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Forest monitoring with airborne laser scanning in Tanzania

Erik Næsset (editor)

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COVER PICTURE
Collection of field data on a sample plot in the miombo forests of Tanzania. Photo: Endre Hofstad Hansen

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Preface

The work presented in this report is the result of four year's research (2011-2015) in the project entitled *"Enhancing the measuring, reporting and verification (MRV) of forests in Tanzania through the application of advanced remote sensing techniques"*. The project has been funded by the Royal Norwegian Embassy in Dar es Salaam, Tanzania, as part of the Government of Norway's International Climate and Forest Initiative. The project has been led by Sokoine University of Agriculture (SUA), Tanzania, and the findings presented in this report are the results of collective efforts by several researchers and students at SUA as well as at INA.

The overall objective of the work has been to demonstrate and evaluate how remotely sensed data from airborne laser scanning can be used to enhance estimates of biomass and carbon stock in different forest types in Tanzania, and thus inform future decisions in countries on design of measurement, reporting and verification systems for carbon reporting.

Numerous scientific reports have been produced in the project. The aim of this INA report is to provide a synthesis of the major findings in a popular form. The report comprises a collection of three separate chapters prepared by individual author teams. Each chapter may be read separately, but the first chapter does present some general introduction to airborne laser scanning which may be found useful even for reading of the subsequent chapters.

We are grateful for the valuable comments and helpful suggestions for improvements of the manuscript that we received from our colleagues Katrine Eldegard and Ole Hofstad.

Ås NMBU, 9 October 2015

Erik Næsset

Summary

Næsset, E. (ed.) 2015. Forest monitoring with airborne laser scanning in Tanzania. - INA fagrapport 31. 30 pp.

The research presented in this report was conducted in three separate study areas in Tanzania. First, an area in Amani Nature Reserve located in the Eastern Arc Mountains was selected to analyze to what extent airborne laser scanning (ALS) could be used to estimate biomass in dense sub-montane rainforests. A number of other issues arose during the course of the work, such as influence of pulse density of ALS systems on the quality of the digital terrain model (DTM) derived from the ALS data. The DTM is of fundamental importance because ALS data for the tree canopies are usually calculated as heights relative to the derived DTM surface. Another important issue was the influence of field plot size for precision of biomass estimates based on ALS.

Second, a large study area in Liwale (Lindi District) was selected to quantify how well ALS data could characterize biomass in tropical savanna. The Liwale area is mainly miombo woodlands. The study area had a size of around 16,000 km^2. It was also used to analyze the potential of use of ALS to estimate change in biomass over short time periods (two years) and to assess the cost-efficiency of use of ALS to enhance biomass and biomass change estimates.

Third, a smaller area of 365 km^2 in miombo woodlands was used to quantify the contribution of different remote sensing technologies to improve estimates of biomass. The technologies were (*i*) ALS, (*ii*) interferometric synthetic aperture radar (InSAR) derived from the TanDEM-X satellites, (*iii*) RapidEye optical imagery, and global forest map products derived from (*iv*) Landsat and (*v*) ALOS PALSAR L-band radar imagery.

The overall findings in the project were that biomass observed on ground plots could be modelled with ALS-derived metrics such as canopy height and canopy cover as explanatory variables with model performance similar to what has been reported in other tropical studies. That even holds true for the high-biomass situations in the rainforest with recorded biomass densities up to around 1000 Mg/ha. Small plot sizes will tend to result in poorer models and therefore larger uncertainty of the final biomass estimates. For high-biomass situations plots larger than 2000 m^2 seem to be suitable for improved biomass estimates. We did not evaluate the cost-efficiency of larger plots. Even for dense forests, it seems sufficient to use ALS data with a pulse density of 1 pulse per meter square. Lower densities should be avoided to ensure accuracy of the DTM suitable for extraction of canopy properties from the ALS data.

For large area surveys for which acquisition of ALS data with complete coverage is cost prohibitive, sampling with ALS carried out by acquisition of ALS data along strips that may be spaced many kilometers apart, can improve the precision of biomass estimates by an order of magnitude compared to pure field sampling, like for example the national forest inventory of Tanzania (NAFORMA). In this situation ALS can also be highly cost-efficient. For *change* in biomass the cost-efficiency of use of ALS to enhance estimates was low, and pure field inventory is probably more cost-efficient – at least if the same field plots are visited on both occasions for which an estimate of change is sought. The current design of NAFORMA strongly restricts the benefits of remotely sensed data to enhance estimates. Further, transaction costs caused by problems with flight permissions to be granted by public authorities hamper efficient use of ALS technology in an operation setting in Tanzania. Different remote sensing techniques will have very different contributions to improve the precision of the biomass estimates, but the cost-efficiency of using different types of remotely sensed data remains an unexplored issue. Stratification of the entire Tanzanian land area in a manner that is consistent with the current NAFORMA stratification may open up for improved cost-efficiency of remote sensing.

Sammendrag

Næsset, E. (red.) 2015. Forest monitoring with airborne laser scanning in Tanzania. [Skogovervåking med flybåren laserscanning i Tanzania.] - INA fagrapport 31. 30 s.

Forskningen presentert i denne rapporten ble utført i tre studieområder i Tanzania. Det første er et område i Amani Naturreservat i Eastern Arc Mountains. Det ble valgt ut for å undersøke i hvilken grad flybåren laserscanning (ALS) kan brukes til biomasse-estimering i regnskog med høye biomassetetthet. Flere problemstillinger ble reist i løpet av arbeidet, som f.eks. effekten av pulstetthet i ALS-dataene på kvaliteten av den digitale terrengmodellen (DTM) avledet fra ALS-dataene. En DTM er av fundamental betydning for informasjon om tresjiktet ekstrahert fra ALS-data fordi vegetasjonsparametre vanligvis blir beregnet som høyder relativt til en beregnet DTM-overflate. Et annet spørsmål som dukket opp, var betydningen av arealet på prøveflater i felt for presisjonen av biomasse-estimater basert på ALS-data.

Det andre området er lokalisert i Liwale (Lindi Distrikt). Det ble valgt ut for å kvantifisere hvor godt ALS-data kan karakterisere biomassen i tropisk savanne. Liwale er for det meste miombo-skog og studieområdet har et areal på ca. 16.000 km^2. Det ble også brukt til å analysere potensialet ved ALS for å estimere endring i biomasse over korte tidsperioder (to år) og for å vurdere kostnadseffektiviteten ved estimering av biomasse og endring i biomasse.

Det tredje området har et areal på 365 km^2 miombo-skog. Det ble brukt til å kvantifisere bidraget fra ulike fjernmålingsdata til å forbedre biomasse-estimater. De analyserte dataene kom fra (*i*) ALS, (*ii*) interferometrisk radar (InSAR) fra TanDEM-X satellittene, (*iii*) RapidEye optiske bilder, and globale skogkart utledet fra (*iv*) Landsat og (*v*) ALOS PALSAR L-bånd radar bilder.

De overordnede funnene i prosjektet var at biomassen observert på bakken kan modelleres ved hjelp av ALS-avledede parametre som vegetasjonshøyde og -tetthet med en modell-tilpasning på linje med det andre studier i tropiske områder har vist. Dette gjelder også for tett tropisk regnskog med biomassetetthet opp mot 1000 Mg/ha. Små prøveflater vil gi dårligere modeller og derfor større usikkerhet i de endelige biomasse-estimatene. For stor biomasse-tetthet synes flater større enn 2000 m^2 å være best egnet for biomasse-estimering. Vi evaluerte imidlertid ikke kosthandseffektiviteten av store flater. Også i tett skog synes en pulstetthet for ALS-dataene på 1 puls per kvadratmeter å være tilstrekkelig. For å sikre egnede data for ekstrahering av vegetasjonsinformasjon bør lavere pulstettheter unngås.

Ved inventering av store områder der vegg-til-vegg kartlegging med ALS er økonomisk uforsvarlig, kan utvalgskartlegging med ALS ved å samle data langs korridorer lokalisert mange kilometer fra hverandre, være et alternativ. Det kan gi en presisjon for biomasse-estimater som er av en annen størrelsesorden enn tilvarende presisjon oppnådd ved tradisjonell utvalgskartlegging på bakken. Den nasjonale inventeringen for Tanzania (NAFORMA) er et eksempel på slik feltbasert kartlegging. I slike situasjoner kan ALS totalt sett også være kostnadseffektivt. For *endring* i biomasse var kostnadseffektiviteten ved bruk av ALS lav, og ren feltinventering er sannsynligvis mer kostnadseffektivt – i alle fall i tilfeller der de samme prøveflatene oppsøkes på begge tidspunkt som skal sammenliknes. Det nåværende design av NAFORMA begrenser fordelene ved bruk av fjernmålte data til å forbedre estimater. Likeledes vil transaksjonskostnader forårsaket av problemer med effektiv tildeling av flytillatelser fra offentlige myndigheter hindre effektiv bruk av ALS i Tanzania. Ulike fjernmålingsteknikker vil gi svært ulike bidrag til å forbedre presisjonen av biomasse-estimater. Kostnadseffektiviteten ved bruk av ulike typer fjernmåling er dog et uutforsket tema. Stratifisering av hele det tanzanianske landarealet på en måte som er konsistent med stratifiseringen benyttet av NAFORMA kan åpne for forbedret kostnadseffektivitet ved bruk av fjernmåling.

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Chapter 1:
Modeling and mapping of forest biomass and tree species diversity

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Introduction

Airborne laser scanning (ALS) is the most promising remote sensing technology for mapping and estimation of forest biomass and other related tree and forest properties. Such properties include for example merchantable volume and carbon with great relevance for operational management of forests as well as for mapping and estimation of quantities required for official reporting purposes, such as to the United Nations Framework Convention on Climate Change (UNFCCC). Thus, ALS can be a useful source of information also for REDD+ (Reducing emissions from deforestation and forest degradation) purposes. ALS has been used operationally to provide data for forest management for more than a decade due to high cost-efficiency and high accuracy of data products.

Technology

ALS is an active remote sensing technology by which near-infrared light is emitted from a laser and towards the ground, and then reflected back to the sensor aboard an aircraft. These measurements are converted to heights of the terrain surface as well as relative heights of objects located on the terrain surface, such as trees, buildings and other man-made objects. ALS typically produce 1-10 height measurements per meter square, and state-of-the art instruments can provide up to 800 000 such measurements per second, with the ability to cover large areas with highly detailed three-dimensional (3D) data. An example of a refined data product from an ALS acquisition of the complex sub-montane rainforests of Amani Nature Reserve in the Eastern Arc Mountains is displayed in Fig. 1.

