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ARTICLE

A sampling design for a large area forest inventory: case Tanzania

Erkki Tomppo, Rogers Malimbwi, Matti Katila, Kai Mäkisara, Helena M. Henttonen, Nurdin Chamuya, Eliakimu Zahabu, and Jared Otieno

Abstract: Methods for constructing a sampling design for large area forest inventories are presented. The methods, data sets used, and the procedures are demonstrated in a real setting: constructing a sampling design for the first national forest inventory for Tanzania. The approach of the paper constructs a spatial model of forests, landscape, and land use. Sampling errors of the key parameters as well as the field measurement costs of the inventory were estimated using sampling simulation on data. Forests and land use often vary within a country or an area of interest, implying that stratified sampling is an efficient inventory design. Double sampling for stratification was taken for the statistical framework. The work was motivated by the approach used by The Food and Agriculture Organization of the United Nations (FAO) in supporting nations to establish forest inventories. The approach taken deviates significantly from the traditional FAO approaches, making it possible to calculate forest resource estimates at the subnational level without increasing the costs.

Key words: forest inventory, double sampling for stratification, sampling simulation, cost assessment, remote sensing.

Résumé : Des méthodes visant à élaborer un plan d'échantillonnage pour effectuer l'inventaire forestier d'un vaste territoire sont présentées. Les méthodes, les bases de données utilisées et les procédures sont démontrées pour un cas réel, soit l'élaboration d'un plan d'échantillonnage pour le premier inventaire forestier national de la Tanzanie. L'approche de cet article consiste à construire un modèle spatial des forêts, du paysage et de l'utilisation des terres. L'erreur d'échantillonnage des paramètres clés ainsi que les coûts de mesure de l'inventaire sur le terrain ont été estimés à l'aide d'une simulation d'échantillonnage sur les données. Les forêts et l'utilisation des terres varient souvent à l'intérieur d'un pays ou d'un territoire d'intérêt, ce qui implique qu'un inventaire stratifié est une stratégie d'échantillonnage efficace. Un plan d'échantillonnage à deux degrés stratifié a été utilisé comme cadre statistique. Ce travail a été inspiré par l'approche utilisée par l'Organisation des Nations Unies pour l'alimentation et l'agriculture (FAO) pour aider les pays à établir des inventaires forestiers. L'approche retenue diffère significativement de l'approche traditionnelle de la FAO et permet de calculer des estimations des ressources forestières à un niveau sous-national sans augmenter les coûts. [Traduit par la Rédaction]

Mots-clés : inventaire forestier, échantillonnage à deux degrés stratifié, simulation d'échantillonnage, évaluation des coûts, télédétection.

1.0. Introduction

Since the early 2000s, the Forestry Department of the Food and Agriculture Organization of the United Nations (FAO) has invested substantial resources in developing a programme of support to national forest monitoring and assessment (NFMA) (Saket et al. 2010; FAO 2013). The NFMA operates mainly in developing countries. Technical, financial, and (or) institutional co-operation is often needed. Currently (2013), NFMA has been completed in 10 countries and is in progress or formulated in 20 countries (FAO 2013).

FAO NFMA has employed a standard approach in sampling design and data collection until 2009. The major sampling unit is a 1 km × 1 km square. Each unit contains a cluster of four plots with a size of 250 m × 20 m, placed in perpendicular orientations. Small trees were measured on nested subplots. The details of the design are described by Saket et al. (2010) and the FAO (2013). Owing to the high workload for each cluster, the sampling intensity of the plots has been low. Estimates could have been computed on the national level only. However, when necessary, the sampling intensity has been increased based on local information needs.

The FAO NFMA has also launched studies to analyse and further develop the design (Tomppo and Katila 2008). Based on these studies, the local information needs, and local studies, a somewhat different approach was designed for use in Tanzania. The decision was made by the experts from the Government and universities of Tanzania, FAO, and Metla. The ultimate purpose was to increase the efficiency of the sampling design compared with the earlier NFMA approach. The objective of this article is to describe the methods, procedure, and results developed to construct a sampling design for the first forest inventory of Tanzania, NAFORMA.

Based on the statistics from the FAO (2010), Tanzania has a total land area of 88 163 827 ha, of which 33.4×10^6 ha (38%) are forests and woodland. Woodland with an open cover of trees occupies about 90% of the total forest area, the rest of which is composed of closed natural forests and plantation forests. The woodlands are subject to frequent grass fires stemming from adjacent human activity (agriculture, etc.). About half of the forested land is reserved under the central government, local governments, and village authorities, the rest is the forest in the village lands and general land, i.e., in land without clear ownership.

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E. Tomppo, M. Katila, K. Mäkisara, and H.M. Henttonen. Finnish Forest Research Institute, PO Box 18 (Jokiniemenkuja 1), FI-01301 Vantaa, Finland.
R. Malimbwi and E. Zahabu. Sokoine University of Agriculture, the United Republic of Tanzania.
N. Chamuya and J. Otieno. Forest and Beekeeping Division of Ministry of Natural Resources, the United Republic of Tanzania.
Corresponding author: Erkki Tomppo (e-mail: erkki.tomppo@metla.fi).

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A recent population estimation gave the population of Tanzania as 44.9 million people, with a population growth rate of 2.7% (NBS 2012). The value of Tanzania's forests is high. The combined annual value of the forest goods and services is estimated at 2.2×10^9 US dollars, equivalent to a GDP of 20.1% based on 2006 prices (MNRT 2008). Forests supply a variety of wood and nonwood forest products (NWFPs), offer employment, and are a source of revenue through the sale of wood as well as NWFPs and services. The majority of the rural communities depend heavily on forest products for their livelihood. Forests therefore contribute to poverty reduction. The sector provides about 3×10^6 person-years of employment (MNRT 2008).

The forests in Tanzania are high in biodiversity. The country contains over 10 000 plant species, hundreds of which are nationally endemic. Of the plant and animal species in Tanzania, 724 species are identified as "threatened" in the Red List of the International Union for Conservation of Nature (IUCN), with 276 species classified as "endangered" (IUCN 2013).

As a developing country, Tanzania has a high potential to receive financial benefits for reducing emissions from deforestation and forest degradation; forest conservation, sustainable management of forests, and enhancement of forest carbon stocks (REDD+). Deforestation and degradation are estimated at 403 000 ha per annum between 1990 and 2010 (FAO 2010). The main reasons for deforestation and degradation are agriculture, overgrazing, charcoal burning, wood fuel harvesting, bush fires for various reasons, and harvesting for industrial wood. This is equivalent to 1.16% of the country's total forest area. With this rate of deforestation and degradation, the country may benefit from implementing REDD+ activities. Tanzania has only about 240 000 ha of plantation forests (FAO 2010). There is therefore huge potential for afforestation and reforestation activities to meet domestic and export demands of forest products as well as climate change mitigation measures such as the Clean Development Mechanism (CDM).

However, most of the forest statistics are outdated. The demand for forest-related information in Tanzania is continuously expanding, especially because of the increasing attention to climate change mitigation and adaptation. The National Forestry Resources Monitoring and Assessment (NAFORMA) project in Tanzania has been formulated to bridge this information gap for national policy and strategy processes and forestry planning in Tanzania.

The primary traditional purpose of national forest inventories (NFIs) has been to provide accurate information about forest resources and their changes, for instance, for forest and environment management planning, forest policy, and planning forest industry investments (Tomppo and Tuomainen 2010). In Europe and North America, forest health monitoring emerged as an important issue during the 1980s. The role of forests in providing nonwood goods and services such as wildlife habitat, recreational opportunities, and contributions to water quality received increased attention in the 1990s and 2000s. Forest inventories are also the basic information source in assessing the role of forests in balancing national, regional, and global CO_2, and other greenhouse gases (GHG) (FAO 2010; Tomppo et al. 2010). Assessing the possibilities to reduce emissions from deforestation and forest degradation (REDD) particularly in developing countries, presumes proper knowledge of forest resources (FAO 2008).

Both the traditional and new roles of forests and the requirements for national reporting and common international reporting have substantially altered the demands for information on forests. Because NFIs are the primary source of forest information for all of these purposes, the scope of NFIs has broadened accordingly, and has resulted in the introduction of a wide variety of new variables requiring assessment. Examples of the other requirements and principles include covering not only forested lands, but the entire land area, and using international definitions, taking into account local conditions. The inventory design should take into account the needs mentioned above, and further fulfill the efficiency requirements and fulfill the budget and other possible resource constraints. The design should also take into consideration possible use of the other data in enhancing the estimates, e.g., remote sensing data.

The basic concepts of sampling theory, also applicable for forest inventories, have been previously described (Cochran 1977). Särndal et al. (1992) focused on survey sampling, in addition to sampling theory, and Gregoire and Valentine (2008) and Mandallaz (2008) also focused on forest inventory questions.

The theory for survey sampling, particularly error estimation, was developed in connection with the early forest inventories. The first forest inventories that rely on statistical principles were developed simultaneously in the Nordic countries: Finland, Norway, and Sweden.

Today, sample-based forest inventories are conducted in most European and North American countries. The situation in many African, Asian, and South and Central American countries is different. In many countries, the first NFI has yet to be done. The exceptions include Brazil, where the first inventory was carried out in the 1980s (Freitas et al. 2010). The new sample-based inventory has been developed, tested, and is currently implemented in some of the states of Brazil (McRoberts et al. 2013).

