18.0 – 23.1°C, respectively (Frost 1996). Unlike other African savannas and woodlands, miombo woodlands are dominated by three key deciduous tree species belonging to the family Fabaceae, subfamily Caesalpinioideae in the genera *Brachystegia, Julbernadia and Isoberlinia* (Frost 1996; Ryan et al. 2011). A similar tree species composition is found in the miombo woodlands of Malawi (Mwase et al. 2007).

Miombo woodlands are multi-species and multi-layered and are regenerated through coppicing as well as seed dispersal. Structurally, the canopy of miombo woodlands is dominated by trees that are umbrella-shaped whose heights usually range from 14 to 18 m. The sub-canopy is composed of a highly variable scattered layer of shrubs, suppressed saplings of canopy layer trees, grasses and sedges (Abbot et al. 1997; Frost 1996). Tree forms in these woodlands vary from small, multi-stemmed trees to tall single-stemmed trees with straight boles (Abbot et al. 1997). Fires occur frequently in miombo woodlands both in time and space (e.g. Tarimo et al. 2015). Fires are regarded essential to the structure and stability of miombo woodlands (Frost 1996), and the biomass may be reduced substantially if the fire frequency is high (Ryan & Williams 2011). Some tree species have a thick bark to protect them from fires (Frost 1996).

In miombo woodlands, tree species richness and densities vary widely with location, i.e. ranging between 70 and 300 species, and up to 4100 stems ha^{-1} depending on rainfall and anthropogenic factors (Abbot et al. 1997; Dewees et al. 2011; Frost 1996; Furley et al. 2008; Giliba et al. 2011; Malimbwi et al. 2016; Williams et al. 2008). In Malawi, the number of tree species is estimated to exceed 130 with tree densities ranging from about 260 to 1640 stems ha^{-1} (Government of Malawi 2012).

Miombo woodlands provide a wide variety of food and ecosystem services to millions of people in the region including fruits, bush meat, edible insects, beeswax, honey, traditional medicines, biodiversity and watershed conservation (Abbot & Homewood 1999; Blackie et al. 2014; Chidumayo & Gumbo 2010; Kajembe et al. 2015; Luoga et al. 2005; Mwase et al. 2007; Ryan et al. 2016). In Malawi, the woodlands constitute 92% of the country's total forest area (Government of Malawi 2010; Government of Malawi 2012). The Malawi government recognizes the role the woodlands play towards achieving sustainable development for the country. However, increases in population growth has led to high demand for firewood, charcoal and timber products leading to deforestation, currently estimated at 1% per annum (Government of Malawi 2001; Government of Malawi 2010).

Dry tropical forests, including miombo woodlands, are currently the least studied compared to wet tropical forests despite their significant contribution to the global carbon budget and to livelihoods of a lot of people (e.g. Dirzo et al. 2011). In recognition of the importance of forests, including the dry tropical forests, the global community, through the United Nations Framework Convention on Climate Change (UNFCCC), established the Reducing Emissions from Deforestation and Forest Degradation, plus forest conservation, sustainable management of forest and enhancement of carbon stocks (REDD+) mechanism (Barquín et al. 2014; Goetz et al. 2015; UNFCCC 2014). This mechanism has given a financial incentive to developing countries in their efforts to reduce deforestation and forest degradation through increased forest conservation and implementation of sustainable forest management. The payment scheme for REDD+ is based on reported national level carbon stock estimates to the UNFCCC (Goetz et al. 2015). To implement REDD+, each participating country is therefore expected to have a credible forest monitoring system that supports the functions of monitoring, reporting and verification (MRV) of forest carbon stocks at a national scale (Gizachew & Duguma 2016). The system is thus expected to establish a national baseline carbon stock estimate as well as changes of carbon stocks over time (Goetz et al. 2015).

Currently, Malawi is in the preparatory phase of implementing REDD+. The first step in this phase has involved establishing legal and institutional frameworks. In 2012, the government released a draft version of the national climate change policy to support all climate change related programs in the country. In the same year, the government also launched the Malawi REDD+ program aiming for streamlining the process of operationalizing REDD+

(Government of Malawi 2015). Through the program, the Forestry Institute of Malawi (FRIM) was mandated with the development of a national forest carbon MRV system.

A fully functional national forest carbon MRV system for REDD+ implementation in Malawi shall require establishment of a data collection and management system comprising three pillars, namely: a) a remote sensing based land monitoring system for collecting and assessing activity data related to forest cover changes over time (Goetz et al. 2015; UNFCCC 2014), b) conducting national forest inventories (NFIs) for quantifying carbon stock changes and c) a data analysis and reporting system for production of reports to the UNFCCC. Among these pillars, NFIs form a critical component since they are directly linked with carbon stock changes, which is a key component of the REDD+ payment system (Gizachew & Duguma 2016; Goetz et al. 2015). NFIs rely on the utilisation of both reliable biomass/volume models and state of the art remote sensing techniques. Currently, reliable biomass and volume models are lacking and modern remote sensing techniques for volume or biomass prediction and estimation are yet to be tested for application in REDD+ in Malawi. So far, through funding from a number of multi-and bilateral donors, including Food and Agriculture Organization (FAO), United States Agency for International Development (USAID), Japan International Cooperation Agency (JICA) and World Bank, national land use and land cover maps have been developed for benchmarking land use and land use change in the forests of Malawi. However, a fully functional national forest carbon MRV system is yet to be established.

Apart from the anticipated financial benefits from carbon credits, the Malawi government considers REDD+ as an opportunity for instituting sustainable forest management in the country. Currently, the management of miombo woodlands is suffering from lack of reliable models and methods that may support forest managers in decision-making. The existence of such models and methods is instrumental in the efforts to accomplish a sustainable management of these resources.

2.0 Objectives

The main objective of this thesis was to develop models and methods for predicting and estimating volume and biomass of miombo woodlands in Malawi. The models and methods developed are based on both field and remotely sensed data and are expected to support forest management decision-making in general as well as the implementation of a REDD+ MRV system in the country. The following specific sub-objectives were addressed in four different papers;

a) Develop general (multiple tree species from several sites) models for volume prediction in miombo woodlands (Paper 1);
b) Develop general (multiple tree species from several sites) models for biomass prediction in miombo woodlands (Paper 2);
c) Explore the possibility of using UAVs in biomass prediction in miombo woodlands (Paper 3);
d) Assess the efficiency of UAV-assisted inventories as well as the influence of sample plot size and sample size on error estimates in biomass estimation in miombo woodlands (Paper 4).

3.0 Conceptual framework

Forest volume and biomass estimates are basic information needed generally for forest management decision-making as well as when implementing a REDD+ MRV system. A conceptual framework for estimation of volume and above- and belowground biomass for forest areas is presented in Figure 1.

When employing field-based methods for volume or biomass estimation, sample plot inventories are first conducted, and subsequently, individual tree volume or above- and belowground biomass models, if readily available, are applied. In cases where reliable individual tree models are lacking, they can be developed. The process of developing the models involves conducting sample plot inventories to guide the selection of representative trees for destructive sampling. The destructive sampled tree data are then used to develop individual tree volume or above-and belowground biomass models, which can finally be used for forest area volume or above-and belowground biomass estimation.