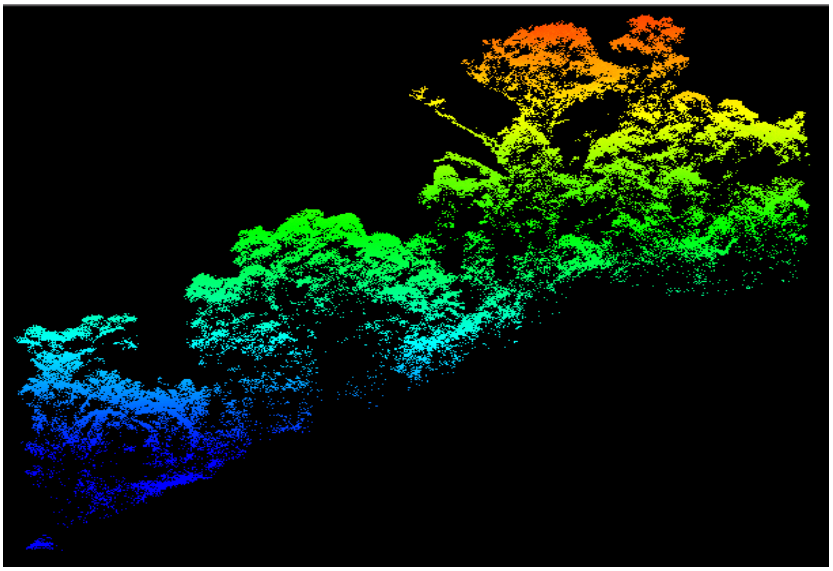

Fig. 1. Example of a profile through a rainforest tree canopy in the Amani Nature Reserve produced from ALS data with a density of 10 height measurements per meter square. Different colors indicate different heights above a defined terrain reference height.

Due to its ability to depict detailed 3D structures as illustrated by Fig. 1, ALS can help producing very accurate estimates of e.g. biomass because canopy heights and densities of tree canopies can be derived from ALS data. Such metrics are highly correlated with biomass and other forest properties.

Significance of the relationship between ALS data and forest biomass

Once ALS data are available through a dedicated flight campaign, a typical first step is to geographically relate the ALS data to available ground observations from the same area. Such ground observations are often forest inventory plots, like the extensive set of ground plots collected as part of the recently established NAFORMA program of Tanzania (the national forest inventory). Height observations from ALS are geo-located with an accuracy of 20-30 cm, and with use of modern GPS receivers the ground data can be positioned with accuracy with similar order of magnitude. An example of geo-positioning of a NAFORMA field plot with a high-precision GPS receiver is displayed in Fig. 2.

Fig. 2. Example of accurate GPS-recording of plot position for a circular NAFORMA plot. The coordinates of the center-point are determined. A 2.9 m tall antenna is used to improve reception of signals from the GPS satellites. Photo: Amiri Mahenge.

When ALS data have been coupled with appropriate field observations, the statistical relationship between field data (for example forest biomass) and metrics derived from the ALS data can be constructed. Typical metrics derived from ALS can for example be the height of the canopy and canopy cover (tree canopy density). The latter is a measure of how dense the tree canopies are. The relationships that are constructed are so-called regression models, and assuming their validity even outside the spatially limited domains of the small ground plots, these models can be used to compute e.g. biomass for the entire area of interest. Such spatially continuous calculations can be displayed in the form of a map. An example of a biomass map produced from ALS data and corresponding ground plot data in Amani Nature Reserve is displayed in Fig. 3.

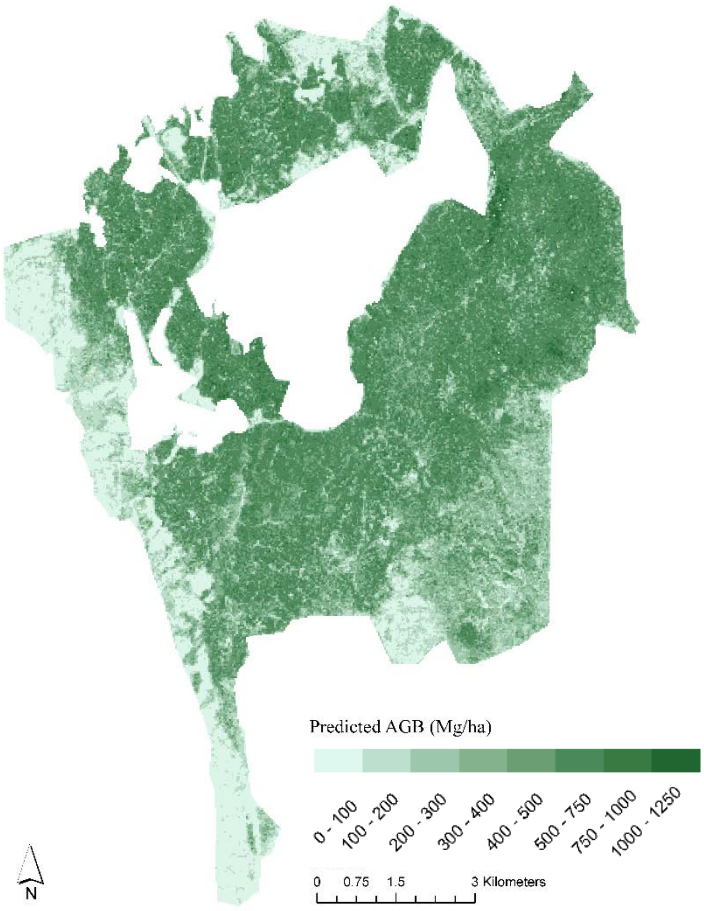

Fig. 3. Example of biomass map of Amani Nature Reserve constructed on the basis of wall-to-wall ALS data and accompanying ground observations of biomass recorded on forest inventory field plots. Numerical values in legend are aboveground biomass (AGB) in Mg/ha.

Such maps may help improving our understanding of the spatial distribution of biomass and other properties of interest. Furthermore, the actual biomass values associated with the individual map pixels constitute an intermediate product to produce estimates of biomass for the region of interest, for example a district or country. Such estimates may be useful for management, especially when the estimates are very local and with fine spatial resolution, but they are also of fundamental importance for reporting purposes. Therefore the step to establish a relationship between the remotely sensed data and the ground data through a statistical model is the key to exploit the remotely sensed data for improved accuracy of estimates. The accuracy of estimates when using ALS data to assist in the estimation process may go far beyond the accuracy which may be obtained with use of field data alone. Improved accuracy of estimates is seen as the main asset of remotely sensed data.

Modeling of biomass and tree species diversity

Modeling of biomass density has a long tradition in ALS studies and goes back to the introduction of ALS as new technology around 1995. There is evidence of the good performance for such models in boreal, temperate and tropical forests, but modeling of such relationships in very dense rainforests – such as those found in the Eastern Arc of Mountains in Tanzania, and in more open forests – like the mimbo woodlands dominating the land cover in the entire East Africa, is less frequent. It is considered to be extremely challenging to model biomass from most types of remotely sensed data in especially high-biomass forests due to the saturation effect. This effect implies that the remotely sensed data are insensitive to

very high-biomass conditions, and that use of remotely sensed data always will lead to an underestimation of the highest biomass values. For optical data like the Landsat satellite data, the saturation typically appears at values around, say, 100 Mg/ha, which is just about 1/10 of the most extreme biomass densities observed in for example sub-montane rainforests in Tanzania (typically around 1000 Mg/ha).

In this study we constructed relationships between biomass observed on the ground and ALS data in two important forest ecosystems: the sub-montane rainforests found in the Amani Nature Reserve, and in the miombo woodlands of Liwale. In Amani we used 153 field plots with an average size of 914 m^2. The locations of the two study sites in Tanzania are displayed in the map in Fig. 4. Fig. 5A and Fig. 5B show the distribution of the field plots in the two regions. In Liwale we used 513 field plots of the NAFORMA program with a plot size of 707 m^2. Data were collected by re-measurements of the official NAFORMA observations in a dedicated field campaign one year after the establishment of the plots in the area. The NAFORMA data are collected in so-called clusters, i.e., 10 plots are located close to each other with a distance of 250 m between plots, while the distance to the next group (cluster) of plots is at least 5 km. Thus, dependency between plots within clusters is an effect that potentially should be accounted for. In the current study we used eight plots per cluster rather than the full cluster of 10 plots because the total size of a NAFORMA cluster (1250 m × 1250 m) is close to the maximum swath with of a single ALS flight-line (1370 m) and in order to have a more robust flight plan and reduce the risk of losing a great number of ground plots in the ALS overflights, we decided to systematically discard the two southernmost ground plots in every cluster.

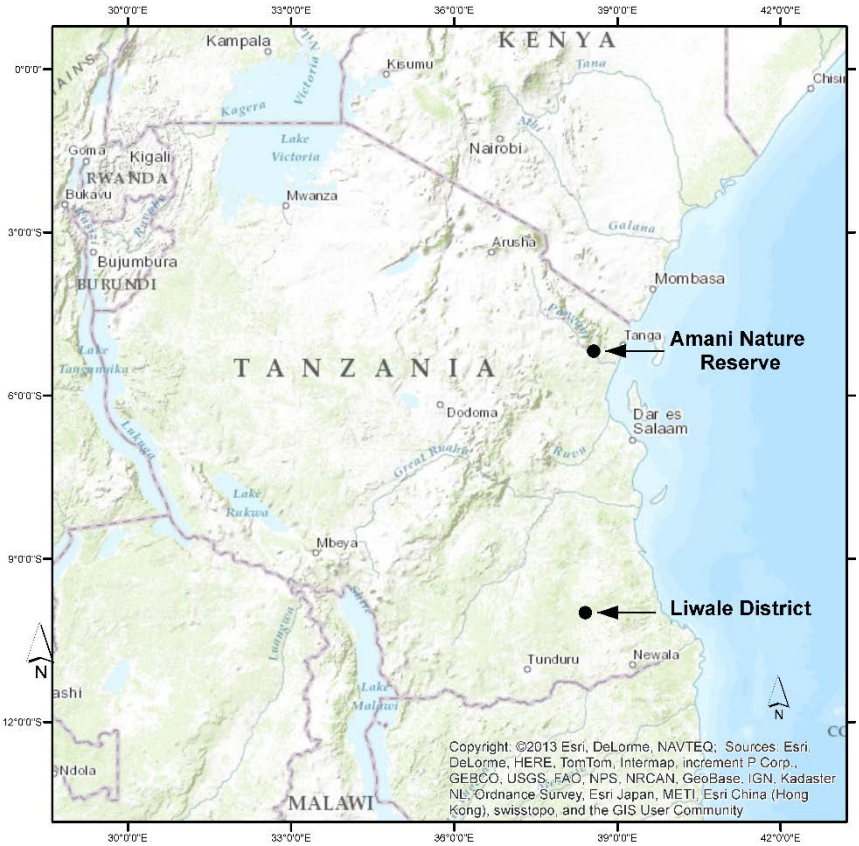

Fig. 4. Location of the two study sites in Amani Nature Reserve and Liwale District in Tanzania.