Design of the sample-based inventory can be formulated as a constrained optimisation problem. It is not possible to design a sampling design that is simultaneously optimal for all parameters. The optimality criterion must weigh the importance of the different parameters. The accuracy assessment of the parameters of interest related to a design is complicated in spatial sampling. Often a mean square error (MSE) $(E(\hat{M} - M)^2)$ or an error variance $(\mathrm{Var}(\hat{M} - M))$ is proposed for a measure of the uncertainty for the estimator $\hat{M}$ of a parameter M. However, these quantities are seldom known and not easy to estimate, therefore their use in defining the optimality is challenging. Even if the errors are known, they vary within a country complicating optimisation. One more factor affecting the efficiency of a design is the spatial autocorrelation of the forest variables, which are relevant at different scales. Additionally, the correlations and scales vary by variables. The constraints in the optimisation are derived from financial and other resources. Furthermore, the sampling design of a practical inventory should not be too complicated. Therefore, a systematic sampling design with the regular spacing of the sampling units is often used in practical inventories, and optimisation determines the number and spatial pattern of the sampling units. An interesting modification of this is the designs of the Forest Inventory and Analysis Programme in USA (FIA). The nation is divided into hexagons, and a field plot location is selected randomly within each hexagon (McRoberts et al. 2010).

A comprehensive study of the variation in the spatial correlations of some area and volume variables in different regions within Sweden is given by Ranneby (1981) and Ranneby et al. (1987). As a result, the sampling intensity varies by regions in Sweden (Axelsson et al. 2010). A similar design with some modifications is used in Finland (Tomppo and Tuomainen 2010; Tomppo et al. 2011). Map form predictions of some key forest parameters have been used in constructing the sampling intensity and the number of the field plots in a cluster in different regions since the early 1990s. The methods are detailed in unpublished reports by Helena Henttonen at the Finnish Forest Research Institute, from 1991 and 2003 (in Finnish), and by Tomppo et al. (2011).

Rennolls (1989) presented an interesting two-phase sampling method for the Woodland survey of Great Britain. Both phases were stratified samples to increase the efficiency. The ideas given by (Rennolls 1989) inspired the development of a method of double sampling sampling for stratification for the inventory of the Northernmost Finland for NFI8 in 1992 and 1994, as well as for NFI9 in 2003. The details of the method are presented in the aforementioned reports by Henttonen and also in Tomppo et al. (2001). Sampling simulation using the forest resource maps, i.e., in the models of forests, were used. This was the basic starting point in developing the design for the Tanzanian NFI.

Examples of sampling studies using simulation in seeking an efficient sampling design for forest inventories are given by Reich and Arvanitis (1991), Scott (1993), Scott et al. (2009), and Tokola and Shrestha (1999). Reich and Arvanitis (1991) presented a sampling simulator starting from the simulation of the locations of the trees and after that, the simulation of the variables of interest for the trees. Several models for the spatial pattern of trees and the distributions of the tree level variables, as well as sampling designs were used. The simulator is interesting particularly as teaching material. Scott (1993) presented a method to determine the optimal cluster design when different plot types are used for different forest resource attributes. The method utilises cost and variance relationships to develop an optimal design. The design was originally developed for the Forest Health Monitoring Program of the USA. The cluster design has also been used in the national forest inventory of the USA. Scott et al. (2009) have developed a design tool for forest inventory and monitoring. The toolkit goes through the typical questions in planning the inventory design, such as identifying the needed attributes as well as setting the precision and cost constraints, and provides the sampling and plot designs based on the attributes as well as the precision and cost constraints specified by the user. Tokola and Shrestha (1999) generated a model forest using Landsat 5 Thematic Mapper data and field plots, picked up optional samples from the forest and compared the sampling errors of the optional sampling designs.

The availability of different types of remote sensing data, and the use of that data together with field measurements, make possible the increased efficiency of inventories while creating additional methodological demands. Gregoire et al. (2011) presented estimators and error estimators for a two-stage sampling design with subsequent model-assisted regression estimation in the design-based framework. They used airborne laser data, either scanner or profiling data together with NFI field plot data, and demonstrated the methods for estimating above ground biomass in Hedmark County in Norway. Ståhl et al. (2011) used the same data as Gregoire et al. (2011) to demonstrate the performance of the model-based approach for the estimators and error estimators. The approach by Gregoire et al. (2011) presumes probability samples both for primary and secondary units and the estimators are thus design-unbiased. Probability samples are not needed in the model-based approach by Ståhl et al. (2011) and can thus be used in cases for which the model-assisted approach is not suitable. The estimators are only model-unbiased.

The method adopted for the design of the Tanzanian inventory was simulation based on the available spatial and statistical data. The spatial data consisted of existing vegetation and land use maps, digital elevation data, and remote sensing images. Spatial maps for several forest variables were computed from these data, and different sampling patterns were evaluated. The sampling errors were assessed for these arrangements and the inventory costs estimated. One should note that the absolute values of the sampling errors and costs estimates are affected by the errors in the maps used. However, an important aspect is that with the methods employed the sampling errors and cost estimates of different designs were comparable. For instance, even when the magnitude of the computed errors is not correct, the spatial structure resulting from the remote sensing data are correct. This structure is the important factor in comparison of the designs.

The final output of this study was (*i*) an assessment of the sampling errors and costs for each sampling options studied, and (*ii*) a digital map showing the location of the inventory plots. The approach used includes (*i*) the construction of a spatial model of the variation of land categories and volume of growing stock, (*ii*) the selection of the basic size of the field plot cluster (the number of the plots on a cluster) and the size of the plot, (*iii*) the error estimation using sampling simulation, and (*iv*) cost assessments based on geographic information system (GIS) analyses. A model of land use and land cover with the road network, elevation variation of the terrain, and volume of growing stock were either acquired or constructed. The ideas presented in Tomppo and Katila (2008) as well as in the reports by Henttonen were used and modified. The main principles of the result calculation system have also been developed.

2.0. Materials

2.1. Input data sets for the sampling study

The spatial model, required by the sampling simulation, consisted of digital, georeferenced data sets on land use and vegetation cover. The model also included the predictions of the relevant forest variables made in this study. Using this model, alternative sampling designs could be compared using the efficiencies of the designs. The efficiencies were assessed in terms of the sampling errors of the basic forest parameters and the measurement costs of the field plots. The first task was to identify the necessary and available data sets.

The following data sets were employed in the study:

1. Landsat ETM+ satellite image mosaic over Tanzania.
2. Land use and vegetation map over Tanzania, made by Hunting Technical Service Ltd., herein called a Hunting map.
3. Digital elevation model.
4. Aggregated forest inventory data from 7 of the 11 districts, Tanzania (see section 3.1).
5. District boundaries in Tanzania.
6. Africover map database (www.africover.org): rivers.
7. The field plot data of the 9th NFI of Finland: 2591 field plots in East Finland from the year 2000.
8. Landsat ETM+ satellite images from East Finland.

The spatial data were originally in different coordinate systems. To simplify processing, all of the Tanzanian data were projected before processing to the UTM projection zone 36S (South) with the WGS84 datum and resampled to a pixel size of 30 m × 30 m. The Finnish data was processed in the Finnish Uniform Coordinate System (YKJ).

2.2. Landsat image data

2.2.1. Image selection and preprocessing

Three sets of images were originally considered as the basis for image data. They were the global land survey (GLS) sets GLS 1990, GLS 2000, and GLS 2005, collected by the United States Geological Survey (USGS). The GLS 2000 data set was selected for this project because the image quality over Tanzania seemed better than in the 2005 data set and was closer matched to the available ground-level data than in the 2005 data set.

The Landsat data set covering Tanzania consisted of 59 images. Visual inspection revealed that three of the images selected from GLS 2000 were too hazy to be used. Substitutes were selected for these images (WRS-2 indices path/row: 172/62, 172/63, and 172/64). The images were from years 1999–2002, from all seasons of the year. The images came from USGS orthorectified to UTM zones 34, 35, 36, and 37, depending on the location of the image. A list of the images is in Table 1.

The regions of the images covered by clouds or cloud shadows cannot be used in predicting forest variables. Cloud and cloud shadow masks were manually made for the images using an image display.

The mosaicking was done by overlaying images one over another. The overlaying order was selected to prefer better quality images. However, the mosaicking order did not enhance the results much because the overlap of the adjacent WRS paths near the Equator is small.

Table 1. The Landsat images over Tanzania used in this project.