In cases where remote sensing is the main method applied for estimating forest area volume or biomass, remotely sensed data can be collected using different sensors mounted on different platforms. Application of imagery captured from UAVs is an example of a method that has recently gained ground in forestry. In addition to the remote sensing based data (processed UAV images), sample plot inventory data are also needed. The processed UAV images, sample plot inventory data and individual tree aboveground biomass models (alternatively individual tree volume models) are then used to develop area-based models that can finally be used to estimate forest area aboveground biomass (or forest area volume).

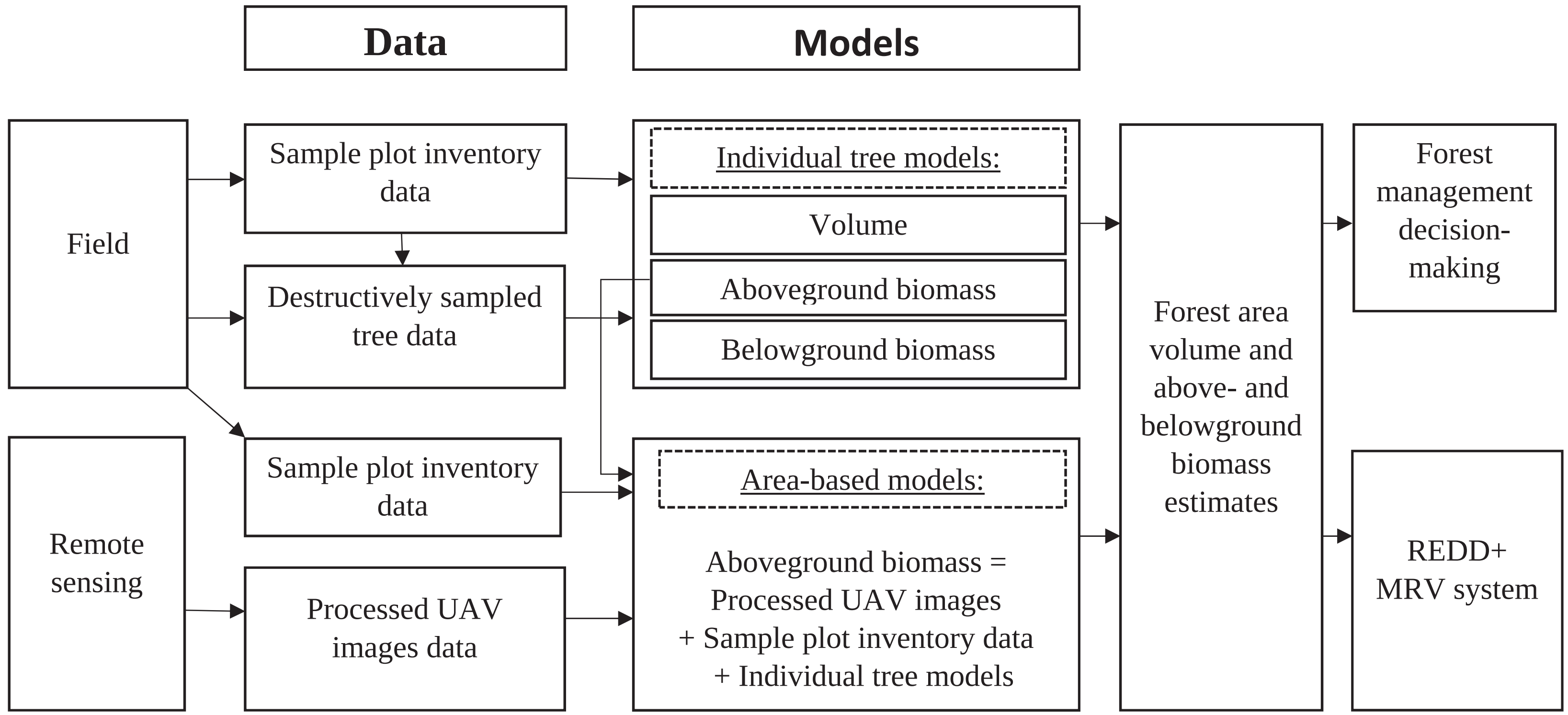

Figure 1. A conceptual framework for estimation of forest area volume and above- and belowground biomass.

4.0 Background

4.1 Volume models

Availability of volume models is regarded as a basic prerequisite for implementation of sustainable forest management. Volume models are important for establishing current growing stock of forests, timber valuation, selection of forest areas in harvest scheduling, growth and yield studies and as a basis for estimation of biomass and carbon stocks. Furthermore, the government of Malawi uses a licensing system that permits the issuance of permits to individuals for accessing timber in public forests. In this context, merchantable stem volume models are required. Merchantable stem volume models may also be useful in cases where compensation payments to tree/forest owners are required when trees are being cleared for infrastructure development, such as roads, railways and buildings. Branch volume models can be used as tools for assessing wood quantities related to brick burning as well as in the production of domestic fuelwood, charcoal and construction poles.

A review by Henry et al. (2011) showed that many models for predicting tree volume in miombo woodlands have been developed previously. Most of these models were developed in miombo woodlands located in neighbouring countries like Tanzania (Chamshama et al. 2004; Malimbwi et al. 1994; Mauya et al. 2014; Mwakalukwa et al. 2014), Zambia (Chidumayo 1988) and Mozambique (Mate 2014). Due to high biogeographical variability in the miombo ecoregion, there is a need for developing models that can be applied locally. The only existing tree volume models for miombo woodlands in Malawi were developed by Abbot et al. (1997). However, application of these models is limited due several reasons regarding the data used for model calibration: a) narrow geographical ranges of study sites, (b) relatively small ranges of diameter at breast height and (c) relatively few tree species.

The main objective of Paper 1 was therefore to develop general total tree volume models, as well as general tree sectional models for branches and merchantable stems, applicable across the entire distribution of miombo woodlands in Malawi.

4.2 Biomass models

Estimation of biomass is the first step towards calculation of carbon stocks in forest ecosystems. Due to the natural capacity of trees to sequester carbon dioxide, miombo woodlands are considered an important element in global climate change mitigation programs such as REDD+. Establishment of credible national MRV systems for REDD+

implementation requires estimation of biomass using either field or remote sensing-based methods. Both these methods rely on the availability of reliable biomass models.

Biomass can be estimated using either direct or indirect methods. Direct methods involve harvesting all trees in a known area and measuring the oven dry weight of the different components of the harvested trees such as the stem, leaves, roots and branches. Although this method determines biomass accurately for a particular area, it is time and resource consuming, strenuous, destructive, expensive and not feasible for large scale analysis (Vashum & Jayakumar 2012). On the other hand, indirect methods involve applying individual tree models for predicting biomass, or expansion factors and/or root to shoot ratios (Brown 2002). Application of individual tree models is now the most widely used method in forest biomass estimation.

By 2011 there were approximately 370 models for predicting tree biomass in sub-Saharan Africa (Henry et al. 2011). The majority of these models were developed for tropical rainforests in western Africa. Among the reviewed models, and those developed after the review in south-eastern Africa, only a few were developed for miombo woodlands (Chamshama et al. 2004; Chidumayo 2014; Kuyah et al. 2016; Malimbwi et al. 1994; Mate et al. 2014; Mugasha et al. 2013; Mwakalukwa et al. 2014; Ryan et al. 2011). Among these, the models developed by Kuyah et al. (2016) are the only ones based on data from Malawi. However, these models are also limited for the same reasons limiting existing volume models (narrow geographical ranges, relatively small ranges of diameters and relatively few tree species). The models developed by Kuyah et al. (2016) were also developed using miombo trees from outside forests, hence limiting their applicability in the REDD+ mechanism which is currently targeting trees in forest reserves.