Another property of interest, which may be useful for biodiversity assessments, is the diversity of tree species. This is an expensive property to inventory by field measurements. However, because different tree species/species groups may display different patterns in terms of tree height distributions and canopy forms, ALS data may be a useful source of data to indicate species diversity due to its ability to capture 3D properties of tree canopies. We therefore wanted to quantify the relationship even between tree species diversity and ALS data. The species diversity was expressed in the form of aggregated diversity indices.

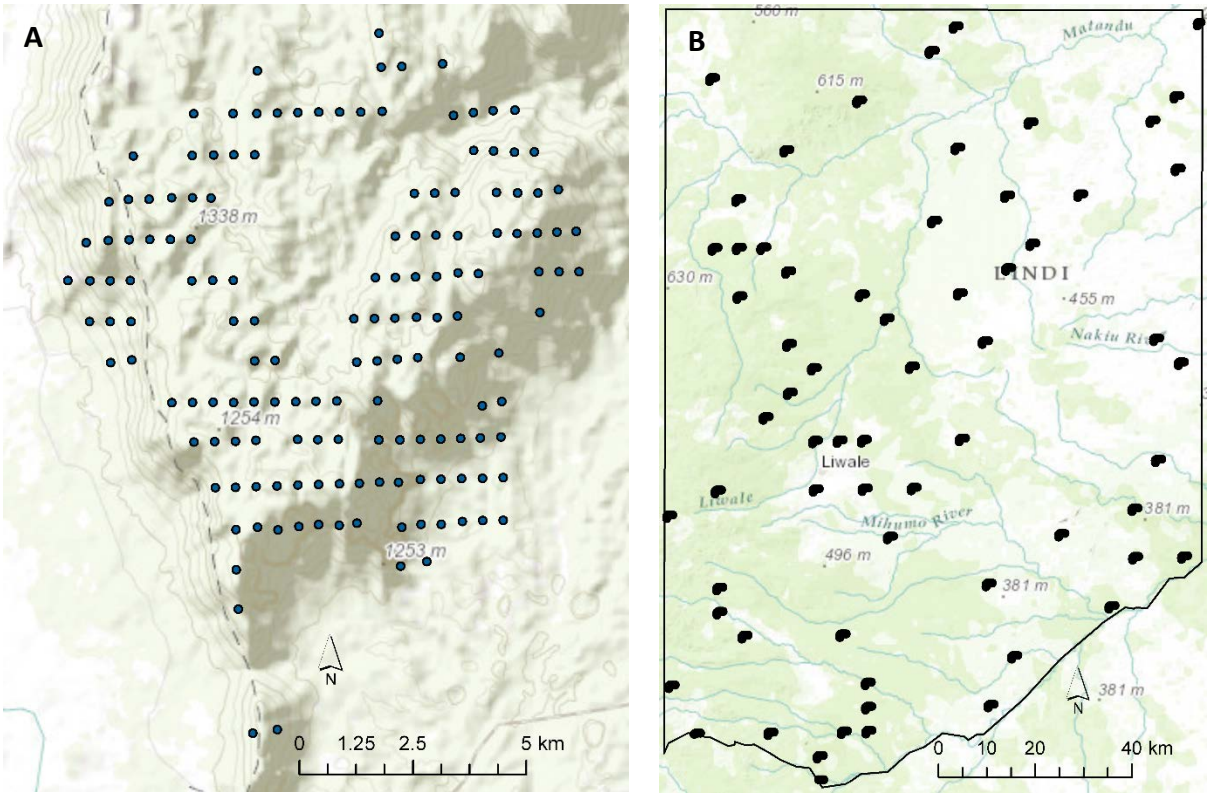

Fig. 5. A: Distribution of field plots in Amani Nature Reserve. B: Distribution of field plots in Liwale District.

Results

The modeling of relationship between biomass and ALS data in the rainforest was challenging and resulted in less accurate models than typically seen in boreal and temperate forests. However, the strength of the relationships was quite similar to what has been reported from other tropical rainforests around the world, and especially in Latin America where most of the previous studies have been carried out. The models explained 71% of the variability in the field-observed biomass on the plots (Hansen et al. 2015). The scatter of the observed biomass plotted against the biomass calculated with the model is displayed in Fig. 6. It may be seen that the fit is poor for high-biomass values. We think the reason for the lack of fit is the small plot size relative to the size of tree crowns, leading to a mismatch between field-observed trees inside the field plots and the measurements of the tree crowns by ALS inside the very same plot, which partly is influenced by crowns from trees rooted outside the plot but with crowns hanging over the plot in question. Larger plots would probably improve model quality. GPS errors for the plot locations is another likely contribution to the lack of fit.

It was seen that canopy density extracted from the ALS data rather than canopy height was the most significant variable to explain biomass. This is an observation that has previously not been reported in the international literature. We think this is due to the limited height growth of large trees at old ages while large trees still can have significant growth in diameter. Thus, height may not be a good indicator of biomass because it is less sensitive to change in biomass than canopy cover in a natural high-biomass forest.

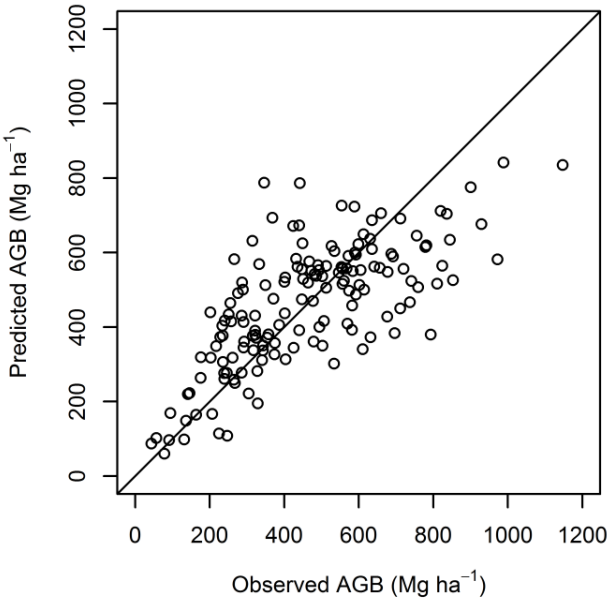

Fig. 6. Scatter plot of aboveground biomass (AGB) observed on the field plots and calculated (predicted) with the biomass model fitted in Amani Nature Reserve. Note that the ALS model underestimated biomass density for very dense rainforest, see text for further details.

In the miombo woodlands of Liwale, the relationships between biomass and ALS data showed a similar goodness of fit as in the rainforest. Several techniques were evaluated to construct the relationships, and when we accounted for the clustered structure of the field data from the NAFORMA program 69% of the variability in the field-observed biomass on the plots could be explained (Mauya et al. 2015a). We also noted that the relationships varied somewhat from one vegetation type to another and that for some vegetation types (e.g. lowland forests) better performing models can be constructed. As a consequence of these findings, stratified models could be a way to improve prediction accuracy if stratification is available from other sources. This issue is discussed in detail in Chapter 3 of this report. The differences in prediction performance for different vegetation types is illustrated by scatter plots of the modelled relationships for three distinct vegetation types in Liwale (Fig. 7).

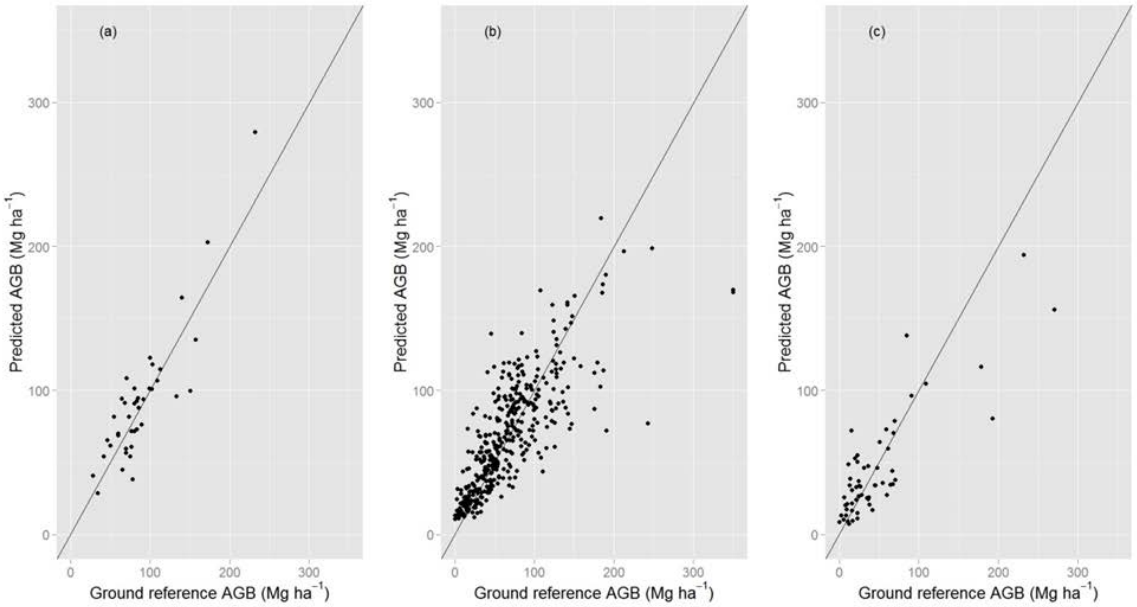

Fig. 7. Scatter plot of aboveground biomass (AGB) estimated on the field plots (ground reference) and calculated (predicted) with the biomass model fitted in Liwale. (a): lowland forest; (b): woodlands; (c): agriculture.

Tree species diversity on the NAFORMA plots in Liwale was expressed in aggregated form by the two indices *tree species richness* and *Shannon diversity index*. They are commonly used measures/proxies of tree species diversity. The relationship between these two indices and ALS data were constructed with similar statistical techniques as used for biomass. The relationships showed moderate goodness of fit, but although the obtained results offered logical interpretations, a fairly large amount of variability remains unexplained.

Metrics related to canopy height and canopy density in various vertical layers of the canopy contributed to explain variations in the diversity indices, which is reasonable (Mauya et al. 2015b). Such densities in vertical layers reflect the vertical distribution of biological material in tree canopies. The relationships were affected by differences in structural properties attributed by the vegetation types. Clearly, there were also differences in diversity between vegetation types. The forest class (lowland forest) reached a lower total richness in tree species across a given number of plots than for example woodlands (Fig. 8). Thus, discriminating by vegetation type can be a means to improve the ability to calculate species richness from ALS data. However, prior information on vegetation type should then come from another source, for example by classification of optical data.