WRS-2 Path	Row	Date	Patch order	WRS-2 Path	Row	Date	Patch order
165	65	2001-09-14	11	169	63	2000-02-12	6
165	66	2000-05-22	38	169	64	2000-02-12	7
165	67	2000-05-22	39	169	65	2000-02-12	8
165	68	2002-05-12	12	169	65	2000-07-21	9
166	63	2000-01-22	40	169	66	2000-07-21	10
166	64	2000-01-22	41	169	67	2001-09-10	4
166	65	2000-06-30	42	170	61	2001-05-12	51
166	66	2000-06-30	43	170	62	2001-05-12	52
166	66	2001-05-16	13	170	63	2000-01-18	27
166	67	2000-05-29	14	170	63	2001-07-15	26
166	68	2000-06-30	15	170	64	1999-10-14	28
167	62	2001-03-04	44	170	64	2000-01-18	29
167	63	2001-03-04	45	170	65	2000-12-19	31
167	64	2001-01-15	16	170	65	2001-10-03	30
167	65	2000-07-07	17	170	66	2000-12-19	32
167	66	2002-05-10	18	170	67	2001-08-16	33
167	67	1999-10-25	19	171	61	2000-07-19	1
167	67	2000-07-07	20	171	62	2000-05-16	53
167	68	2001-12-01	21	171	63	2000-05-16	54
168	61	2000-02-21	46	171	64	2002-05-22	55
168	62	2000-02-21	47	171	65	2002-05-22	56
168	63	2000-02-21	48	171	66	2002-05-22	57
168	64	2001-03-11	22	172	61	1999-07-08	2
168	65	2000-02-21	23	172	62	2002-05-13	34
168	66	2002-06-18	49	172	63	2002-05-13	35
168	67	2000-02-21	24	172	64	2002-05-13	36
168	67	2002-06-18	50	172	65	2002-05-13	37
168	68	2000-08-31	25	173	63	1999-09-17	58
169	61	2000-01-27	3	173	64	1999-09-17	59
169	62	2000-02-12	5				

Note: The image later in the patch order overwrites earlier data in the mosaic.

In addition to the Tanzanian data set, two adjacent Landsat 7 ETM+ images from North-Karelia in Finland were used for development of the volume model (WRS-2 path/row: 186/16, 186/17, 2000-06-10). The pixel size in processing these images was 25 m × 25 m (in the YKJ coordinate system).

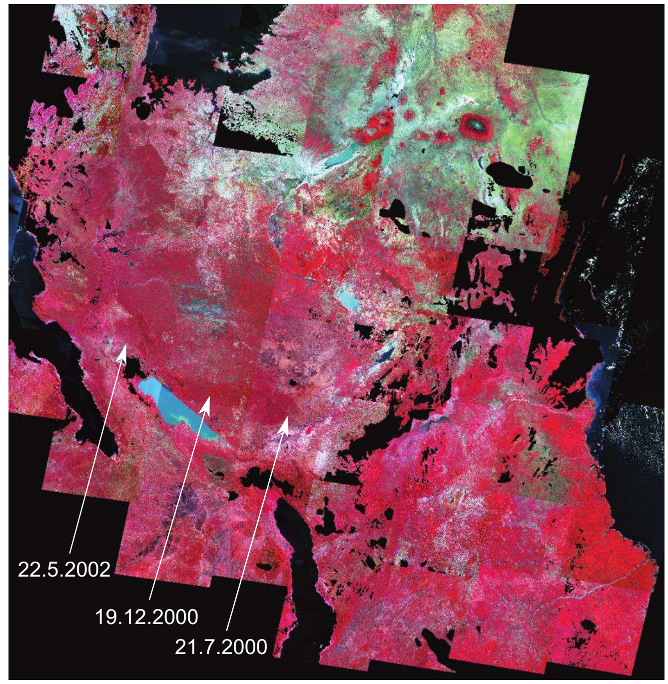
2.2.2. Radiometric processing

The intensity levels of the images used in the mosaic must be equalised to use a single model to analyse the whole mosaic. The intensity differences caused by the different imaging conditions (atmosphere, angular dependence of the target reflectance, etc.) and seasonal differences in vegetation were clearly visible in the mosaic before correction. To use the prediction model made from Finnish data in Tanzania, the image data values had to be made comparable in images from both countries. These goals are achieved by computing an approximation of the surface reflectance from the radiances observed by the satellite instrument. The method chosen for this used a surface reflectance image with large pixel size and covering the whole area of the mosaic. The image data of the individual Landsat images were then adjusted to match this coarse image.

The image data produced by the MODIS instrument (modis.gsfc.nasa.gov) of NASA was used as the reference image. MODIS instruments are currently operating on two platforms: the TERRA and the AQUA satellites of the NASA Earth Observing System (EOS). The surface reflectance product (MOD 09), computed from the original MODIS data uses a very advanced atmospheric correction method (Vermote and Vermeulen 1999). The mosaic from the best data over 8 day periods (MYD09A1) was used in this project. The pixel size in this format is 500 m × 500 m.

Using another image as the reference for atmospheric correction requires that both the corrected image and the reference image include compatible spectral channels. This is the case for Landsat channels 1, 2, 3, 4, 5, and 7 (MODIS channels 3, 4, 1, 2, 6, and 7). Three tiles of data covering the mosaic area (h20v9, h21v9, and h21v10) were acquired and transformed into the UTM projection. The time interval of the data should be somewhere between January and April, because the normalisation is done to the growing season conditions. The data should be as cloud-free as possible. Taking these things into account, the best data found was from the MODIS instrument on AQUA satellite from 26 February to 5 March 2003.

Fig. 1. The atmospherically corrected Landsat image mosaic over Tanzania. The Landsat ETM+ spectral channel 4 (NIR) is shown in red, channel 3 (red) is shown in green, and channel 2 (green) is shown in blue.



The North-Karelia image was also atmospherically corrected. In this case, MODIS AQUA image from 4 July 2002 was used (tile h19v02).

The atmospheric correction was computed separately for each Landsat image before mosaicking. The correcting function was a simple linear mapping:

$$y_i = a_i x_i + b_i \quad (1)$$

where x_i is the uncorrected data for channel i, y_i is the corrected data, and a_i and b_i are parameters computed for each channel. The parameters are computed to equalise the mean and the variance of the data in both images, taking into account the different pixels sizes. Only pixels free of clouds in both images were used to determine the parameters.

The atmospherically corrected mosaic is seen in Fig. 1. The result shows that the atmospheric correction is fairly efficient but not perfect. Using image-wide correction parameters does leave within-image variations in the data.

2.3. Map data

Hunting map sheets were downloaded from the FAO web site. The selected themes were the vegetation maps and roads. The map sheets were combined and projected to UTM 36S system with 30 m × 30 m pixel size. The vegetation types were recoded to numerical values (vegnbr) (Table 2). A reclassification of vegetation

Table 2. Hunting map vegetation types, pre-stratified land classes 1–7, walking speed assumptions, and average plot measurement time by vegetation types.

Vegcode	Vegnbr.	Pre-strat.	Vegetation type	Walking speed (min/km)	Plot meas. (min)
Fn	10	1	Natural forest	60	40
Fm	11	1	Mangrove forest	40	40
Fp	12	1	Plantation forest	20	40
Wu	23	2	Woodland (unspecified density)	30	30
Wc	20	1	Closed woodland	30	30
Wo	21	2	Open woodland	30	30
WSc	22	3	Woodland with scattered cropland	30	30
Bu	30	3	Bushland (unspecified density)	30	25
Bd	31	3	Dense bushland	30	25
Bo	32	4	Open bushland	15	25
BSc	33	4	Bushland with scattered cropland	30	25
B(et)	34	5	Bushland with emergent trees	30	25
Bt	35	3	Thicket	40	40
Bt(et)	36	3	Thicket with emergent trees	40	40
Gw	40	4	Wooded grassland	15	25
Gb	41	5	Bushed grassland	30	25
Go	42	6	Open grassland	15	15
0GSc	43	6	Grassland with scattered cropland	25	15
Gws	50	5	Wooded grassland (seasonally inundated)	25	25
Gbs	51	5	Bushland grassland (seasonally inundated)	25	25
Gos	52	6	Open grassland (seasonally inundated)	25	15
Cm	60	3	Mixed cropping	25	20
Ctc	61	2	Cultivation with tree crops	25	20
Ctc(st)	62	2	Cultivation with tree crops (with shade trees)	25	20
Cbc	63	5	Cultivation with bushy crops	25	20
Chc	64	6	Cultivation with herbaceous crops	25	15
BSL	70	6	Bare soil	30	10
SC	71	6	Salt and crusts	40	10
RO	72	6	Rock outcrops	40	10
ICE	73	6	Ice cap–snow	200	10
Ocean	91	7	Ocean	200	0
IW	90	7	Inland water	200	0
S/M	54	5	Swamp/marsh (permanent)	100	15
Ua	80	6	Urban areas including air fields	10	10

Fig. 2. Re-classified vegetation types based on Hunting map, the Singida district.