Furthermore, most of the described models for miombo woodlands focused on aboveground biomass only. However, estimation of belowground biomass is also vital. Existing belowground biomass models for miombo woodlands in neighbouring countries were developed by Mugasha et al. (2013), Chidumayo (2014) and Ryan et al. (2011). For Malawi, however, no belowground biomass models exist.

The main objective of Paper 2 was therefore to develop general above- and belowground biomass models applicable across the entire distribution of miombo woodlands in Malawi.

The models were also accompanied with information on their covariance structure to enable quantification of model-related uncertainties in biomass and carbon estimation.

4.3 Application of UAVs in biomass prediction

Remote sensing methods can be used to collect data for estimating forest volume or aboveground biomass. Prediction of these attributes using this approach involve conducting sample plot forest inventories based on a relatively small number of sample plots to determine field reference biomass. The field reference biomass is then regressed with metrics derived from remotely sensed data for the respective sample plots. The developed models are finally used to predict volume or biomass for the entire study area. For forestry applications, remotely sensed data is mainly sourced from three main systems, namely, airborne laser scanning, radio detection and ranging (e.g. synthetic aperture radar) and optical (e.g. satellite and aerial images) (Kumar et al. 2015). Currently, application of UAVs for predicting volume or aboveground biomass is slowly gaining ground due to UAVs ability to acquire high quality 3D data on forests at relatively low costs (Dandois & Ellis 2013; Getzin et al. 2012; Puliti et al. 2015; Tang & Shao 2015). Furthermore, the availability of user-friendly image processing software has made the application of the technology attractive (Dandois & Ellis 2013; Puliti et al. 2015). Application of this technology to potential REDD+ projects in Malawi could be an attractive option since the sizes of approximately 50% of potential project areas are ideal for efficient application of UAVs in biomass prediction (see Puliti et al. 2015). However, the application of this newly developed technology for biomass prediction in the miombo woodlands of Malawi still needs to be tested.

Successful prediction of forest attributes using remotely sensed data is dependent on the availability of a reliable digital terrain model for correct estimation of ground elevation for the study area. Images collected by UAVs may not be suitable for generating reliable digital terrain models since it is mainly concentrated in the top of the forest canopy. Reliable digital terrain models are usually generated from airborne laser scanning data. However, due to the high costs associated with acquiring such data, it is imperative for researchers utilizing UAVs in developing countries to strive to search for relatively accurate, but also cost efficient digital terrain model generating approaches.

The main objective of Paper 3 was therefore to evaluate the application of photogrammetric point cloud data generated from UAV acquired images in aboveground biomass prediction for miombo woodlands. Digital terrain models generated from the photogrammetric point cloud based on different methods and parameter settings were also compared.

4.4 Influence of plot and sample size on UAV-assisted biomass estimates

Data from field-based probability sample plot inventories are important for estimating forest biomass/volume during UAV-assisted inventories as they reportedly improve the estimates (Næsset et al. 2011). Determination of field plot size is an important design decision when planning field-based probability sample inventories. In estimation based on field-based probability sample data combined with auxiliary data from remote sensing i.e. design-based and model-assisted inferential framework, an appropriate geographical correspondence between plots on the ground and the remotely sensed data is paramount. An increased sample plot size can reduce the effects of errors arising from co-registration problems (Frazer et al. 2011). Larger plots will also tend to reduce the plot boundary effects (McRoberts et al. 2014).

Several authors have studied the effect of sample plot size on biomass estimates and other forest attributes in inventories assisted by remotely sensed data in tropical wet forests (Asner et al. 2009; Hansen et al. 2015; Keller et al. 2001; Mascaro et al. 2011; Mauya et al. 2015b; Saatchi et al. 2011), temperate forests (Frazer et al. 2011; Levick et al. 2016), boreal forests (Gobakken & Næsset 2008; Næsset et al. 2015) among others. Apart from sample plot size, sample size, i.e. the number of sample plots employed during an inventory, will also have a large effect on the efficiency of biomass estimates and the associated total inventory costs (Eid et al. 2004; Gobakken & Næsset 2008; Strunk et al. 2012).

To the best of our knowledge, no studies on the influence of sample plot size and sample size on efficiency of biomass estimates (or other forest attributes) have been done in UAV-assisted sample plot inventories, i.e. using design-based and model-assisted inferential framework in miombo woodlands. The main objective of Paper 4 was therefore to assess the efficiency of using a UAV-assisted estimation of biomass in a case study in miombo woodlands of Malawi based on different sample sizes and sample plot sizes.

5.0 Materials and methods

5.1 Study sites

Figure 2 presents the location of the study sites. The sample trees for the development of volume and biomass models in Papers 1 and 2 were selected from four forest reserves, namely Mtangatanga (northern Malawi), Kongwe (central Malawi), Mua-livulezi (central Malawi) and Tsamba (southern Malawi). The selection of sites was based on geographical location and climatic conditions to capture a wide range of factors influencing tree growth. Data for Papers 3 and 4 was collected from Muyobe community forest reserve in the northern Malawi.