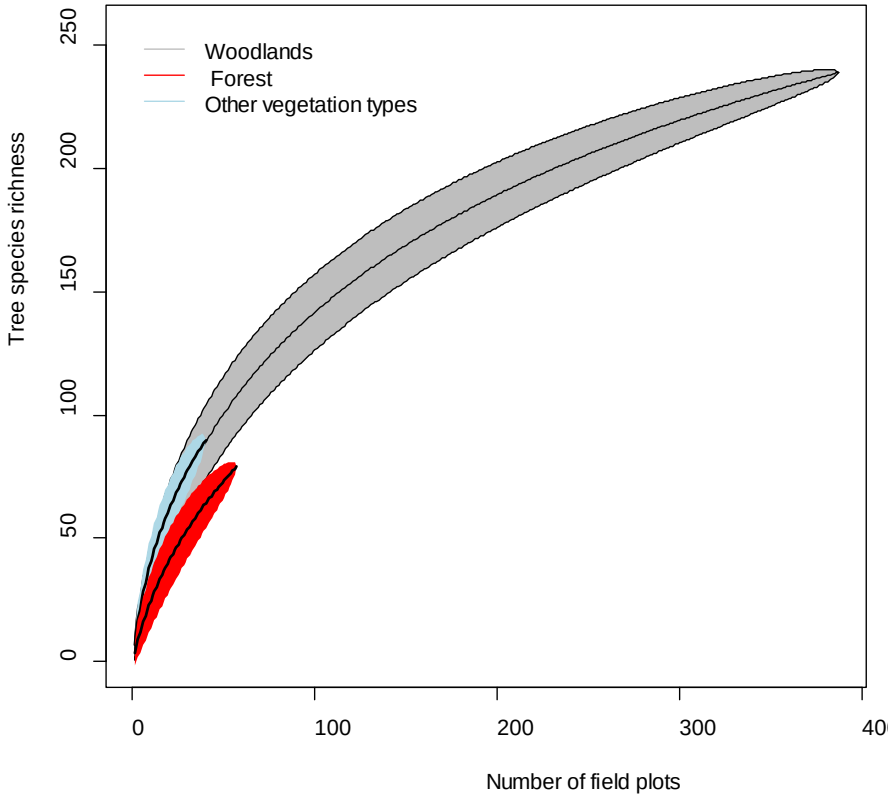

Fig. 8. Species accumulation curves in Liwale for all field sample plots pulled together.

Conclusions

Model relationships between biomass and ALS data are fundamental for exploiting the potential of ALS for improved accuracy of biomass estimates, for example for reporting purposes. The studies in sub-montane rainforests and miombo woodlands show quality of models similar to what has been reported in other countries, and they do indeed point to great promises for ALS in the forest types considered in Tanzania. Some imperfections were noted in especially the models for dense rainforests, and they pertained primarily to small field plot sizes which may have been suboptimal for use of ALS. In the miombo woodlands it was noted that appropriate and promising relationships could be constructed for biomass while prediction of tree species diversity remains a challenge, despite clear trends of logical relationships between species diversity and canopy structural metrics derived from ALS data. For biomass as well as species diversity relationships may potentially be improved by distinguishing (stratifying) by for example vegetation type. Such information may come from classifications based on other types of remotely sensed, for example optical data, and especially hyperspectral data.

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Chapter 2:
Technical issues related to improved performance of laser scanning for topographic terrain modelling and biomass estimation

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Introduction

Airborne laser scanning is the most commonly used remote sensing technique to produce terrain models of the bare earth surface, and has over the past 10 years replaced photogrammetry as the main technique for production of topographic maps (contour lines) in most countries. ALS is also the most promising remote sensing technology for mapping and estimation of forest biomass and other related tree and forest properties. Dense rainforests in steep terrain are probably among the most challenging forest environments on the earth for terrain modeling and biomass estimation with ALS. Inabilities to "see" through solid biological material and challenges related to the size of the trees and a potential mismatch between ground observations of the trees and what is observed by the laser from above the tree canopy are seen as a the main challenges. The terrain model is also of fundamental importance for biomass estimation because the ALS data that are used to characterize the biomass are basically the heights of the tree canopies as measured by the ALS, which is derived with the terrain as reference surface.

Terrain modeling in high-biomass rainforests

When ALS is used for topographic mapping, light pulses that are emitted from the laser aboard the aircraft and penetrate through the tree canopies and down to the ground, are reflected back to the sensor. They are used to characterize the ground surface. Other laser measurements, for example those reflected from various parts of the canopy, are discarded in the terrain modeling. Thus, the primary data from ALS used to model the terrain are simply all the height measurements on the terrain surface with x, y and z coordinates. These measurements constitute a cloud of points in the three dimensional (3D) space. An example of an ALS point cloud with classified ALS measurements representing both the terrain surface and vegetation is displayed in Fig. 1.

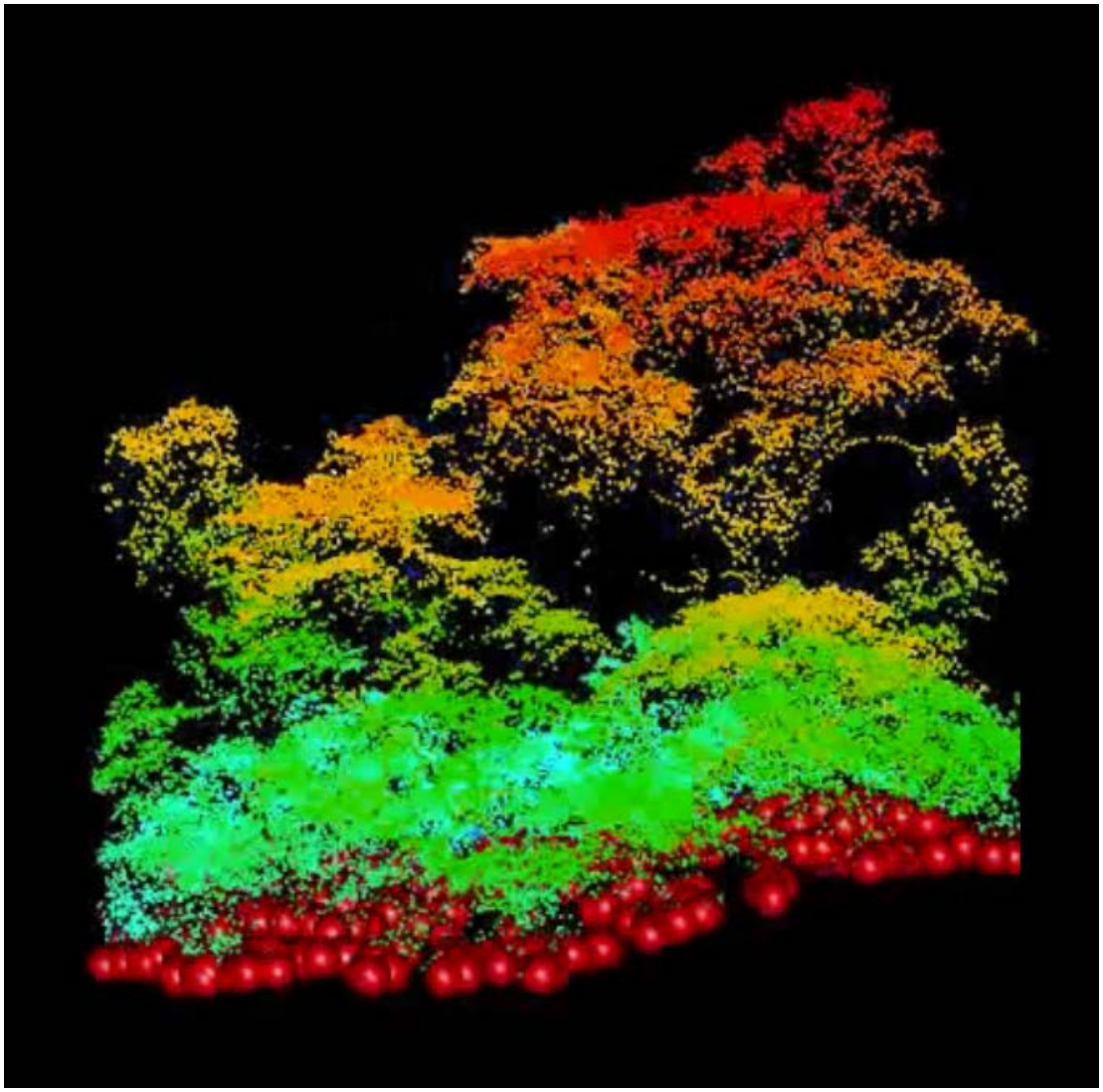

Fig.1. Example of ALS point cloud with classified terrain measurements (large red dots) and height-colored non-terrain measurements.

Because light cannot penetrate solid biological objects, dense rainforest tree canopies are seen as challenging regarding the ability to collect a sufficient amount of height observations from the terrain surface. Increasing the number of emitted laser pulses is a way to mitigate this problem by increasing the probability of getting at least some response from the terrain surface. There is, however, a strong relationship between acquisition costs and number of pulses emitted by the laser per unit area. Thus, in order to reduce costs, it is important to understand the consequences of reducing the measurement intensity. Low measurement intensity will reduce costs but may also reduce the quality of the topographic information and subsequently the accuracy of estimates of biomass because they rely on a well-defined terrain surface.

In the dense sub-montane rainforests of the Amani Nature Reserve we examined the consequences of reducing the measurement intensity on the quality of the modelled terrain surface, and subsequently the quality of the metrics that are extracted from the ALS canopy measurements. These metrics are typically used to calculate biomass, like for example canopy height above ground and canopy density. An illustration of the ground conditions in one of the field locations in Amani Nature Reserve is provided in Fig. 2.

Fig. 2. Example of ground conditions in one of the field locations in Amani Nature Reserve. Photo: Endre Hofstad Hansen.

The ALS data acquired over Amani Nature Reserve has a measurement density of more than 10 laser pulses per meter square, which is a very high density and seen as superfluous for accurate terrain modeling. This dataset was thinned in a simulation by randomly discarding measurements to different pre-defined levels of measurement density, namely to 8, 4, 2, 1, 0.5 and 0.25 measurements per meter square. For every level of thinning, the terrain surface was identified in the remaining data. The elevation of the modelled topography was compared to elevation obtained by precise GPS on 612 ground control points established in conjunction with tree measurement on 153 forest inventory plots (see details in Chapter 1). An illustration of what the cloud of ALS measurements may look like for a particular control point with different levels of thinning is provided in Fig. 3. The point cloud comprises terrain as well as vegetation measurements.