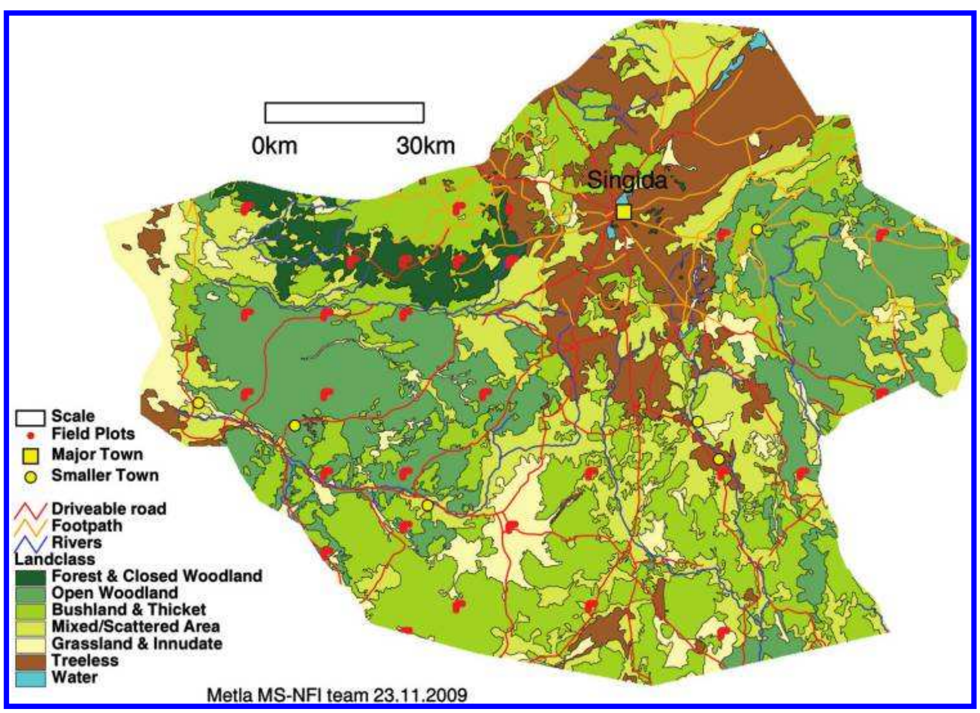
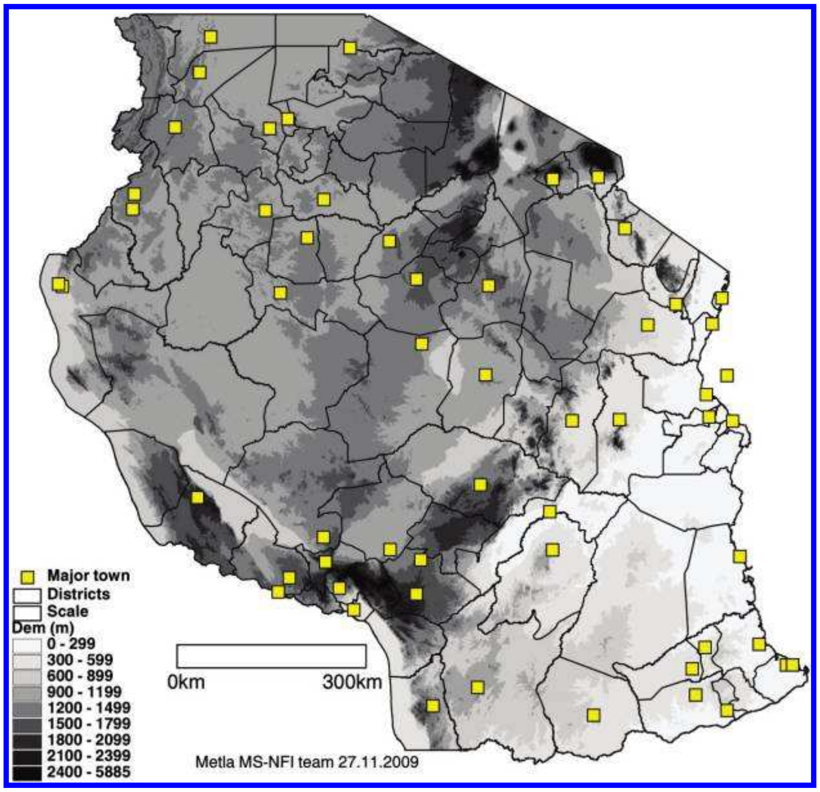


Fig. 3. Input data, digital elevation model over Tanzania.



types to seven strata ("Prestrat" in Table 2) was done, and a corresponding raster layer produced (Fig. 2). The aim of the reclassification was to form strata large enough for sampling simulation purposes and to define land classes (forest, wooded land) for which the growing stock density within that class was on average similar and for which the sampling simulation results had to be calculated. The average growing stock was estimated for each vegetation type, based on expert opinion, and the vegetation types were regrouped into the seven strata using this information. The Hunting road classes 1–5 (roads and footpaths) were rasterized. Laid over the Landsat images, it was found that there are locational errors in the road data ranging from 100 to 300 m. The rivers were taken from the Africover database, and rasterized to a grid. The Political boundaries and the district boundaries were also taken from the Africover database. The Africover (www.africover.org) map data were originally in the geographic coordinate system with the WGS84 datum.

The vegetation types belonging to the Pre-strat codes 1–3 are called forest in the following, although the stratum is not necessarily compatible with the FAO forest definition. Similarly, the stratum consisting of the vegetation types with Pre-strat codes 1–5, is called wooded land in the following.

A digital elevation model (DEM) with pixel size of 90 m originates from SRTM data (Farr et al. 2007). The DEM data were in geographic projection with the WGS84 datum and projected to UTM 36 South system with the WGS84 datum. There were problems in the use of DEM in calculating the slope of terrain with the algorithm employed, owing to the much smaller output pixel size (30 m) than in the original data. Extra stripes appeared in the slope image. A linear filtering (low pass) was therefore carried out on the DEM (Fig. 3). The slope was calculated from the filtered DEM using diagonal differences in a 3 pixel × 3 pixel window.

3.0. Methods

The methods include estimation of the volume of the growing stock for each land element of 30 m × 30 m, cost assessments for measuring the field plots, and especially constructing optional sampling designs. Sampling errors of some key forest parameters and the cost estimates of the field measurements were used in evaluating the optional designs when seeking the optimal design. The phases in estimating the sampling errors and cost estimates for the area in question through simulation were as follows:

1. A dense grid of clusters was overlaid over a map of Tanzania using equal distances between the clusters: for the selected design we used 5 km × 5 km distances.
2. Cluster level mean volumes were calculated per land type, as well as per reclassified Hunting classes 1–5 (wooded land) and per reclassified Hunting classes 1–3 (forest).
3. Cluster level costs (times) were calculated.
4. The clusters were classified for the second phase sample. Several class numbers and class intervals were tested. In the selected classification, four volume classes, three cost classes, and three classes of the median of slope of the plots were used (Table 3). The volume intervals were determined using the optimal classification by Neyman (Cochran 1977).
5. The sampling intensities in different strata were selected using optimal allocation (Cochran 1977). The sampling intensities were proportional to the quantity $s^t/\sqrt{c}$, where s is within stratum standard deviation of the mean volume of the growing stock on land on a cluster, c is the average costs (measurement) time of a cluster, and t is an exponent to be determined to control the effect of the s on the strata weights (intensities). The optimal allocation based on one time inventory could be criticized when the purpose is to repeat the inventory. Only 1/4 of the plot clusters were marked to be re-measured in the coming inventories. The small proportion mitigates a problem arising from the possible changing strata. The question is discussed in section 5.0.
6. The intensities were adjusted to different total cost levels, and are presented later for 1.0, 2.5, and 4.0 × 10^6 US dollars.

Table 3. The stratification used for the first phase clusters, the number of the clusters in the first phase sample, and the sampling intensities (thinning) used in the second phase.

Stratum	Measurement time of a cluster (min)	Mean volume of land (m^3/ha)	Median slope of plots (degrees)	1st phase clusters	Sampling intensity for 2nd phase
1	0–479	0–27	0–10	3080	12
2	0–479	28–61	0–10	626	10
3	0–479	62–118	0–10	254	8
4	0–479	119-	0–10	83	2
5	480–959	0–27	0–10	8852	13
6	480–959	28–61	0–10	7282	12
7	480–959	62–118	0–10	4149	9
8	480–959	119-	0–10	896	4
9	960-	0–27	0–10	2252	20
10	960-	28–61	0–10	2766	17
11	960-	62–118	0–10	2033	13
12	960-	119-	0–10	673	5
13	0–959	0–61	11–20	741	7
14	0–959	62-	11–20	738	4
15	960-	0–61	11–20	165	13
16	960-	62-	11–20	598	5
17	0-	0–118	21-	243	6
18	0-	119-	21-	94	4

7. The sampling errors of the estimates of the parameter of interest, e.g., mean volume, were estimated for each design as follows. A high number of samples were picked up. The standard deviations of the estimates of parameters from the samples were calculated. This standard deviation can be considered as the sampling error. A high number of the samples is needed to get reliable estimates for the sampling errors, that is, the standard deviation of the estimates over the space of the samples. In the case of Tanzania, 1000 samples were taken for each design. The needed number of the samples was decided by analysing the variation of the sampling errors as a function of the number of the samples.

3.1. Volume estimation and calibration

The map form predictions for the volume of growing stock were employed in analysing the cost-efficiency of different sampling designs. Plot level field data from Finland were used because of the lack of plot level data in Tanzania. Only the plots on forest land, poorly productive forest land, or unproductive land with distance to the nearest forest stand boundary or land use boundary greater than or equal to 20 m were used. The number of plots amounted to 2591. A robust model was estimated and employed. It was assumed that the ratios of the spectral values of different Landsat ETM+ spectral bands are not as sensitive to the change of the vegetation zones as are the absolute reflectance values. Other variables were also tested.

The parameters of the model were estimated using field data, image data transformed to approximate surface reflectance (see section 2.2.2), and nonlinear estimation.

The number of the explanatory variables was intentionally kept low and the model simple to preserve the robustness of the model. The selected model for the mean volume v_i on plot i was

$$v_i = c \cdot \exp(a + b_1 u_{3,i}/u_{2,i} + b_2 u_{7,i}/u_{5,i}) + \epsilon_i \tag{2}$$

where $u_{j,i}$ is the reflectance of the Landsat ETM+ spectral band j for plot i as given in the section on *Radiometric processing*, and c, a, b_1, and b_2 the parameters of the model. The error terms (ϵ_i) were assumed to be independent and identically distributed for simplicity. Note that the model predictions are used for stratification only.