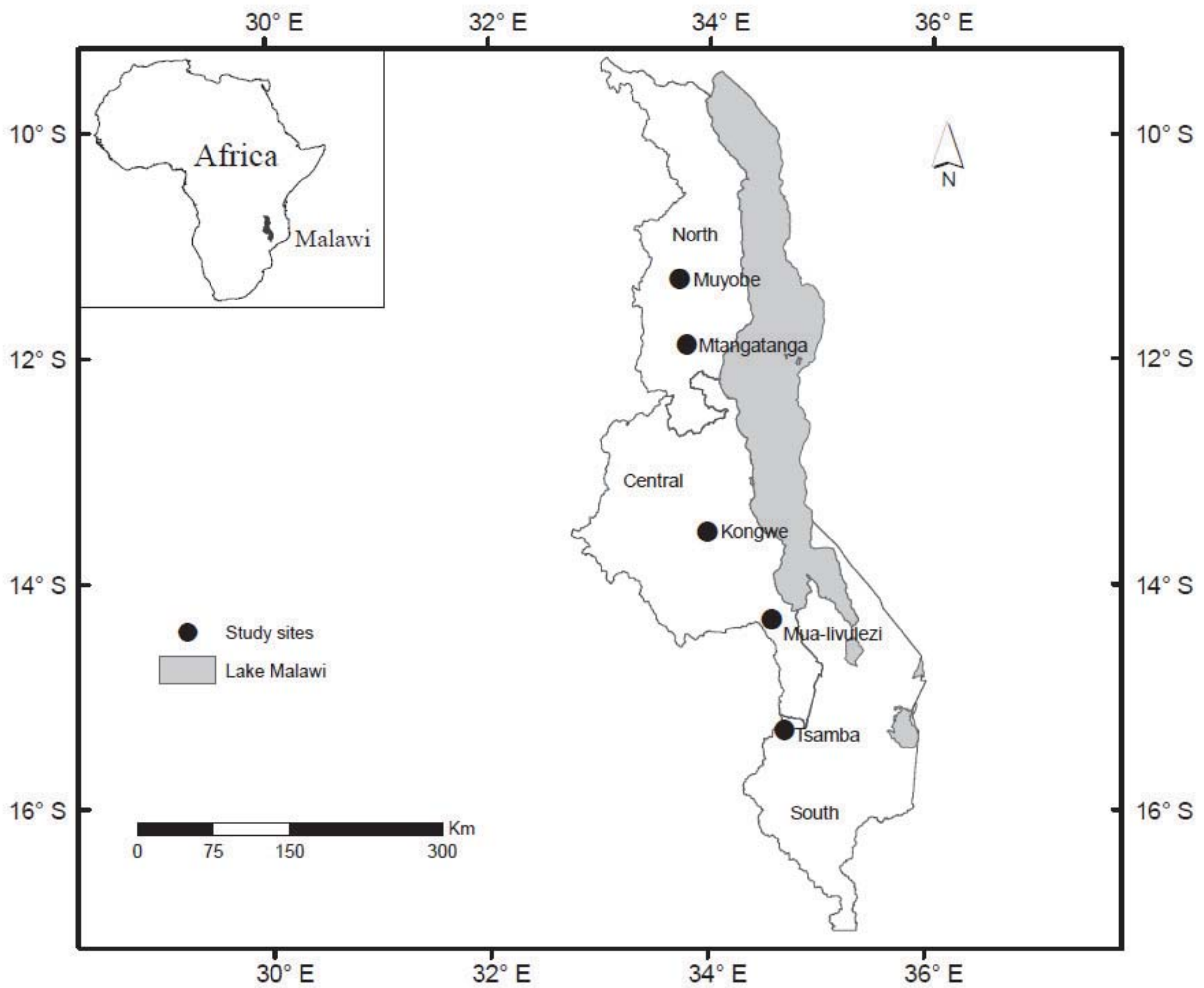

Figure 2. Map of Malawi showing the location of the study sites.

5.2 Data collection

a) Sample plot inventory data

Sample plot field inventory data was required for all the four papers. For Papers 1 and 2 the inventories were conducted on systematically distributed 0.04 ha circular plots. The inventories covered a total of 221 plots with 70, 30, 71 and 50 plots for Mtangatanga, Kongwe, Mua-livulezi and Tsamba, respectively. On each plot, all trees with diameters at breast height > 4 cm were identified and had their diameters at breast height measured. In addition, we sampled three trees within each plot (with the smallest, medium and largest diameters at breast height), and measured their total height using a Vertex hypsometer. In total, for all the study sites, we identified 139 tree species. The sample plot inventory data was then used for selection of sample trees that were destructively sampled.

For Papers 3 and 4, the inventory was conducted on 107 systematically distributed probability sample plots which were circular (radius = 17.84 m, 0.1 ha each). On each plot, the following tree variables were recorded: Total horizontal distances from the plot centres to each tree (using a Haglöf vertex hypsometer), diameter at breast height (using a caliper or a diameter tape) and scientific name of all trees ≥ 5 cm. The total horizontal distances from the plot centres to each tree were calculated as the sum of the horizontal distance to the front of each tree and half of the tree's diameter at breast height. These distances were subsequently used to subset the sample plot data into different sizes, i.e. 250, 500, 750 and 1000 m^2, for further analysis.

In order to assess the effect of sample size on precision of biomass estimates we considered three different systematic samples of different sizes, i.e., the full sample of 107 plots, one sample with half the size (54 plots) in which every second plot was excluded, and finally one sample of one third of the full size (36 plots) in which every third plot was retained. In total 12 datasets (i.e. four sample plot sizes × three sets of sample sizes) were created and used for the analyses.

Furthermore, total tree height of up to 10 randomly selected sample trees within each plot were measured using a Haglöf vertex hypsometer. Precise registration of the positions of centres for sample plots is very important in remote sensing-assisted forest inventories. In this study, positions of the plot centres were measured with a differential Global Navigation Satellite Systems (dGNSS) unit. The dGNSS unit is comprised of two Topcon legacy- E +40 dual frequency receivers. One of the receivers was used as a base station unit and the other as a rover field unit. The receivers observe pseudo-range and carrier phase of both the Global Positioning System (GPS) and the Global Navigation Satellite System (GLONASS). During the study, the baseline between the base station and rover units was approximately 25 km. The position of the base station was determined using Precise Point Positioning (PPP) with GPS and GLONASS data collected continuously for 24 hours as suggested by Kouba (2015) before commencement of the forest inventory. The rover field unit was placed at the centre of each sample plot on a 2.98 m rod for an average of 33±20 minutes using a one-second logging rate. The recorded plot centre coordinates were post-processed using the RTKLIB software (Takasu 2009) and the results revealed that the maximum deviations for northing, easting and height were 1.16 cm, 3.02 cm and 3.06 cm, respectively.

b) Destructively sampled tree data

For development of above- and belowground biomass models, as well as volume models in Papers 1 and 2, a total of 74 trees were selected based on the observed diameters at breast height and tree species frequency within the sites. We ensured that the trees were selected from all diameter at breast height classes observed in the sample plot inventories. In addition, we selected a total of eight trees with larger diameter at breast height than those observed in the sample plot inventories to reduce uncertainty when predicting biomass of very large trees. We also selected at least one tree among the eight most frequently observed species in each site. The remaining sample trees were selected randomly among all species. In total, 33 tree species were selected, comprising 10, 10, 12 and 10 different tree species in Mtangatanga, Kongwe, Mua-livulezi and Tsamba, respectively. Before felling the selected trees, we measured their diameters at breast height and total tree height, and also determined their species names. Out of the 74 trees, 41 trees were excavated for determination of belowground biomass.

For determination of aboveground biomass, the aboveground portion of each of the 74 trees was separated into the following components: merchantable stem (from the stump at 30 cm above ground to the point where the first branches start), branches (all parts of the tree above the defined merchantable stem and up to a minimum diameter of 2.5 cm) and twigs (all branches with a diameter less than 2.5 cm). For small trees not considered suitable for timber production (diameter at breast height < 15 cm, in total 14 trees), merchantable stem volume/biomass were allocated to branches. To facilitate measurements, the stems and branches were crosscut into manageable logs of approximately 1–2 m in length. We measured the lengths and the mid-diameters over bark of each of the logs and then weighed their fresh weight using a mechanical hanging spring balance (0 – 200 kg). Twigs from each tree were separately bundled and weighed to determine their fresh weight.

For determination of belowground biomass, our strategy involved root sampling at two levels (Mugasha et al. 2013), namely main roots (roots branching directly from the root crown) and side roots (roots branching from the main roots). The first step in excavation involved clearing the topsoil around the tree base to expose the points at which the roots were branching. We then selected three main roots, i.e. the main roots with the largest, medium and smallest diameters and recorded their diameters at the points where they joined the root crown. The diameters of all main roots not excavated were recorded at the point where they joined the root crown. From each of the selected main roots, we selected up to three side roots, i.e. the side roots with the largest, medium and smallest diameters. For each of the selected side roots, we recorded the diameter where they joined the main root. For the remaining side roots, we also recorded the diameters at the branching point from the mainroot. The selected side and main roots were then fully excavated up to a minimum diameter of 1 cm and then weighed.