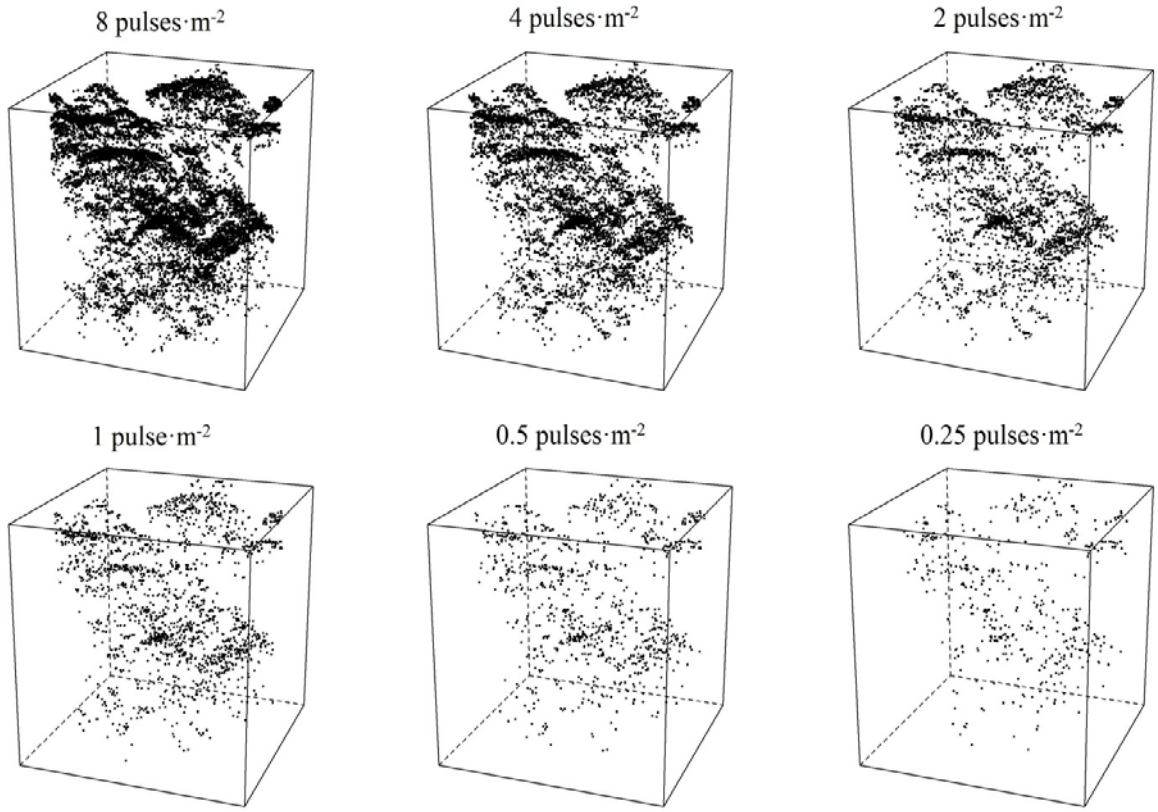

Fig. 3. Example of ALS data in Amani Nature Reserve thinned to different levels of measurement density (8, 4, 2, 1, 0.5 and 0.25 measurements per meter square). The data comprise terrain as well as vegetation measurements.

The results suggest that the quality of the terrain model is relatively insensitive to reduced densities down to a level of about 1 measurement per meter square (Hansen et al. 2015b). Higher quality may be obtained with higher density, but the gain in quality is marginal. This is good news, because it indicates that there is sufficient ability by the laser to penetrate all the way down to the ground surface even in dense rainforest canopies, and by that reduce acquisition costs.

When we analyzed the effects of reduced measurement density on the vegetation metrics derived from the ALS data, it was revealed that most of them, like metrics related to height of the canopy and density of the canopy, were fairly stable for measurement densities down to around 1 measurement per meter square (Hansen et al. 2015b).

Influence of field plot size on efficiency of ALS for biomass estimation

Field plot sizes in forest inventories in tropical, temperate and boreal forests typically range between, say, 200 m^2 to 1000 m^2. The latter has been a commonly adopted plot size in tropical inventories during the last decades. The plot size of the official NAFORMA program of Tanzania (707 m^2) is well in line with inventories in other countries.

Plot size is an important design property of an inventory, and there is a balance between the size of the individual plots and the number of plots required to reach a certain precision of estimates of for example biomass or volume for an area of interest. Large plots tend to increase precision of estimates, but at the same time on-plot costs will be increased. On the other hand, larger plots may lead to a need for fewer plots and thus reduce costs.

A reasonable balance between plot sizes and plot numbers is therefore driven by cost structure and precision requirements of estimates.

Experiences from initial studies of biomass modeling and estimation with ALS data in the Amani Nature Reserve (see Chapter 1) suggested that small plots may be suboptimal in biomass estimation using ALS data because of discrepancies between ground observations and ALS observations of the same plots. In field, trees with their stems rooted within the plot periphery are recorded regardless of the crowns' positions in the canopy, while the laser primarily measures the crown elements within the periphery of a plot. These crown elements may belong to the trees with their stems inside the plot, but also trees rooted outside the plot. This discrepancy will cause errors (noise) in the relationships between ground observations of biomass and the ALS data. Likewise, co-location errors, such as GPS errors and alike, will also create discrepancies. The relative impact of these sources of error will diminish with increasing plot size relative to the size of the tree crowns.

In the Amani Nature Reserve a specific set of field plots was established ad hoc to address this important issue. A dataset of 30 circular plots with sizes up to 0.3 ha were measured. Because we also measured the distance from the plot center to every individual tree, we could reconstruct even smaller plots of different sizes, for example sizes in steps of 100 m^2, like 100, 200, 300, …, 3000 m^2. These 30 plots were established on the grid of existing ground plots already collected in Amani (see Chapter 1). Fig. 4 displays the geographical distribution of the initial 153 plots on a systematic grid and the 30 circular plots of larger size.

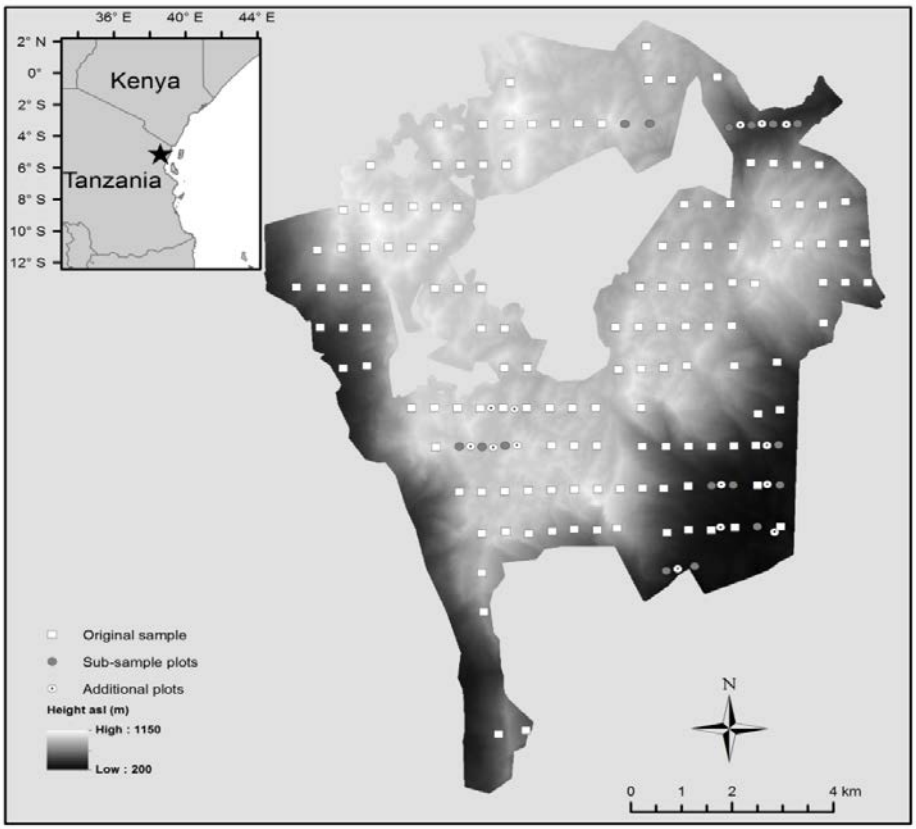

Fig. 4. Distribution of 153 initial field plots on a systematic grid (white rectangles) and 30 large circular plots (gray and white circles) with sizes up to 3000 m^2 in Amani Nature Reserve. Gray shading in the map indicates terrain elevation above sea level (meters) derived from a terrain model produced from ALS data, see legend.

Based on the reconstructed field plots of different sizes, we developed relationships between biomass on the ground and ALS data. The quality of these relationships increased significantly with increasing plot size (Mauya et al. 2015c). We subsequently used the constructed relationships to produce biomass maps which then were used to estimate total biomass for the entire study area. We also estimated the precision (variance) of these estimates. Corresponding estimates of variance based only on the field plots were also produced. The ratio between the variance of a field-based estimate of biomass and an ALS-supported estimate using the same field dataset is often called *relative efficiency*. Relative efficiency is a measure of how much an estimate is improved by one method compared to another. If for example the relative efficiency is 2, it means that twice as many field plots would be required to obtain the same precision with the least precise method as with the most precise method.

The results showed that the relative efficiency improved from a plot size of 100 m^2 to a plot size of 3000 m^2, with a marginal improvement from 2000 to 3000 m^2 (Mauya et al. 2015c). The relative efficiency ranged from around 2 to around 4-6. The results are displayed in Fig 5. The results are unstable due to small sample size, and further investigations are required to confirm this finding.

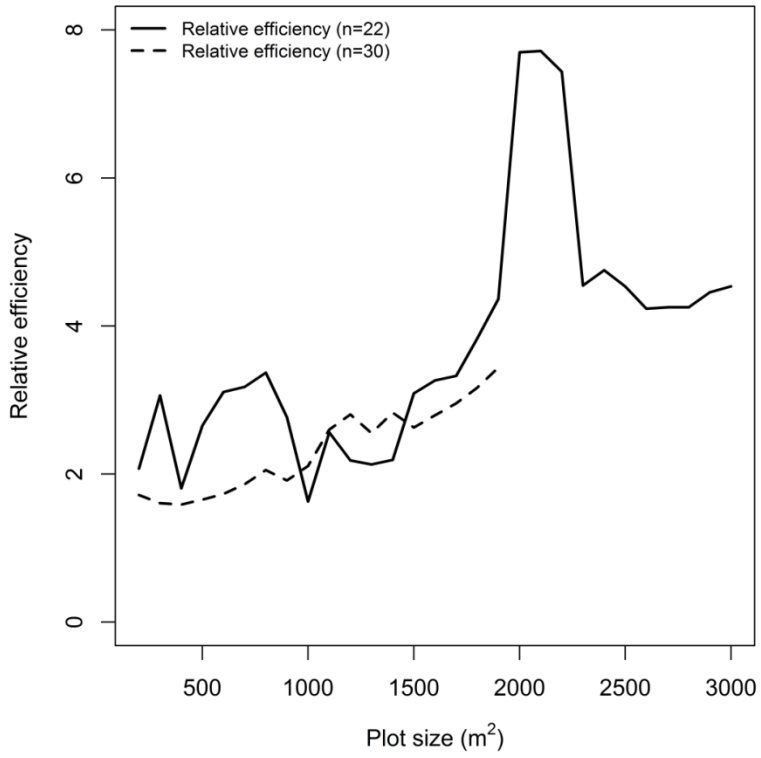

Fig. 5. Relative efficiency (relative variance) of biomass estimates in Amani Nature Reserve for different plot sizes. A sample of 30 plots cover the range from 100 to 1900 m^2 plot sizes (dashed line), while a smaller subsample of 22 plots cover the entire range from 100 to 3000 m^2 (solid line).