The parameters of the model were estimated using nonlinear regression with the SAS NLIN procedure (SAS/STAT). The model explained 75% of the variation of the volume.

The model was calibrated using the volume estimates based on a forest inventory of seven districts (see Fig. 4). The districts were in the southeastern and western parts of Tanzania comprising a total of 3.323×10^6 ha in 72 areal units.

The final parameters of the model after the calibration were c = 1.2146 m^3/ha, a = 15.943, b_1 = –29.3802, and b_2 = 3.2762. The parameters a, b_1, and b_2 were estimated from the Finnish data (eq. (2)). The parameter c comes from the calibration. The standard errors of the estimates of a, b_1, and b_2 were 1.2642, 2.0320, and 0.1281, respectively.

The volumes for the land areas covered by the clouds or cloud shadows were predicted as follows. The averages and standard deviations of volume predictions were calculated by the Hunting map categories (Table 2). The prediction for each pixel under the cloud or cloud shadow was randomly drawn from the normal distribution with the mean and standard deviation equal to the empirical mean and standard deviation of the volume predictions for the corresponding Hunting map category. Note that this procedure does not take into account the spatial correlation of the variables in the target area.

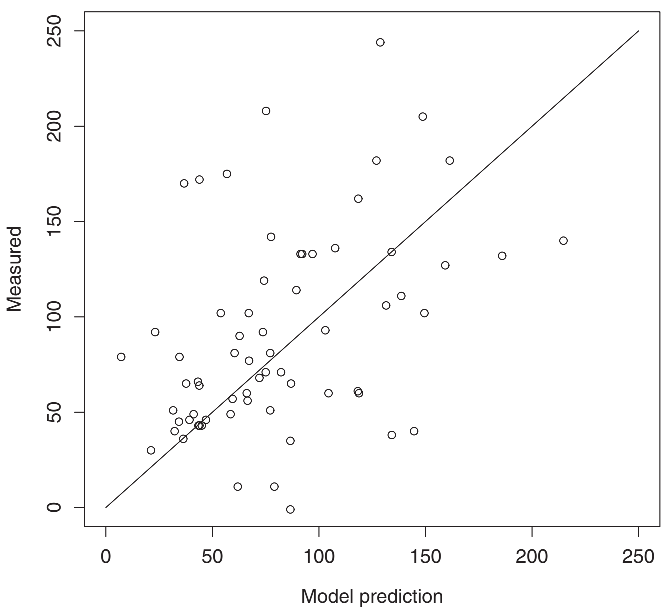
The volume predictions after the calibration are shown for the whole of Tanzania in Fig. 5.

3.2. Time consumption in the field work of different sample designs

In this project, the time used by a field crew to measure a field plot or a cluster of field plots was divided into several phases. The time (minutes) needed for each phase in the field work was based on information given by the Tanzanian participants of the project: walking speed on different vegetation types and assumed time needed to measure a field plot on different vegetation types. The average walking speed raster layer was produced from the Hunting vegetation map using the estimates given for different vegetation types in the Table 2. The rasterized roads and rivers were overlaid on the walking speed raster with values 10 min/km and 200 min/km, respectively. In this way, the barriers in the walking paths caused by major rivers were to be taken into account. The available GIS data and software were used to estimate distances and cost of reaching clusters from the nearest road. Note that the rivers were not considered as transportation corridors. They were not used for transportation in practical field work in Tanzania in 2010–2012, but could be used in other conditions, e.g., in the Amazonia region.

Several assumptions were made to produce the time-costs of simulated clusters, e.g., the walking speed with a GPS device in the field as well as the daily lunch break in the field were assumed

Fig. 4. The field data based estimates (Measured) of the volume of growing stock (m^3/ha) against the estimates of the volume of growing stock based on the model using Finnish field plot data and Landsat ETM+ 7 images (Model prediction).



to be independent of the design selected. A daily pause of 60 min was included, and this was included with what are referred to as "other actions" in the field, apart from measuring the plots. If a cluster could not be completed in one day, a field crew stayed in the field overnight and the measurements were completed the following day(s). Additional costs from staying in the field (camping) are not included.

For a sampling design with the clusters of an L-shape, walking speed assumptions and average plot measurement times by vegetation types are given in Table 2. The same walking speeds by vegetation types (Table 2) were used for moving from the road to the cluster and for moving along the tract.

The components considered in time calculations were: (*i*) driving to a cluster from the lodging (50 min), (*ii*) walking in the field (with a GPS) to a cluster, (*iii*) walking along a cluster, (*iv*) measurement of the plots in a cluster, estimated time per plot according to Hunting map vegetation class (Table 2), (*v*) daily pause (lunch break) and other actions in the field (60 min), and (*vi*) walking back to the road. Walking speed in the field depended on the Hunting map vegetation class (Table 2).

3.2.1. The driving times, distance from road to field plots, walking in the field

Only one-way driving time to a cluster was included in the measurement time (daily working time, 480 min), following the practice in other countries. An average driving time of 50 min between the lodging and the road point closest to the cluster was used.

The distance from the road to the field plot was estimated using the Hunting map road network (Hunting road classes 1–5, including "Footpaths"). It seemed that some roads or road parts were missing in some regions. Therefore, the inclusion of the Footpath road class to the road network can be justified. The estimate of time used to reach a cluster was calculated using Arc/Info Pathdistance function (ArcGIS desktop help 9.2 2007).

Pathdistance determines the minimum accumulated travel costs from a source (in this case the Hunting map roads) to each cell location on a raster (a field plot). In Pathdistance, we used the accumulated costs over the cost surface, dictated by the assumed walking speed affected by Hunting map vegetation class (Table 2), the elevation model for compensating for the actual surface distance travelled, and the vertical factors. This procedure takes into account the downhill and uphill walking speeds. All of these data affect the total cost of moving from one location to another.

The formula by Langmuir (1984) (based on Naismith's rule for walking times) was used to estimate the vertical cost factors of different slopes (eq. (3)):

$$T = aS + bH_u + cH_m + dH_s \tag{3}$$

where T is the moving time in seconds and S is the distance in metres. H_u, H_m, and H_s are altitude differences in metres in different classes of slopes; uphill, moderate downhill $5° < \alpha < 12°$, and steep downhill $\alpha > 12°$, respectively. Here α is the angle of the slope, the angle between the vector combining two adjacent cells in the elevation model and the horizontal plane. Parameter a is 1/walking_speed, the average for Tanzania being 1.8 s/m (from 30 min/km). For the parameters b, c, and d the values of 6.0, 1.9998, and –1.9998 were used. For details, see the r.walk function by the GRASS Development Team (2007).

The time estimates T_α for different angles α were related to the one on flat terrain, T_0: The vertical factors V_F were calculated as an average of both up- and downwards direction (The same path was assumed to be used for return) $V_{F\alpha} = (T_\alpha + T_{-\alpha})/2T_0$. The final V_Fs used with Pathdistance function are presented in Table 4.

Outside of the range of these slope values, the V_F was set to infinity (inaccessible) in the Pathdistance analysis.

Only field plots on land were considered in the cost estimation. Note that the plots on water can be used in the final estimation because they are known exactly after field measurements. For the L-shaped NFI clusters, the walking distance between the field plots was the distance along the tract line between the two furthermost field plots on land plus the Euclidean distance between them, i.e., the length of the sides of a triangle. Along the tract line (the legs of the triangle), the walking speed was estimated as walking speed on plot points (depending on the Hunting vegetation type) multiplied by V_F (Table 4). The average of these speed estimates was taken for the entire tract line. Along the hypotenuse, the average walking speed was estimated from the ratio of the differences between minimum and maximum pathdistance (min) and the minimum and maximum Euclidean distance (m) among the cluster plots *i*. For this purpose, the Euclidean distance was calculated in the horizontal space from the nearest road point to all field plots on a cluster (Figs. 6 and 7).

A coefficient of 1.1 was used to multiply all of the walking distances or walking time estimates to approximate the need to avoid bodies of water and other obstacles. The time needed to reach possible plots on small islands was not considered separately in the calculations.

3.2.2. The time cost for a cluster

The total daily working time was assumed to be 480 min. Three types of clusters were considered: the time to complete a cluster is (*i*) less than 350 min, (*ii*) more than 350 min but not more than 480 min, and (*iii*) more than 480 min. For case (*i*), a crew will start another cluster in the same day; for case (*ii*), a crew will not continue to another cluster on that day; and for case (*iii*), a crew will continue measuring the cluster on the next day, staying in the field overnight (see section 3.2). The total working time in days is obtained by dividing the total minutes by 480 for cases (*i*) and (*iii*), whereas for case (*ii*), each cluster takes one full day.

The costs in time (minutes) were calculated using the assumptions above, GIS data, and analyses for each cluster of a systematic grid of clusters. The cost estimates could then be used in the allocation of the sample plots in each stratum (see section 3.3.3) as well as to estimate the total cost of a particular sample.

Fig. 5. Predicted volume of growing stock.