In cases where the full roots could not be excavated due to obstacles such as rocks, the diameter of the last bit of the root was recorded and we treated the remaining unexcavated part as a side root. An effort was made to ensure that all the taproots were fully excavated up to a diameter of 1 cm. In total, 38 out of the 41 trees had taproots. Out of these 38 trees, we were not able to fully excavate the taproots of 16 trees. In such cases, the diameter at the breaking point of the unexcavated taproot was recorded and treated as a side root. On average, tap roots were dug down to 2.5 m depth. Lastly, we recorded the fresh weight of the root crown for each tree. For all sample trees, three small sub-samples, varying in weight between 0.1 and 1.0 kg, were taken from each main and side root, and one was taken from the root crown. We obtained the fresh weight of the sub-samples using an electronic balance and brought them to the laboratory for oven drying.

Photo 1. Miombo woodlands during dry season (a), weighing a log during destructive sampling (b), Sensefly eBee Unmanned Aerial Vehicle (c), preparing to fly the Sensefly eBee Unmanned Aerial Vehicle (d).

c) Processed UAV images data

The images used in Papers 3 and 4 were acquired using a SenseFly eBee fixed-wing UAV (Sensefly 2015). The UAV was made from flexible foam weighing 537 g without camera. The UAV was equipped with a Canon IXUS 127 HS Digital camera. The dimensions and weight of camera with battery and memory card were 93.2 × 57.0 × 20.0 mm and 135 g, respectively. The camera produces 16.1 megapixel images in the red, green and blue spectral bands. The UAV is also equipped with an inertial measurement unit as well as an on-board Global Navigation Satellite Systems (GNSS) to control the flight and to provide rough positioning (Sensefly 2015). Prior to taking images, positions of ground control points (GCPs) as well as landing and take-off points, e.g. on open areas with no trees within the forest and agricultural fields near the forest, were identified and measured. The GCPs were made of a set of 1 × 1 m cross-shaped timber planks painted white and some black and white 50 × 50 cm checkerboards. The position of the centre of each GCP was fixed using the same procedure as used when locating plot centres for the sample plot inventory described above. The data were collected for an average of 13±6 minutes for each GCP with a 1-second logging rate. The recorded coordinates for each GCP were post-processed similarly as the sample plots. The results revealed that maximum deviations for northing, easting and height were 2.24 cm, 4.50 cm and 4.46 cm, respectively.

Acquisition of images was controlled from a laptop computer with a mission control software eMotion 2 version 2.4 (Sensefly 2015). All the flights were planned in the mission control software prior to flying. For navigation purposes, a georeferenced base map from Microsoft Bing maps covering the study area. For this study we applied percentage end and side image overlaps of 80 and 90% respectively, as well as a fixed flight height above the ground of 325 m. In total 20 flights were carried out to cover the forest.

5.3 Data analyses

For development of volume models (Paper 1), volumes of individual logs were calculated by multiplying the basal area of the mid-section of each log by its length. Subsequently, the stem and branch volumes for each tree were determined by summing all individual log volumes for the respective sections. Total tree volumes were determined by summing the merchantable stem and branches volumes for individual trees.

Development of biomass models (Paper 2) started by first drying all sub-samples from both above- and belowground portions of each tree in an oven at a temperature of 80°C until a constant weight was achieved (constant weight was observed in 2–3 days) and subsequently recording their dry weights. The sub-sample dry and fresh weights were then used to determine the tree- and section specific dry to fresh weight ratios (DF-ratios) which were then used to calculate the dry weight of each section as a product of tree- and section specific DF-ratios and the fresh weights of the respective trees and tree sections. Subsequently, we computed the total aboveground dry weight each tree by summing the dry weights of the merchantable stem, branches and twigs.

To determine the total belowground dry weights of the excavated parts of the trees we first converted all the fresh weights from the different sections to dry weight biomass by multiplying the tree- and section specific DF-ratios and their respective fresh weights. We then developed a general (combining data from all sites) side root model by regressing the dry weight biomass of the fully excavated side roots and their diameters (cm). The side root model was used to predict the dry weight biomass of all the side roots that were not excavated for the main sample root. The total dry weight of all side roots for each main sample root was then determined by summing dry weights of the excavated side roots and predicted dry weights of unexcavated side roots. Finally the complete dry weight of the sample main root was determined by summing the total dry weights of all side roots and the excavated parts of the main root. A main root model was then developed and applied to predict the dry weights of main roots not excavated. To determine the dry weight of unexcavated parts of the taproots (16 trees), we applied the general side root model. Total belowground dry weight biomass for each tree was finally determined by adding the dry weights of all excavated and unexcavated main roots, dry weight of the taproot and the dry weight of the root crown.

Using the respective datasets, general and site specific volume, aboveground and belowground models for total tree, merchantable stem and branch were developed utilizing diameter at breast height, total tree height and species-specific mean wood specific gravity as independent variables. The species-specific mean wood specific gravity values were extracted from the global wood density database (Chave et al. 2009; Zanne et al. 2009). Since the data demonstrated heteroscedasticity for volume, above-and belowground biomass, we applied generalized methods of moments (GMM) estimation method for volume models and weighted nonlinear regression for above- and belowground biomass models. The analysis was implemented using SAS Institute (2012) software. For all models, pseudo-R^2, root mean square error and mean prediction error values were reported. However, model efficiency and performance were based on root mean square error values calculated using leave-one-out cross validation procedure. Previously developed models were also tested and compared with the models developed in the current study.

Both Papers 3 and 4 required calculating aboveground biomass of each tree in respective sample plots. Before calculating aboveground biomass, total heights of trees whose height was not measured were predicted using a height-diameter model developed (Paper 3) using the measured heights of sample trees from all the sample plots. We then calculated aboveground biomass for each tree in the sample plots by using a model developed in Paper

2, with diameter at breast height and total tree height as independent variables. Per hectare values for aboveground biomass of the respective plots were calculated by first summing up the individual tree aboveground biomass values within a given plot and scaling them to per hectare values.

For both Papers 3 and 4, Agisoft Photoscan Professional version 1.1 (AgiSoft 2015) was used to generate a 3D dense point cloud from the acquired UAV images. To normalize the point clouds and subsequently extract metrics describing canopy height, canopy density and canopy spectral information in both Paper3 and 4, we developed, tested, and selected the best digital terrain models in Paper 3 using different approaches, and compared their performance to determine a suitable digital terrain model since the study area did not have an existing one. The tested approaches included a) supervised ground filtering based on visual classification, b) supervised ground filtering based on logistic regression, c) supervised ground filtering based on quantile regression and d) Shuttle Radar Topography Mission with quantile regression. In Paper 4, the metrics were extracted for each of the datasets for respective plot sizes (i.e. 250, 500, 750 and 1000 m^2).

To compare the performance of the different DTMs in Paper 3 as well as to estimate aboveground biomass for the study area in Paper 4 models relating reference aboveground biomass and the generated metrics were fitted on square root transformed dependent variables using multiple linear regression in R software (R Core Team 2016).

For both Papers 3 and 4, the developed models were evaluated using the squared Pearson correlation coefficient, root mean square error, relative root mean square error, mean prediction error and relative mean prediction error. Model selection was however based on the root mean square error values.