Another study (Hansen et al. 2015c) based on the same dataset but with another methodological approach confirmed the results detailed above. In this study, a so-called model-based approach to estimation and inference was used. As a benchmark for comparison, we used a model for biomass estimation which only depended on terrain elevation as explanatory variable. The study by Hansen et al. (2015c) also compared precision of ALS-

based estimates of biomass with precision of biomass supported by TanDEM-X InSAR data. A few more details on the latter technology can be found in Chapter 3 of this report.

The relative efficiency for both ALS and InSAR increased with increasing field plot sizes up to 1900 m^2, and ranged from 3.5 to 6.7 for ALS and from 2.7 and 4.0 for InSAR (Fig. 6).

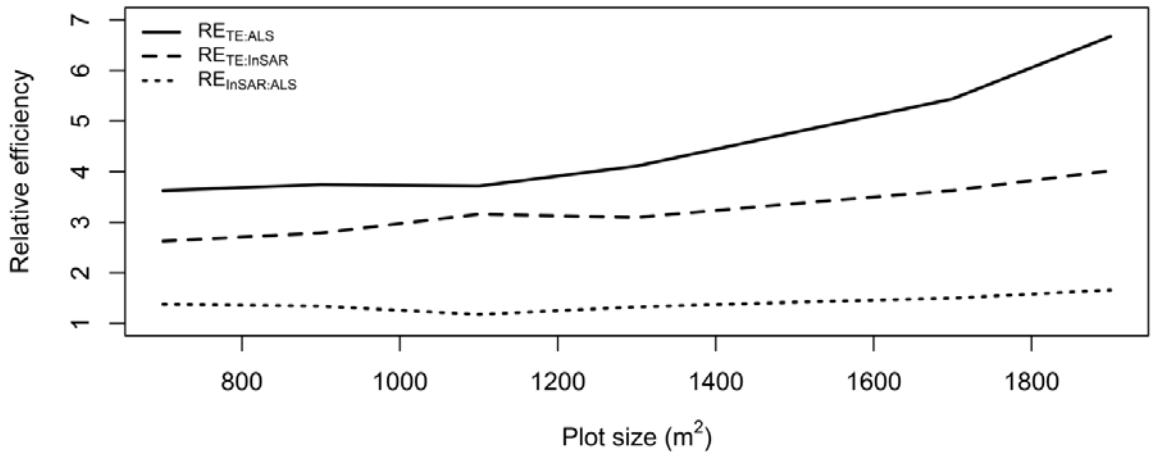

Fig. 6. Relative efficiency (relative variance) of biomass estimates in Amani Nature Reserve for different plot sizes for ALS (legend: RE_{TEALS}), InSAR (legend: $RE_{TEInSAR}$) and ALS relative to InSAR (legend: $RE_{InSARALS}$).

Conclusions

Accurate terrain models seem to be attainable from ALS data even in dense tropical rainforests if the laser measurement density is not less than 1 measurement per meter square. The quality of the terrain models may increase with increasing density of the measurements, but only marginally. Higher densities can therefore be hard to justify from a cost/utility perspective. The results obtained for terrain models seem to be consistent with results for metrics used to describe the vegetation canopy: measurement densities below 1 per meter square will reduce the quality of the data, but there is only a marginal gain in quality with increased density beyond 1 per meter square. Field plot size is another property which may influence the utility of ALS data for biomass estimation. Larger plot sizes are relatively more favorable than smaller plots compared to estimation based purely on a sample of field plots. From a pure technical point of view, it therefore appears to be efficient to increase plot sizes in ALS-assisted inventory beyond what has been the tradition in field surveys. The current findings suggesting plot sizes beyond at least 2000 m^2 to be suitable in dense tropical rainforests must be confirmed by more comprehensive studies. Finally, it should be noted that this is purely a technical finding. Future studies should look at cost-efficiency of such a strategy, and not only the technical aspects.

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Chapter 3:
Estimation of biomass and biomass change at regional level using laser scanning in combination with the nation-wide NAFORMA sample survey – performance and cost efficiency

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Introduction

Airborne laser scanning (ALS) has been shown to be highly efficient for precise estimation of biomass at local scales and when the ALS data have a wall-to-wall coverage. In such applications, a sample of field plots for which ALS data are derived for each individual plot, is used to establish the relationship between biomass observed on the ground and highly correlated variables of tree height and canopy density derived from the laser. Examples of such relationships are described in Chapter 1 of this report. These relationships (models) are subsequently used to calculate biomass from the ALS data for every individual location on the ground for which the ALS data provide coverage. Finally, estimates of biomass can be produced for the area of interest by aggregating calculated biomass values across that area. Under a so-called design-based and model-assisted inferential framework such aggregated estimates for the area of interest is finally corrected for model prediction bias using the ground plots that initially were used to fit the models. This inferential framework (design-based estimation) is essentially the same probability-based approach that is used by national forest inventories based on field data alone.

The application

For larger areas – like districts, regions or entire nations, it is not economically feasible to collect ALS data with full wall-to-wall coverage. ALS may still be a viable source of valuable information to improve estimates of biomass beyond the precision of estimates that may be achieved by the use of field data alone. ALS may even be seen as a useful source of data for estimation of other properties, such as for example forest area.

For larger areas the ALS data may be collected along individual flight-lines spaced many kilometers apart. That will reduce acquisition costs. Thus, the acquired data will simply be a sample of individual strips rather than having a wall-to-wall extent. In fact, the remotely sensed ALS data will then actually be a sample with many of the same fundamental properties as the NAFORMA plots, which also just constitutes a sample of the ground conditions. It is a fundamental requirement though that the ALS strips are collected along the existing grid of NAFORMA ground observations so that the airborne and ground-based samples can be geographically co-registered and data extracted from both data sources for the very same locations.

In the current project, such a sampling-based approach to estimate biomass and change in biomass over a short time period was developed and validated. We also quantified to what extent ALS could help improving the precision of biomass and biomass change estimates

obtained from NAFORMA plots. Cost-efficiency was also evaluated to see if the high costs associated with ALS acquisition could be justified by reduced need for field observations.

Study area and design

The study was conducted in Liwale in Lindi District, and the size of the study area was almost 16,000 km^2. The area was mainly miombo woodlands. A total of 65 NAFORMA clusters within the area were used, and in total they comprised 513 individual NAFORMA plots. These plots were established by the NAFORMA field teams in 2011 and revisited and re-measured twice for the purpose of this study; namely in 2012 and in 2014. Fig. 1 illustrates the conditions on the ground for one of the NAFORMA field plots in Liwale.

Fig. 1. Example of NAFORMA ground plot in Liwale and recording of precise position by GPS for accurate co-registration with the ALS data. Photo: Endre Hofstad Hansen.

ALS data were collected for temporal consistency with the ground plots in 2012 and 2014. The ALS data were collected along 32 E-W oriented flight-lines spaced 5 km apart, which is consistent with the spacing of the NAFORMA systematic sampling grid. The flight-lines represented approximately 1370 m wide corridors across the landscape. The distributions of ALS flight lines and NAFORMA clusters in Liwale are displayed in Fig. 2.

A special note is merited on the design of the field-based NAFORMA national forest survey because it restricts the use of remotely sensed data and will therefore result in lower efficiency of use of any type of remotely sensed data than had the design been more flexible. NAFORMA was designed as so-called double sampling for stratification. This design can be very efficient for field-based surveys and the specific properties of the design were determined after comprehensive simulations with the objective of minimizing the uncertainty (variance) with given budget restrictions (Tomppo et al. 2014). In the applied double sampling for stratification, a 5-km × 5-km point grid was generated for the entire country.

One among 18 mutually exclusive strata was assigned to each of these points. Thus, the collection of points on the 5-km × 5-km point grid constitutes the first-phase sample. The strata were based on information about timber volume from Landsat, terrain slope and field measurement time. Thus, a lot of information correlated with biomass is already built into the estimation through the stratification, which is why stratified sampling can be so efficient even when only field data are used for estimation. Then in the second phase of sampling, a systematic sample of these points was chosen within each stratum for the second-phase sample. This second-phase sample was visited in field and for each of the locations a cluster of multiple plots (typically 8-10) was laid out and measure on the ground. Plot size was 707 m^2. The sampling intensity in the second phase varied a lot among strata and corresponded to plot clusters on the ground for every second to every twentieth of the first-phase samples. The stratification for all other areas apart from the points on the 5-km × 5-km point grid is unknown. Therefore, even if the remotely sensed data have a wall-to-wall coverage, the stratification for areas in between the individual points will be unknown. If one wish to use remote sensing as part of the estimation, the choice is therefore either to use a stratified approach and thus ignoring all remotely sensed data across the landscape apart from the locations where the stratum is known (i.e., 0.03% of the area), or to disregard the stratification and use the full extent of remotely sensed data instead. Then the benefit of the stratification is lost, and it is hard for remote sensing-assisted estimation to be as cost-efficient as a pure stratified field survey.