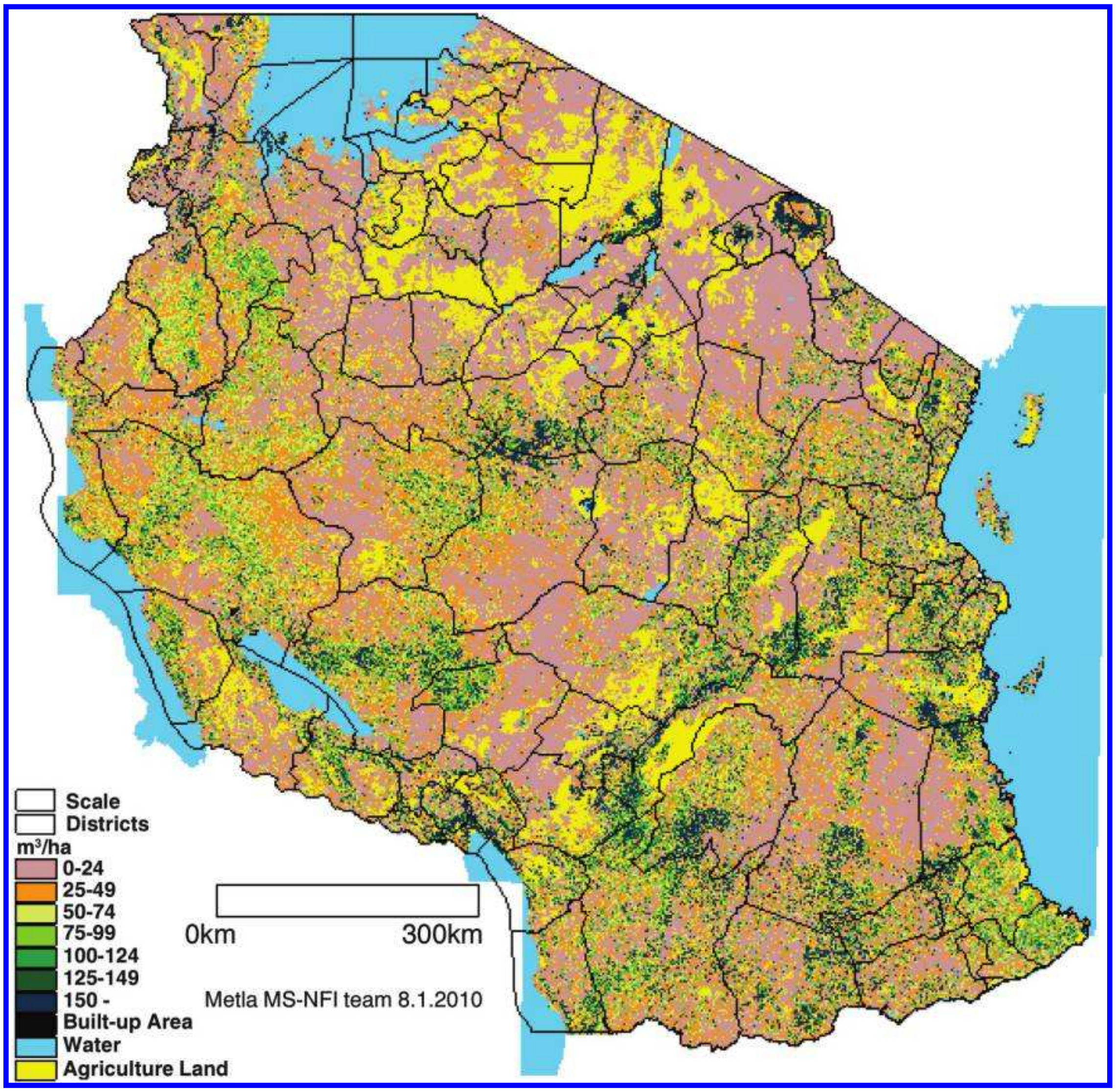


Table 4. Vertical factors used with the Pathdistance function.

Slope (degrees)	Vertical factor
±50	3.65
±40	2.86
±30	2.28
±20	1.81
±15	1.60
±12	1.47
±11.99	1.24
±8	1.16
±5	1.10
±4.99	1.15
±3	1.09
0	1.00

3.3. Design

3.3.1. Elements of a design

A sampling design for a forest inventory is affected by several factors. Examples are (*i*) sample plot size, (*ii*) sample plot shape, (*iii*) spatial layout of the plots, such as detached plots/plot clusters, distances between the plots, distances between possible clusters, (*iv*) stratified design/non-stratified design, definition and number of the strata, the questions in item 3 for each stratum in case of stratified design, and (*v*) permanent or temporary plots, and if both, the ratio of them.

The construction of a design is demanding, and depends also on the parameter in question, e.g., area estimate, volume estimate, estimate of rare events, estimate of changes. For practical considerations, the measurement unit should be, on average, the work-load of one day for a field crew. In theory, the optimal design could be sought by minimising the standard errors of the parameters with the fixed costs, or minimising the costs with a given standard error. In case of only one parameter of interest, e.g., the mean or total volume of growing stock, a stratified sampling design with an optimal allocation is one solution to be considered (Cochran 1977). In practice, a unique solution does not exist because different parameters may require different designs.

The selection of the sample plot size and shape are far from easy decisions in designing a forest inventory. It significantly affects the efficiency of an inventory. Relatively few studies exist that address these questions. Some examples are Reich and Arvanitis (1991), Scott (1993), Scott et al. (2009), and Tomppo et al. (2011). One

Fig. 6. Input data, distance to the nearest road, the Singida district.

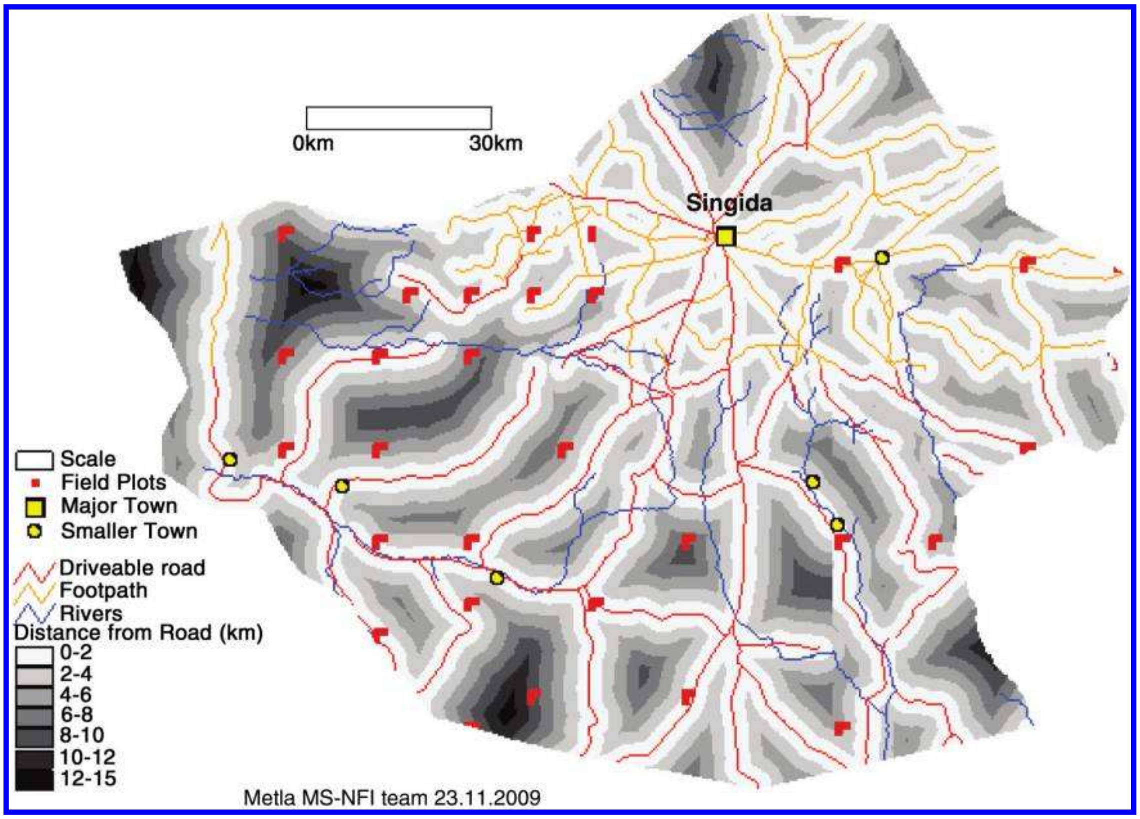
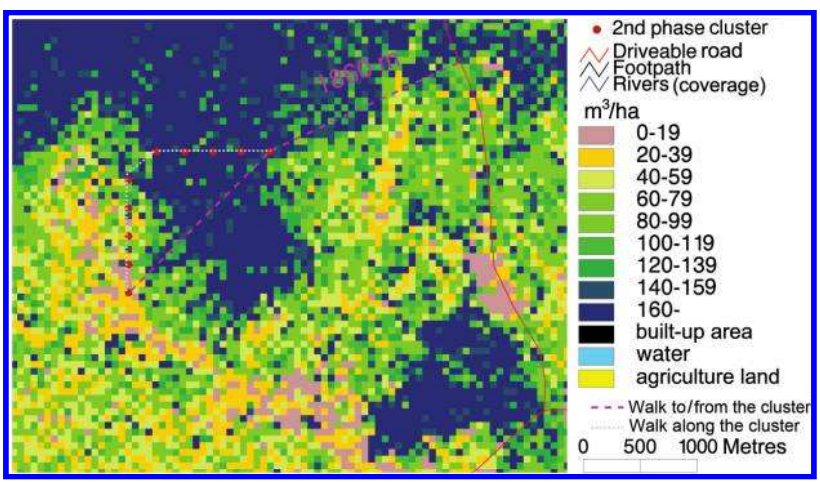


Fig. 7. The minimum Euclidean distance (1860 m) from the road to the closest field plot of a NAFORMA cluster. The estimated mean volume of growing stock for the sampling study is displayed on the background.



reason could be that the solution would presume information about the small scale variation of tree sizes and tree species, including tree locations and tree parameters, which are not easily available. A rough principle is that each tree measured should bring new information. This usually leads to a small number of trees on one plot and a relatively small plot size. A circular plot is often preferred, particularly in Boreal and Temperate forests, whereas a rectangle is sometimes used in the Tropics (Freitas et al. 2010; Saket et al. 2010; McRoberts et al. 2013).