To assess the efficiency of UAV-assisted as well as the effect of sample plot and sample sizes on error estimates in biomass estimation in Paper 4, field-based biomass estimates and corresponding variances were based on the simple random sampling estimator. On the other hand, a model-assisted regression estimator described by Särndal et al. (1992), and its corresponding variance estimator, were applied for UAV-assisted biomass estimation. The relative efficiency (RE) of UAV-assisted inventory was assessed by a ratio of the variance estimates for the biomass based on purely field-based inventory data to that based on UAV-assisted inventory data.

Furthermore, to assess the cost efficiency of UAV-assisted over pure field-based inventories in Paper 4, during field work we randomly selected 16 sample plots and for each plot recorded three categories of time consumption, i.e. fixed time (time spent when recording sample plot attributes such as plot number, date, etc.), variable time (time spent on measuring trees) and walking time (time spent during walking from one plot to another). The average recorded time consumption was 7.5, 25.0 and 7.0 minutes for each of the aspects, respectively. We then set the relative cost of a sample plot inventory of 107 sample plots (1000 m^2 each) in a 220 × 220 m grid to 100% based on the recorded information. We then used the cost information from the current inventory (4 persons working for 15 days with a daily salary of USD 25.13 each) to calculate the variable costs for each plot scaled according to plot size and walking distance.

The costs for the UAV data acquisition were fixed for all sample plot sizes and sample sizes because the need for auxiliary remotely sensed information would be the same regardless of plot size and sample size. The cost was computed based on the experience from the current study. The cost included pre-flight preparations and the actual flying where a two-man crew was required. Each person worked five days with a salary similar to the field crew. Post-processing of the acquired images required four days.

6.0 Main findings and discussion

6.1 Volume and biomass models

The developed volume, above- and belowground biomass models (Papers 1 and 2) offer options for forest inventory scenarios in which data on diameter at breast height only or both diameter at breast height and total tree height are available. For both volume and biomass, the root mean square error and mean prediction error values of the models with both diameter at breast height and total tree heights as independent variables were better than those of the models with diameter at breast height as the only independent variable. This result also conforms to previous studies (Abbot et al. 1997; Mauya et al. 2014; Mwakalukwa et al. 2014) for volume models and Mugasha et al. (2013) for aboveground biomass models. On the other hand, for belowground biomass, the only viable model had diameter at breast height as the only independent variable. The fit of this model is similar to that of the models developed by Mugasha et al. (2013), Chidumayo (2014) and Ryan et al. (2011).

If diameters at breast height and total heights of all trees are measured in an inventory, the model including both variables should, of course, be applied. Otherwise, models with diameter at breast height alone are still reliable since much of the variation in volume and aboveground biomass was explained by diameter at breast height, while the addition of total tree height resulted in only small improvements. Since total tree height measurements are time consuming, they are usually estimated from height-diameter models developed from a few sample trees. If all tree forms in the forest are not represented among the sample trees, additional uncertainties in predictions are introduced. With appropriate sample trees and small measurement errors in tree heights, the accuracy of predictions will probably be improved by including total tree height as an independent variable, in spite of the uncertainty added by using a height-diameter model. For aboveground biomass models, inclusion of species-specific mean wood specific gravity values in place of total tree height did not improve the performance of the model. This could be attributed to the fact that the species-specific mean wood specific gravity values were not obtained directly from the sampled trees, but from the global wood density database (Chave et al. 2009; Zanne et al. 2009).

Tree component volume and aboveground biomass models, i.e. for twigs, branches and merchantable stem, may be useful when planning commercial extraction of timber or quantification of volume or aboveground biomass for domestic fuelwood or charcoal production. All tree component models with significant parameter estimates produced mean prediction error values not significantly different from zero, an indication of appropriate model performance.

When the selected volume and aboveground biomass models were tested on our dataset over different sites, none of the mean prediction error values were significantly different from zero, except for the volume model with both diameter at breast height and total tree height as independent variables in Tsamba, where volume was over-estimated. Furthermore, when previously developed models were tested on our dataset, the results showed that these models either over- or underestimated biomass (Table 1) or tree volume (Figure 3). These results demonstrate the importance of developing local models and also highlight the dangers of applying models beyond their geographical ranges because a change in geographical site in most cases also mean changes in ecological, climatic and edaphic conditions.

Table 1. Performance of previously developed biomass models tested on our dataset.

Component	Model	Independent variable(s)	No. of trees	Observed	Predicted	MPE	
				(kg)	(kg)	(kg)	(%)
Above-ground	Mugasha et al. (2013)	dbh	74	1239.7	1135.7	104.0	8.4
	Mugasha et al. (2013)	dbh, ht	74	1239.7	1076.7	163.0	13.2 **
	Ryan et al. (2011)	dbh	74	1239.7	1068.8	170.9	13.8 *
	Chidumayo (2014)	dbh	74	1239.7	1205.6	34.1	2.8
	Chave et al. (2014)	dbh, ρ, ht	74	1239.7	953.7	286.1	23.1 ***
Below-ground	Mugasha et al. (2013)	dbh	41	527.2	377.5	149.7	28.4 ***
	Mugasha et al. (2013)	dbh, ht	41	527.2	364.8	162.4	30.8 ***
	Ryan et al. (2011)	dbh	41	527.2	426.9	100.3	19.0 ***
	Chidumayo (2014)	dbh	41	527.2	551.9	−24.7	−4.7

***** MPE is significantly different from zero at ($p < 0.05$); ** MPE is significantly different from zero at ($p < 0.01$) and *** MPE is significantly different from zero at ($p < 0.001$), dbh = diameter at breast height, ht = total tree height, ρ = species-specific mean wood specific gravity.