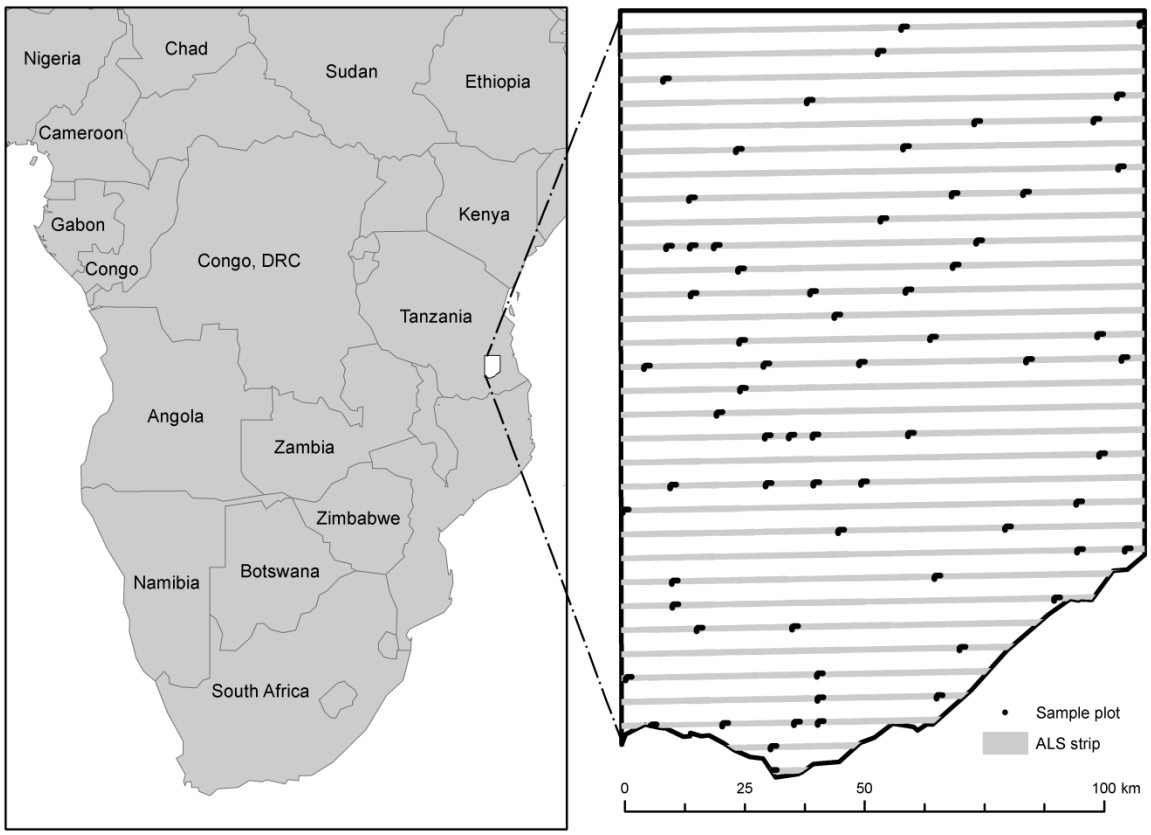

Fig. 2. Distribution of the 32 E-W oriented 1370 m wide ALS flight-lines and the 65 NAFORMA clusters in Liwale.

Estimating biomass in 2012

Based on (*i*) the NAFORMA field survey only and (*ii*) a combination of ground data and ALS data we estimated biomass across the entire study area for 2012.

Based on the 2012 field sample survey the biomass in Liwale was estimated to an average of 59.9 Mg/ha (Ene et al. 2015a). The corresponding estimate when ALS was used in combination with the ground data to enhance the estimates was 58.9 Mg/ha. Thus, the two estimates were almost identical, and not significantly different in the statistical sense. The uncertainties of the estimates – expressed by the standard error of the estimates, which is the square root of the variance, were 5.02 Mg/ha and 1.48 Mg/ha, respectively. This corresponds to 8.4% and 2.5% of the mean value, respectively.

Thus, a 95% confidence interval for the field-based estimate would be approximately 50.1-69.7 Mg/ha while a corresponding confidence interval for the ALS-assisted estimate would be 56.0-61.8 Mg/ha. Clearly, ALS contributed to a much smaller confidence interval of the estimate. If the design was simple random sampling rather than double sampling, the gain in precision by use of ALS would translate to an increased need for field samples for the pure field-based estimate to be equally precise as the ALS-based on the order of 11.5. Thus, a reduction of field sampling effort by a factor of 1/11.5=0.087 illustrates the potential of ALS to reduce the need for field work. Herein lays the potential gain in efficiency of using ALS to assist in the estimation, even though ALS by itself is a costly technology to apply. It should be noted that the relationships are slightly more complicated under double sampling than assumed here, but these numbers nevertheless illustrate that ALS can improve precision of biomass estimates by an order of magnitude.

As noted above, the complicated design of NAFORMA did not permit use of all the ALS data, given that one wanted to keep the benefits of a highly efficient stratification. Thus, the numbers reported above were from a stratified design under which 99.92% of the ALS data were discarded. That is, we only used the ALS data for the first-phase sample of NAFORMA plots mentioned earlier. Had the NAFORMA design been such that use of all remotely sensed data had been permitted, it is reasonable to assume even higher relative efficiency of the ALS-assisted estimation.

Estimating biomass change from 2012 to 2014

Estimating biomass change over short time periods with high degree of precision can be challenging because subtle changes can be hard to detect with any ground-based or remote sensing-based technique. Even dramatic changes such as deforestation may offer substantial difficulties for precise estimation because over the course of a two-year period deforestation is usually a relative rare event in a landscape. Nevertheless, change estimation over short time periods is seen as mandatory for REDD+ (Reducing emissions from deforestation and forest degradation) applications.

Based on the repeated and coincident NAFORMA ground observations and ALS acquisitions, change in biomass was estimated for the entire 16,000 km^2 study area. The field-based estimate showed a loss of biomass over the two-year period of 0.11 Mg/ha, which corresponds to a loss of 0.2%, or about 0.1% per year (Ene et al. 2015b). The ALS-assisted estimate indicated a loss of 0.26 Mg/ha (0.2% per year). The estimated standard errors were however relatively large. For the field-based estimate the standard error was 0.85 Mg/ha whereas it was 0.81 Mg/ha for the ALS-assisted estimate. This clearly shows that the changes were not statistically different from zero.

These results illustrate two important points. First, for small changes – positive or negative – it is very difficult to produce estimates that are significantly different from zero, suggesting

that one cannot with statistical confidence declare the change to be neither positive nor negative. It would require a very large ground sample to produce change estimates that are significantly different from zero, and thus to declare with confidence that a gain or loss of biomass has taken place.

Second, the results illustrate that for change estimation the ALS data offered little to improve precision and ALS acquisition could hardly be justified. It should be noted though, that a likely reason for the relatively poor performance of ALS compared to the field-based estimation is the fact that the NAFORMA survey is optimized for field-based estimation and not for use of ALS data, cf. the discussion on stratification of NAFORMA above. If ALS is to be used for change estimation, other designs than the one employed by NAFORMA may be beneficial. Experiences from boreal forests suggest that ALS may be highly efficient even for biomass change estimation if the ground sampling design is better adopted to serve ALS-assisted estimation. For example, a reduction of uncertainty (variance) of biomass change estimates by up to 97% has been reported for certain change categories (Næsset et al. 2013).

Cost-efficiency of ALS-assisted surveys for biomass change estimation

Cost-efficiency is a fundamental concept in forest surveys because it combines the pure technical aspects of estimation – expressed by the statistical precision of an estimate, and the costs associated with the survey. For example, ALS may be more cost-efficient than pure field survey – despite the high costs associated with ALS data acquisition, if the gain in precision can result in reduced need for ground plots and thus lower total costs compared to a pure field-based survey that would require a much larger field sample and thus considerably higher field costs.

In order to study cost-efficiency it is often useful to consider different sampling designs because one particular design, like double sampling for stratification used by NAFORMA, may favor one particular application (pure field-based estimation) and thus hinder insights into designs that may be overall more favorable if e.g. ALS data is expected to be available. Different designs and their respective cost-efficiencies may be analyzed by sampling simulations. In this project, such simulations were undertaken for Liwale.

Because the cost-efficiency to a large extent will depend on the cost structure, a sampling design or estimation method (e.g. with or without ALS) may be favorable in one forest type but not in another, or in one country with certain labor costs and infrastructure, but not in another country with other labor costs and different infrastructure. In the current study we had to assume certain costs associated with the kind of field work that was undertaken by NAFORMA as well as certain costs for ALS acquisition. We assumed a cost of 1000 USD per field cluster and 60 USD per strip-kilometer with ALS data.

Several important findings were noted (Ene et al. 2015c). First, it was found that ALS-assisted estimation often outperformed pure field-based estimation for *biomass* estimation but not necessarily for biomass *change* estimation. Second, if a repeated survey was assumed, i.e., that the same ground plots were measured on both occasions for change estimation, then field-based estimation was highly efficient. Third, if independent surveys were conducted, i.e., that different plots were visited on the two occasions, then ALS-assisted estimation was more cost-efficient. Finally, it should be emphasized that these results are sensitive to changes in cost structure. Further, it is likely that ALS surveys may have greater potentials for improvements, for example by post-stratification.

Comparison of various remote sensing techniques for biomass estimation

In a small sub-region of the 16,000 km^2 large study area in Liwale, a field sample with higher sampling intensity than the NAFORMA survey and wall-to-wall coverage of several types of remotely sensed data were used to quantify the contribution of the various remotely sensed data types to enhance biomass estimates beyond the precision that the field sample alone would permit. Such comparisons may inform decisions on sampling designs and choice of data sources for estimation of biomass. The study area covered 365 km^2 (Fig. 3) and the remotely sensed data that were considered were (*i*) ALS, (*ii*) interferometric synthetic aperture radar (InSAR) derived from the TanDEM-X satellites, (*iii*) RapidEye optical imagery, and global forest map products derived from (*iv*) Landsat and (*v*) ALOS PALSAR L-band radar imagery.

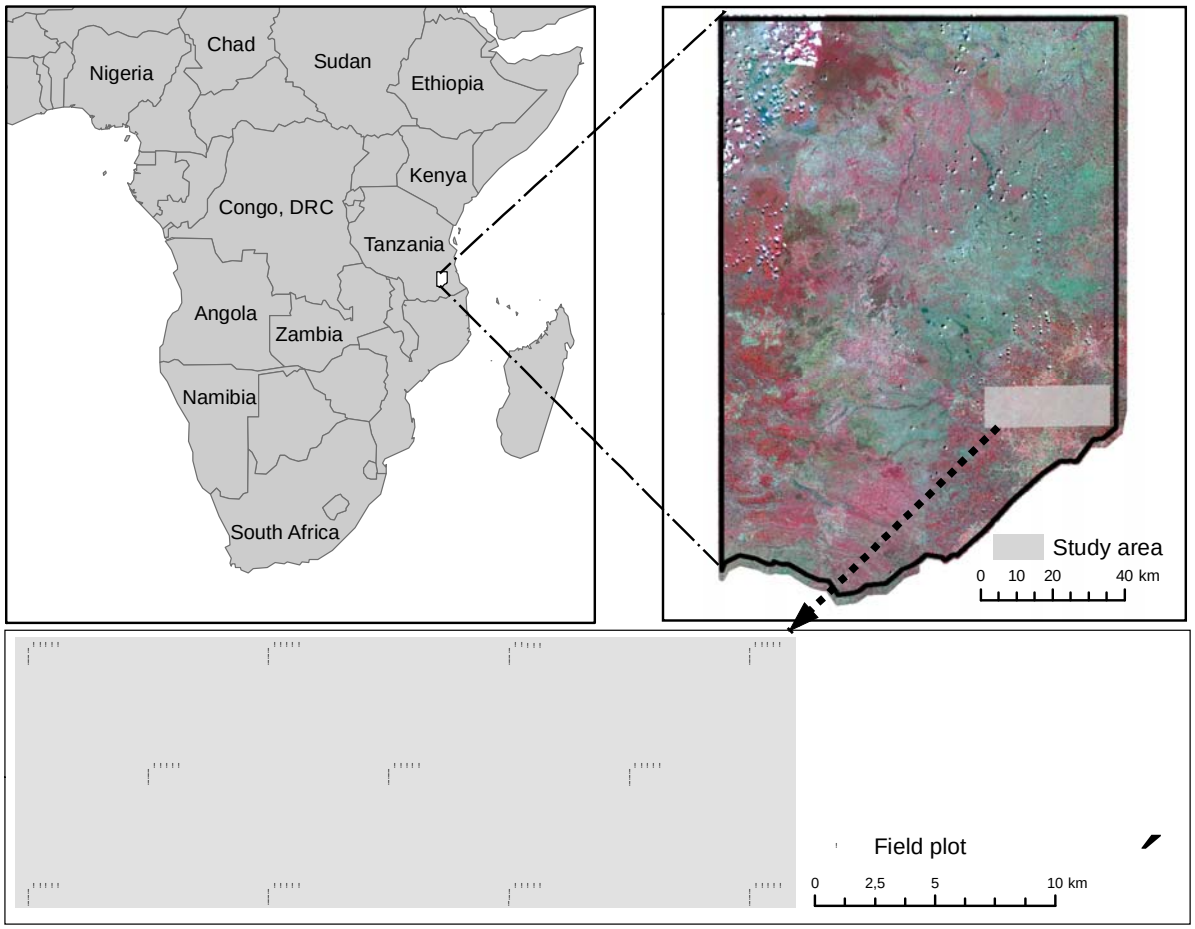

Fig. 3. Location of small 365 km^2 study area within the larger Liwale area. The lower box in the panel shows the distribution of the field plots within the study area.