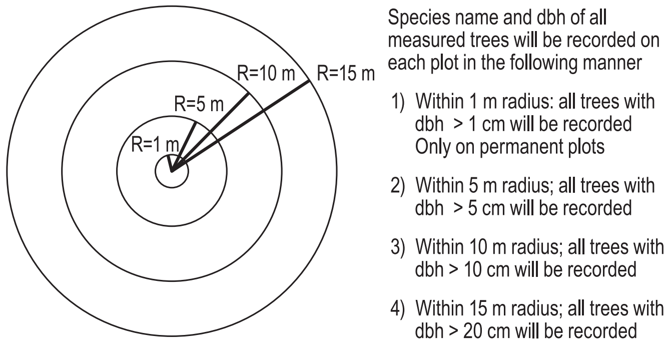
No mapped tree-level data were available for this study. The field plot shape and size was agreed in collaboration with the Tanzanian experts. The plot size was based on the studies carried out earlier by Rogers Malimbwi and Eliakimu Zahabu, and their teams at the Sokoine University of Agriculture. A concentric plot with a maximum radius of 15 m can be argued for the Tanzanian conditions because of sparse forests and large scattered trees. The other radii were 1, 5, and 10 m. The shortest radius was changed from 2 m to 1 m after the first field measurements, when the number of the small trees to be measured turned out to be high (Fig. 8).

3.3.2. The field plot cluster shape and size

Detached clusters of the plots instead of detached individual plots can be argued using the cost-efficiency criteria. These types of designs are currently employed in most European countries (Tomppo et al. 2010).

Relevant questions are thus the distances between the plots in a cluster and distances between the clusters. The distance between the plots should be high enough so that each field plot will bring

Fig. 8. A concentric field plot in the cluster designs with the maximum radius of 15 m.



new information. On the other hand, however, the distance always increases the walking time between plots and also the measurements costs. A trade-off between new information and measurement costs should be adopted.

The between plots distance was studied with the robust semivariance (Cressie and Hawkins 1980):

$$\text{(4)} \qquad \hat{\gamma}(r) = \frac{\left(1/N(r)\Sigma_{S(r)}\left|z(x) - z(y)\right|^{1/2}\right)^4}{0.914 + 0.988/N(r)}$$

where, $z(x)$ and $z(y)$ are the values of the variable at points x and y, $S(r)$ is the set of the points x and y (observation points) in the plane with a distance of r, and $N(r)$ is their number. The semivariances calculated from the volume predictions of the reclassified vegetation types of Hunting map, for Pre-strat categories 1–4 (Table 2), are shown in Fig. 9*a*) and for distances 0–1000 m in Fig. 9*b*). The semivariances level off at the distance of about 250 m, and thus support that as the appropriate field plot distance between the field plots on a cluster.

Possible shapes of the field plot clusters are for example a rectangle, an L-shape cluster, a line, a hexagon, etc. An advantage of a closing configuration, e.g., a rectangle, is a short return time to the starting point of the work on a cluster and to the transportation facilities. A disadvantage is a higher number of the plots close each other than in a nonclosing configuration, e.g., in a line or in an L-shape cluster.

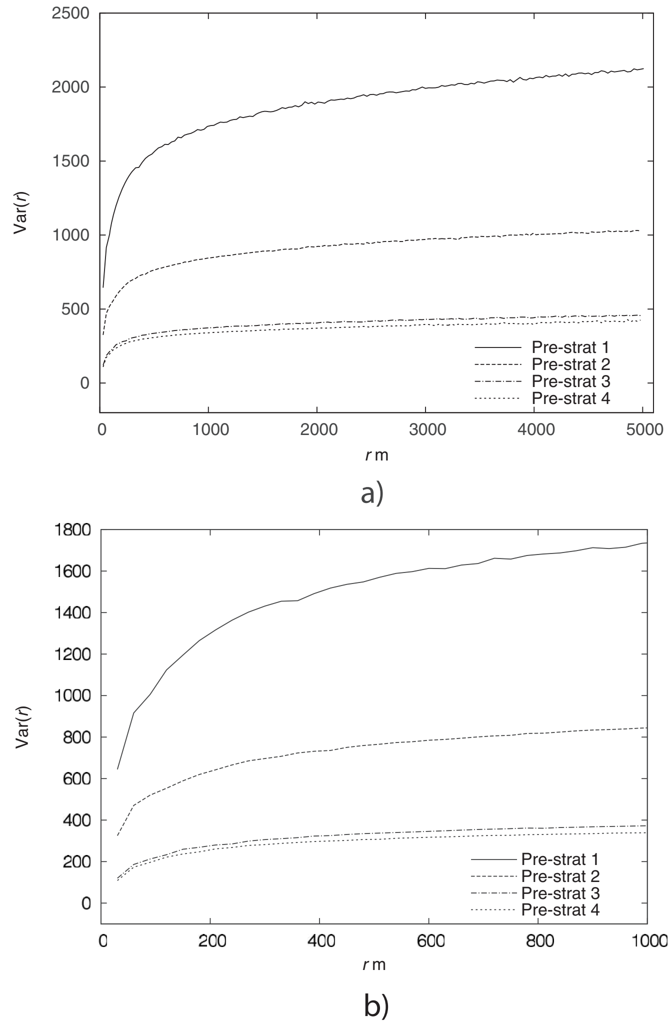
In NAFORMA, separate personnel were available for transportation of a crew along the roads, to take a crew to the road point nearest to the first plot of a cluster and back to the lodging from the road point nearest to the last plot of a cluster. A cluster shape such as a rectangle or square versus half rectangle was not a cost item in selecting the cluster shape. Comparing an L-shape and a line-shape cluster, an advantage of the L-shape is that it is not as sensitive as a line-shape for possible systematically oriented features in land cover and land use structures. The possibility to drive in the field was not assumed in the cost calculations. This was possible in practical measurements in a few cases. Furthermore, in the simulation, a return to the same point by the road was assumed, for simplicity.

An L-shape cluster was thus selected in collaboration with the local experts (Fig. 10*a*). The distances between the clusters as well as the number of the plots on a cluster remained to be the main decisions in selecting the design (see section 3.3.4).

3.3.3. Double sampling for stratification: a framework for the design

Possible sampling designs in a country such as Tanzania include (*i*) cluster sampling with equal cluster spacing, (*ii*) cluster sampling in which the cluster intensity varies by region, that is, the stratification is constructed by geographical regions, or (*iii*) double

Fig. 9. Semivariances of predicted volume in categories 1–4 of the re-classified vegetation types (Stratum) of Hunting map, (*a*) for distances (r) of 30–5000 m, (*b*) for distances (r) of 30–1000 m.



sampling for stratification in which each cluster is attached to a specific stratum and the areas of the strata are estimated from the first phase sample. High variation of the landscape and forests together with patchiness of the landscape and with separate forest patches of different types, as well as high variation of accessibility of the regions are arguments supporting double sampling with stratification. In addition to landscape and forest variation, the time to reach each sampling unit should be taken into account when allocating resources to field measurements. Double sampling for stratification was thus the selected statistical framework for the design.

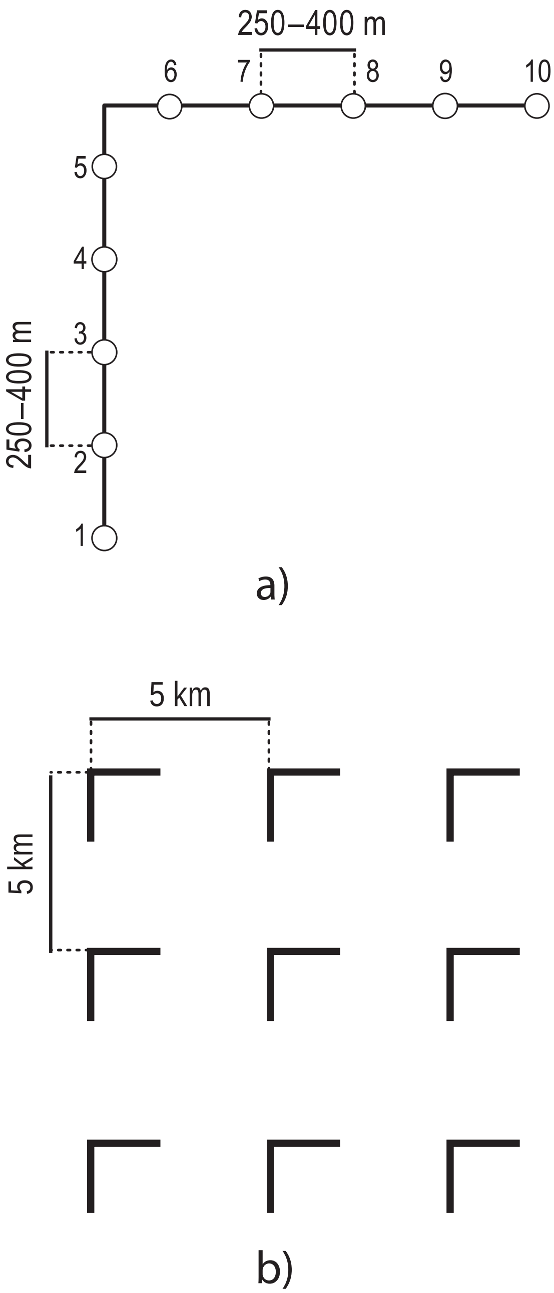
In double sampling for stratification, a large sample, denoted by s_a, of size n_{s_a} is drawn according to a given design. For each element, some information is either observed or predicted, which allows stratification. The information is used to stratify s_a into H_{s_a} disjoint strata s_{ah}, $h = 1,\ldots, H_{s_a}$ with n_{ah} elements in stratum h and thus the union of s_{ah} is