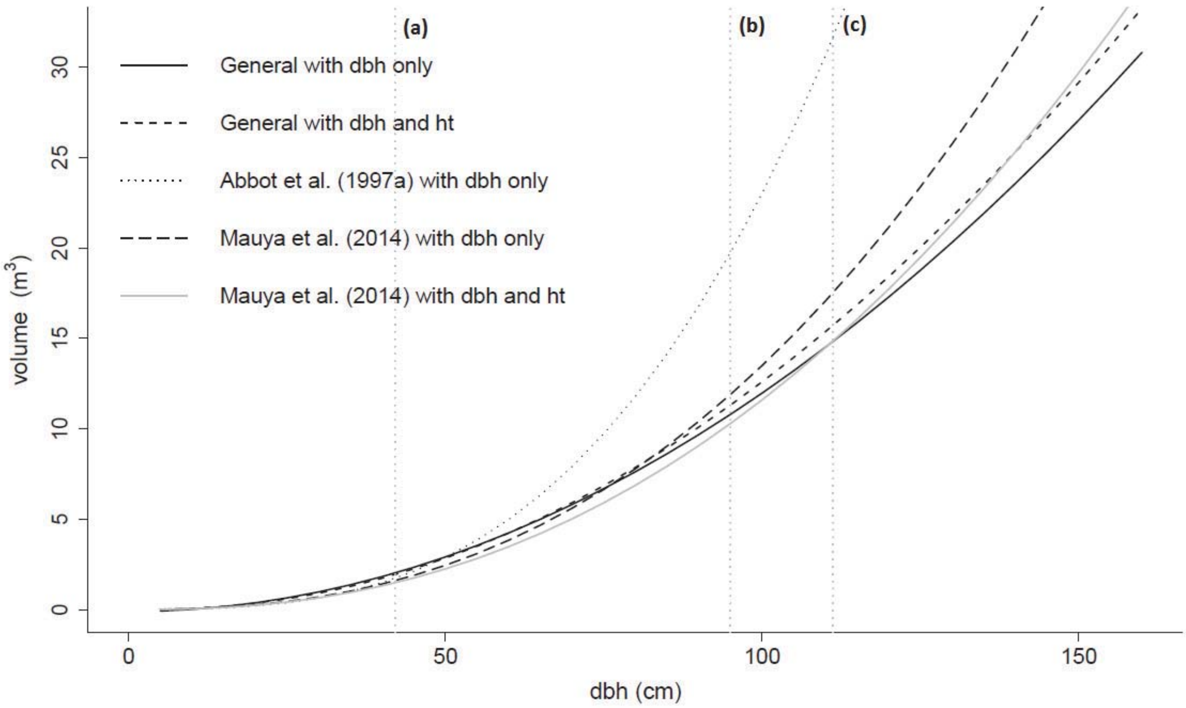

Figure 3. Display of total tree volume over diameter at breast height (dbh) for models developed in this study and previously. For the models with total tree height included as an independent variable, a height–diameter model developed from our sample trees was applied. Vertical dotted lines are the maximum diameter at breast height of the modelling datasets used by Abbot et al. (1997) (a), Mauya et al. (2014) (b) and in this study (c), respectively.

Recently, Kuyah et al. (2016) also developed aboveground biomass models for miombo woodlands in Malawi. These models were based on miombo trees outside forests collected from three sites in the central and southern region of Malawi. These models are thus suitable for biomass estimation for miombo trees in agroforestry systems during national forest inventories when biomass of trees outside forests is also considered (Schnell et al. 2014). Unlike the models developed in this study, application of models developed by Kuyah et al. (2016) for the REDD+ mechanism in Malawi is limited, since the potential project areas are forest reserves scattered across the country.

6.2 Application of UAVs in biomass prediction

Reliable biomass estimates from remotely sensed 3D data are heavily reliant on the availability of a good digital terrain model. In paper 3 we first tested different methods of generating digital terrain models. The comparisons of plot centre height predictions from different digital terrain models showed that predictions from the digital terrain model generated using Shuttle Radar Topography Mission data are unreliable as compared to those derived from the other methods. This indicates that when digital terrain models based on Shuttle Radar Topography Mission data are used in biomass estimation, the estimates can hardly be trusted.

Biomass predictions from the digital terrain models developed based on the tested approaches show that the digital terrain model developed using unsupervised ground filtering based on a grid search approach performed slightly better than others. This performance demonstrated that with some effort, it is possible to find good parameter settings in the AgiSoft Photoscan software (AgiSoft 2015). Furthermore, despite performing slightly less than the digital terrain model developed using unsupervised ground filtering based on a grid search approach, the digital terrain model based on supervised ground filtering using visual classification, was equally good. However, since unsupervised ground filtering is relatively easier to implement, future studies should consider application of this approach. On the other hand, the relatively poor performance of the digital terrain model developed from unsupervised ground filtering based on Shuttle Radar Topography Mission could be attributed to the inherent random errors in heights associated with shuttle radar topography mission data (Hofton et al. 2006; Karwel & Ewiak 2008; Rodríguez et al. 2006).

The root mean square error value for the best model from our study is similar to that reported in a study conducted in miombo woodlands of Tanzania by Mauya et al. (2015a) when using ALS data. On the other hand, in a study by Puliti et al. (2015), where data acquired from UAV was applied in boreal forests, a smaller root mean square error value compared to our study was observed when estimating forest stand volume. This might be attributed to the differences in forest structures between miombo woodlands and boreal forests. It should also be noted that Puliti et al. (2015) utilized ALS data for digital terrain model determination, which are superior in describing forest ground surface compared to optical sensors such as those applied in the current study (Baltsavias 1999). It is worth noting that the observed root mean square error in Puliti et al. (2015) is comparable to that observed in a study by Gobakken et al. (2015) also conducted in boreal forests. However, Gobakken et al. (2015) used exclusively ALS data. This demonstrates the efficiency of UAV data in forest inventories.

The findings from our study have also demonstrated that data generated by the UAV system have potential of being successfully used in estimating forest biomass in dry tropical forests such as miombo woodlands. Similar studies in other dry tropical forests are however recommended to validate the results of the current study because of the wide range of variations in structure, weather and terrain conditions seen in these forests.

6.3 Influence of plot and sample size on UAV-assisted biomass estimates

The results from Paper 4 have demonstrated that incorporation of UAV derived photogrammetric data in a forest inventory can improve forest biomass estimates beyond what can be achieved by purely field-based sample plot inventories (see Table 2). The relatively smaller mean biomass standard error values for the UAV-based estimates indicate that inclusion of remotely sensed data from UAV-imagery can improve the precision of biomass estimates. Thus the application of UAV-assisted inventories for REDD+ implementation in Malawi could potentially result in improved biomass estimates compared to pure field-based inventories.

Table 2. Relative efficiency (RE), estimated mean biomass and associated standard error (SE) estimates based on field-based and UAV-assisted estimation for different sample plot sizes and sample sizes.

Plot size (m^2)	**Sample size *(n)***	**Field-based ($Mg\ ha^{-1}$)**		**UAV-assisted ($Mg\ ha^{-1}$)**		**Relative efficiency**
		$\hat{B}_{field}$	SE	$\hat{B}_{uav}$	SE	
250	107	36.86	3.29	44.12	2.75	1.44
250	54	36.23	4.58	43.63	3.79	1.47
250	36	36.37	6.21	49.69	5.20	1.43
500	107	37.38	2.96	42.49	2.22	1.77
500	54	39.87	4.57	45.60	3.59	1.62
500	36	34.21	4.68	42.42	3.52	1.76
750	107	38.12	2.79	42.16	1.86	2.26
750	54	39.50	4.13	43.39	3.07	1.81
750	36	32.63	4.15	43.81	2.56	2.63
1000	107	38.99	2.85	43.30	1.72	2.75
1000	54	39.59	4.09	43.11	2.30	3.16
1000	36	33.12	4.39	40.96	2.36	3.46

$\hat{B}_{field}$ = Estimated mean biomass from ground-based sample, $\hat{B}_{uav}$ = Estimated mean biomass from UAV-assisted data, SE = Estimated standard error of mean biomass, RE = ratio of the variance estimates for the biomass based on purely field-based inventory data to that based on UAV-assisted inventory data.

Furthermore, correct choice of sample plot sizes is critical to the precision and accuracy of biomass estimates in remote sensing based forest inventories (Frazer et al. 2011). This is demonstrated by the increase in the magnitude of relative efficiency values with increasing sample plot size and the decrease in RMSE values with increasing sample plot sizes. The same trend was observed by Frazer et al. (2011) and Mauya et al. (2015b). The improvement of biomass estimates with increasing sample plot sizes shows that large sample plot sizes favour UAV-assisted inventories. This could be attributed to reduction in plot boundary effects as the sample plot sizes increases as suggested by Goetz and Dubayah (2011). Thus for small sample plots, canopies of trees with wide crowns such as those in miombo woodlands (Frost 1996) tend to be partially included and thus under predicting sample plot biomass. On the other hand, as the sample plot sizes increase, this effect tends to decrease substantially since these variations are averaged out at larger sample plot sizes (Saatchi et al. 2011).