The procedure described in the introductory part of this chapter was followed for the estimation. Thus, the field plots were connected with the various remotely sensed datasets, relationships (models) between biomass observed on the ground plots and variables derived from the remotely sensed data were constructed, and these models were then used to calculate biomass for the entire study area. Such calculations (model predictions) may result in a map. Biomass maps produced from the different types of remotely sensed data are presented in Fig. 4. The variables that were used in the models were for example tree height and canopy cover for ALS, canopy height from InSAR, reflectance values for the various spectral bands of

RapidEye, tree cover in the global Landsat maps, and classifications of forest/non-forest in the global ALOS PALSAR maps.

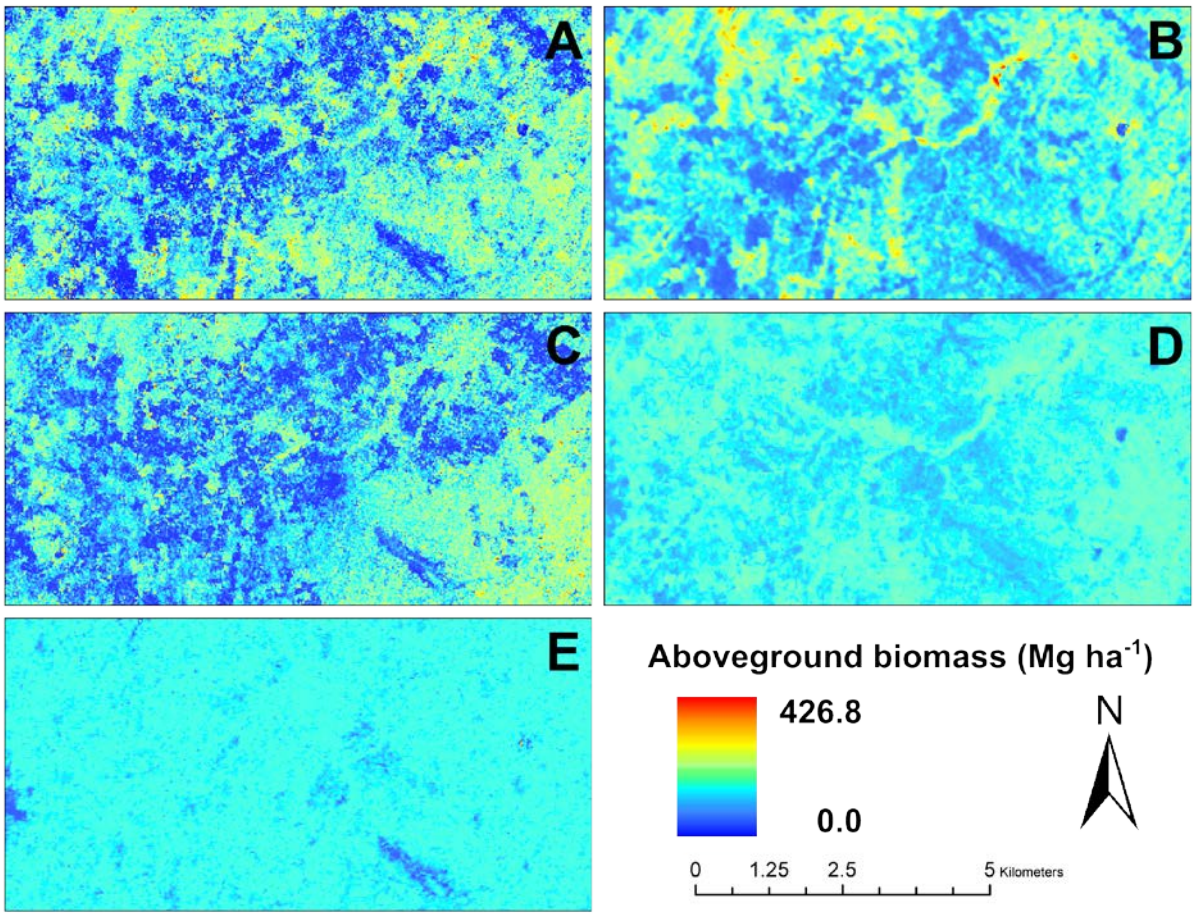

Fig. 4. Biomass maps for a minor part of the 365 km^2 study area based on the five remotely sensed datasets. **A**: ALS; **B**: InSAR; **C**: RapidEye; **D**: Global Landsat maps; **E**: Global ALOS PALSAR maps.

The biomass maps may be seen as intermediate products when estimating biomass. Based on these maps, design-based and model-assisted estimators were used to produce biomass estimates and associated estimates of precision (standard error). The mean biomass ranged from 51.3 Mg/ha for the pure field-based estimate and the estimate assisted by ALOS PALSAR data, to 60.1 Mg/ha and 60.4 Mg/ha for the estimates assisted by InSAR data and ALS data, respectively (Næsset et al. 2015). All the remote sensing-assisted estimates were within a 95% confidence interval of the field-based estimate, and the general level of biomass density corresponded well with what was found for the larger 16,000 km^2 area in Liwale.

The estimates of standard error (precision) ranged from 2.8 Mg/ha for ALS to 5.2 Mg/ha for the pure field-based estimate. These estimates are indicative for the savings that may be obtained by a need for fewer field samples when remotely sensed data are used to improve the estimates. Thus, relative to the field-based estimate, the ALS-assisted estimate suggests improved precision which translates to a need for only 29% of the field plots, for RapidEye 31% of the plots, for InSAR 40% of the plots, for global PALSAR maps 72% and for global Landsat maps 82%. The savings by using e.g. Landsat are small, but on the other hand the global Landsat maps are freely available and easy to use. It should therefore be noted that cost-efficiency was not considered in this study; just the gains in precision expressed in statistical terms.

Concluding remarks

The results of these studies demonstrate that ALS data can improve precision of biomass estimates beyond what a pure field survey can provide. In these studies we adopted a framework to estimation that assumed access to field data as well as remotely sensed data. However, the contribution of ALS data to improve biomass change estimates was moderate, depending on how the samples were collected. ALS was relatively more effective when independent field data were collected at the two points in time, but given the current design of NAFORMA, use of permanent plots alone without any support of ALS data seems to be favorable.

There is some evidence in the conducted research that over short time periods ALS data may not need support from ground observations at the second time of observation for change estimation, which suggests potential for great savings in field survey and also greater flexibility in repetition frequencies of change estimation because a single ALS campaign can more easily be organized than a full field survey. This issue was not fully explored though, and requires further investigations.

Cost-efficiency studies are of fundamental importance in assessing different sampling designs and approaches to estimation. For example, under given circumstances, Landsat data that contribute only marginally to improve estimates, may be highly cost-efficient because they are freely available and easy to use. Some of the examples provided in the studies illustrate that even costly ALS data can be cost-efficient in a country with low labor costs like Tanzania because the gains in precision can be large and the savings in field work can be substantial when ALS is used to enhance estimates.

It should be noted though that significant transaction costs were experienced in the project as far as the ALS acquisitions were concerned. They were not accounted for in the cost-efficiency analysis. The data vendor, a Norwegian company, was contracted by NMBU under a fixed price regime. The vendor experienced problems with obtaining flight permits on time which resulted in delays of the overall project with several months and significant additional costs due to mobilization of equipment and personnel from Norway and aircraft from South Africa that was interrupted after several weeks of standby at the base in Tanzania. Such practical problems will increase costs also in operational projects and restrict the opportunities for repeated acquisitions at regular time intervals for conventional reporting, as required by e.g. the UNFCCC.

The design of the NAFORMA field survey is highly efficient for estimation of current resources based on the field data alone, but this design is not the most efficient when used in combination with remotely sensed data. Because double sampling for stratification was used for the NAFORMA design, remotely sensed data outside the NAFORMA clusters cannot be used to its full potential. The research presented in the current report has not allowed a search for the overall most efficient designs given availability of different types of remotely sensed data because it was restricted to the properties of the existing NAFORMA survey. Therefore, it remains an unanswered question whether the NAFORMA design will be the most efficient for biomass and biomass change estimation assuming increasing amounts of different types of remotely sensed data in the future.

A complete-cover stratum map consistent with the stratification in NAFORMA would mitigate this problem and enable improved efficiency of use of all types of remotely sensed data. It should therefore be a priority to produce such a stratum map for Tanzania, which

effectively would allow the design to be regarded as a single-phase stratified design, enabling complete use of good remotely sensed data in wall-to-wall mode or as strip samples like for ALS.

Finally, it should be noted that this project was designed to answer questions related to use of ALS technology for large-scale (national) reporting purposes only. Estimation at finer geographical scales, such as at village or district levels may be relevant for national authorities for distribution of benefits generated through carbon credits or even for local carbon projects through e.g. the clean development mechanism. At such scales small field sample sizes may hamper field-based estimation and highly correlated remotely sensed data may be seen as the only viable alternative to provide local estimates. Interestingly, it is at the very local level (stand-wise and estate-wise) that ALS has become an operational and commercial reality in northern countries for practical forest inventory, not at national scale. This also points to the opportunities and need for data for improved forest management, which requires access to many more essential forest resource parameters than the biomass. Enhanced forest management is a vital part of REDD+ as well, and will in the long run be more critical for the welfare of a country than the carbon which is only one among a great number of services that the forests provide.

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