The fact that the results in the current study indicate that larger plots and larger sample sizes favour UAV-assisted forest inventories does not imply that larger sample plots and sample sizes should always be applied during the UAV-assisted inventory because of the associated costs. The results on cost efficiency analysis indicate that there is a trade-off between costs and required precision. On one hand, acquiring UAV data and field reference data from many large plots is expensive but produces more precise results. On the other, acquiring the data from many small plots is less expensive but produces less precise results. Based on the observed trends, if a standard error estimate of less than approximately 3 Mg ha^{-1} was targeted during a forest inventory, then a UAV-assisted forest inventory should be applied to ensure cost efficient and precise estimates. This demonstrates the need for carrying out a cost analysis during UAV-assisted inventory in order to determine the optimal sample plot size and sample size to apply.

Finally, it should be noted that careful planning is needed for application of UAV-assisted inventories under the REDD+ mechanism in Malawi to be accomplished. For example, if the inventory is intended for smaller forest reserves, wall-to-wall coverage using a UAV is possible. On the other hand, in cases where inventories are conducted in larger forest reserves, the UAV can be applied as a sampling tool because wall-to-wall operations maybe found economically and logistically infeasible. Furthermore, this study was conducted on a single site and thus represents a forest inventory scenario at specific location. Although this case study has provided evidence of great efficiency of UAV-assisted inventory, similar studies should be conducted in other reserves across the country in order to be able to generalize and provide guidance for future operational inventories.

7.0 Concluding remarks and future studies

The main objective of the thesis was to develop models and methods for estimating volume and biomass of miombo woodlands in Malawi (Figure 1). The results from this thesis have taken us some steps forward that are expected to support and improve forest management decision-making in general as well as the implementation of a REDD+ MRV system in the country. Still, however, much work and research are needed. In the following, we point at main achievements as well as some weaknesses and corresponding suggestions on more research directly linked to the individual papers. We have also tried to go beyond the scope of the thesis, and have identified a few interesting and relevant topics for future studies that potentially could provide valuable inputs for further improvements in forest management decision-making and REDD+ MRV implementation in Malawi.

The performances and the evaluations of the models developed in Papers 1 and 2 suggest that they can be used over a wide range of geographical and ecological conditions in Malawi with an appropriate accuracy in predictions. The appropriateness of the models, and the importance of using local models in biomass estimation, was also supported by the fact that their mean prediction errors were much lower than some previously developed models tested on our data. In addition to the models for facilitating carbon assessments, we have also developed section models that can be applied when quantifying fuelwood and for timber valuation in compensation payments.

It should, however, be noted that the number of tree species included in the modelling datasets were relatively low when considering the total number of tree species found in miombo woodlands. Future studies should therefore aim at updating the current datasets (displayed in full in Papers 1 and 2) with additional species to improve the robustness of the models (e.g Chave et al. 2014).

The leaves were excluded from the biomass modelling dataset because most of the trees had started to shed leaves when the destructive sampling was carried out. Future studies may therefore attempt to collect the data when all the trees have leaves on them. Furthermore, inclusion of wood specific gravity as an independent variable, in addition to diameter at breast height did not improve the biomass predictions probably because the wood specific gravity values were obtained from the global wood density database. According to Baker et al. (2004), inclusion of wood specific gravity values from sample trees in biomass modelling is important as it helps in explaining variation in aspects of forest structure that vary significantly at regional scales (Baker et al. 2004; Chave et al. 2014; Ramananantoandro et al. 2015). So future studies should aim at utilizing wood specific gravity values from the sample trees.

The results from the biomass predictions based on a combination of remotely sensed data captured using UAV and field-based inventory data (Paper 3), show that the observed prediction errors are similar to those from previous studies using ALS data in miombo woodlands, thus showing the potential of applying this technology in miombo woodlands. Furthermore, the study highlighted that digital terrain models developed using unsupervised ground filtering based on a grid search approach can produce reliable results in miombo woodlands. Additional studies, however, are recommended to validate these results under other conditions using different flight settings, i.e. flying altitude and image overlaps, to search for the optimum settings. According to Bohlin et al. (2012), both flight altitude and degree of image overlaps influence the accuracy of the 3D data produced.

The results presented in Paper 4 demonstrated that UAV-assisted inventories produced more precise biomass estimates compared to those utilizing exclusively field-based methods. Furthermore, larger plot and sample sizes favour UAV-assisted estimates. The results on cost analysis of UAV-assisted inventory has shown that if a standard error estimate of mean biomass of less than approximately 3 Mg ha^{-1} is targeted during a forest inventory, then a UAV-assisted forest inventory should be applied to ensure cost efficient and precise estimates. However, similar studies should be conducted in other forest reserves across the country in order to be able to generalize and provide guidance for future operational inventories.

If we go beyond the scope of this thesis, an exercise where questions related to error propagations in biomass estimation are approached, would be very important, since the Intergovernmental panel on climate change (IPCC) requires biomass and carbon estimates reporting under the REDD+ mechanism to be accompanied by appropriate measures of uncertainty. Such uncertainties occur when applying the sampling design (sample plot size and shape, sample size), during tree measurements and when applying biomass models (Chave et al. 2004; Clark & Kellner 2012; Magnussen & Carillo 2015; McRoberts & Westfall 2016; Molto et al. 2013). All datasets described in this theses could be applied for error propagation in volume or biomass estimation. This could be done by using different biomass models (with corresponding covariance matrices as displayed in Paper 2), exclusively field-based methods and in combination with UAVs.

Another step would to be study methods and uncertainty related to determination of biomass changes over time. This is also important in the context of IPCC requirements on biomass and carbon reporting under the REDD+ mechanism. In particular, uncertainties related to different biomass change detection procedures (e.g. Magnussen et al. 2015; McRoberts et al. 2015) would be important. A study directly relevant for the miombo woodlands of Malawi could be done for the same study area as used in Papers 3 and 4, where, after some years, the sample plot inventory in combination with the UAV acquisition is repeated for estimating biomass.

A third step to ensure a sustained reduction in emissions from deforestation and forest degradation should be to conduct further research to understand the drivers of deforestation and forest degradation (Gizachew & Duguma 2016; Kissinger et al. 2012). Further studies on the establishment of sustainable forest management regimes capable of enhancing forest conservation and carbon stocks are also necessary (Edwards et al. 2010). In order to facilitate a better planning environment, a decision-making tool based on growth, mortality and recruitment models, like the one developed from miombo woodlands in Tanzania, is required (see Mugasha et al. 2016a; Mugasha et al. 2016b).

Finally, participation of local communities is critical for the sustainability of REDD+ in Malawi. Studies on assessing the feasibility of incorporating aspects of participatory MRV in the current preparatory phase of REDD+ implementation would therefore be important to check the interest of local communities surrounding the forest reserves (Danielsen et al. 2011; Hawthorne & Boissière 2014; Zahabu 2008).

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