$$\text{(5)} \qquad s_a = \cup_{h=1}^{H_{s_a}} s_{ah}$$

and

$$\text{(6)} \qquad n_{s_a} = \sum_{h=1}^{H_{s_a}} n_{ah}$$

Fig. 10. Field plot clusters, (*a*) the plot distances tested, (*b*) cluster distances for the first phase sample.



From each stratum h, a sample $s_h \subset s_{ah}$ of a size of n_h is drawn and the variables of interest are measured (Cochran 1977; Särndal et al. 1992). For the total subsample s, the decomposition is

$$s = \cup_{h=1}^{H_{s_a}} s_h \tag{7}$$

and

$$n_s = \sum_{h=1}^{H_{s_a}} n_h \tag{8}$$

3.3.4. Application of the double sampling for stratification

In our application, the first phase sample s_a consisted of a dense grid of field plot clusters with the volume estimates, land use data, vegetation type data, digital elevation model and other georeferenced data. A dense grid of clusters was overlaid over Tanzania using equal distances of 5 km × 5 km between the clusters (Fig. 10*b*).

Table 5. The number of plots per cluster for each stratum group and the total land area within each group.

Strata	No. of plots	Land area (×10^6 ha)
1–12	10	83.0
13–16	8	4.6
17–18	6	0.5

The cluster level variables used for stratification were (*i*) the mean volume of growing stock, predicted for the plots using the model in eq. (2) and aggregated for cluster level mean volumes, (*ii*) the median slope derived from DEM calculated as a median of the slopes on the plots in the cluster when slopes were classified into three classes (Table 3), and (*iii*) the estimated time to measure the plots of a cluster, including all components listed in section 3.2.

The cluster level mean volumes were calculated as the averages (*i*) per land area, (*ii*) per wooded land (Pre-strat 1–5), and (*iii*) per forest land (Pre-strat 1–3). Reclassified Hunting map classes were used in (*ii*) and (*iii*) (Table 2).

The simple area and volume estimates used in sampling simulations for stratification were as follows. The land area of each stratum h was estimated using the first phase sample and the known land area A of Tanzania, assumed to be error-free

$$\hat{A}_{ah} = A\frac{n_{ah}}{n_{s_a}} \tag{9}$$

The area estimate $A_{h,l}$ of a land category l in stratum h based on the second-phase sample was estimated using the ratio of the number of the second-phase plots on the category $n_{h,l}$ and the number of the second-phase plots on land in stratum h, n_h, and the estimated land area of the stratum from the first phase sample and was

$$\hat{A}_{h,l} = \hat{A}_{ah}\frac{n_{h,l}}{n_h} \tag{10}$$

The mean volume on land category l for stratum h based on the second-phase sample was

$$\hat{\bar{v}}_{h,l} = \frac{\sum_{i=1}^{n_{h,l}} v_{h,l,i}}{n_{h,l}} \tag{11}$$

where $v_{h,l,i}$ is the volume on pixel i on land category l in the second phase sample in stratum h and $n_{h,l}$, is the number of the second-phase plots on land category l in stratum h. The mean volumes were calculated for the entire land, for wooded land, and for forest land. Note that each plot within a stratum has the same areal weight.

The total volume of the stratum h on a land category l was estimated as the product of the area estimate and the mean volume estimate

$$\hat{V}_{h,l} = \hat{A}_{h,l}\hat{\bar{v}}_{h,l} \tag{12}$$

The mean volumes for an aggregate of several strata were calculated through the totals, by first calculating the total volume and total area estimates, and dividing the total volumes estimate by the area estimates in question.

Table 6. The number of the plots and the coefficient of variation for the stratified designs with the plot distances of 250 m corresponding the costs of about 1.0, 2.5, and 4.0 × 10⁶ US dollars and non-stratified designs of 2.5 × 10⁶ US dollars for all of Tanzania.

Cost (×10⁶)	1.0	2.5	2.5	2.5	4.0	2.5
Plot distance (m)	250	250	200	300	250	250 No stratif.
Plots on land	13 011	32 551	32 906	32 230	52 536	33 166
Plots in wooded land	11 635	29 086	29 424	28 786	47 133	29 164
Plots in forest	7806	19 472	19 697	19 256	31 704	18 759
Crew days	2517	6259	6168	6397	10 189	6240
Exact cost (USD)	1 006 648	2 503 600	2 467 158	2 558 618	4 075 421	2 496 004
Coefficient of variation						
Area wooded land	0.77	0.44	0.47	0.45	0.33	0.50
Area forest land	1.88	1.16	1.16	1.15	0.81	1.03
Mean vol. wooded land	0.99	0.60	0.62	0.63	0.48	1.00
Mean vol. forest land	1.54	0.85	0.97	0.96	0.69	1.09
Total vol. wooded land	0.81	0.53	0.53	0.50	0.42	1.07
Total vol. forest land	1.81	1.12	1.16	1.01	0.86	1.67

Note: The results for the stratified design with about 2.5 × 10⁶ US dollars are given also for the designs with the plot distance of 200 m.

The clusters were classified for the second-phase sample. Several class numbers and class intervals were tested. In the selected classification, four mean volume, three cost, and three slope classes were used (Table 3). The volume intervals were determined using "optimal classification" by Neyman (see Cochran 1977, Section 5.A.7). The three cost (time) classes were used, (*i*) not more than one day, (*ii*) two days, and (*iii*) more than two days per cluster.

The relative sampling intensities in different strata were selected using optimal allocation, as presented by Cochran (1977). In our case, the sampling intensities were proportional to the quantity $\hat{\sigma}_{ah}^t/\sqrt{c_{ah}}$, where $\hat{\sigma}_{ah}$ is the within-stratum standard deviation of the mean volume of the growing stock on land on a cluster on stratum ah, c_{ah} is the average costs (measurement time) of a cluster within a stratum, and t is an exponent to be determined to control the effect of the $\hat{\sigma}_{ah}$ on the strata weights (intensities). The exponent t was used to mitigate the effect of volume variation owing to the fact that the volume is not the only interesting variable of the inventory. The sampling intensities are given in Table 3.

The comparisons of the different designs in terms of costs and sampling errors of the area and volume estimates used were calculated using sampling simulation and cost assessments. The simulation was done for all designs as follows. The starting point of a grid was selected randomly within a square corresponding to the distances in south–north and west–east directions of two adjacent clusters (Fig. 10*b*). For a design, 1000 samples were selected. The estimates of the parameters of interest, such as areas of forest land and wooded land as well as mean and total volumes on those land classes were computed from each sample. The mean of the estimates of the parameter values as well the standard deviation over samples were calculated. The standard deviation of the estimates calculated over the samples can be used to approximate the sampling error.

One may ask why not delineate the area of the country, or an area in question, into spatially connected strata and select the sampling intensities by those strata. When using variables such as we used for stratification, the areas of the connected strata would be low, in sizes similar to forest stands. It would be very likely that one cluster would intersect several strata. It would make the estimation and error estimation complicated, at least when using design based estimation. On the other hand, using clusters of plots instead of detached plots in an inventory is efficient for practical reasons, as has been discussed. To our understanding, the solution used here is the only feasible one in this situation, i.e., using cluster level averages of the variables and to allocate the clusters into the strata.

Note also that the when sampling intensity of the first phase sample increases, i.e., n_{ah} and n_{s_a} in eq. (6) increase, the errors of the area estimates (eq. (9)) approach zero.

4.0. Results

The methods outlined in section 3 were used to seek the optimal design with the given constraints for NAFORMA, that is, the number of the strata and the intervals of variables used for stratification, as well as the number of the plots on a cluster and the distances between the clusters by stratum. Several classifications were tested for the variables used in stratification. The number of the strata in the final design was 18 (Table 3). After some trials and comparisons of the sampling errors of volume and area estimates, a value of 0.7 for t in $\hat{\sigma}_{ah}^t/\sqrt{c_{ah}}$ was used in the final design (Tables 6 and 7).

The estimates and error estimates were calculated for the whole of Tanzania and for selected districts. The estimates and error estimates are presented and discussed here for the entire country and for one example district, the Singida district. The number of the plots in the second phase sample, i.e., the sampling intensities, were adjusted to different total cost levels, for example, 1.0, 2.5, and 4.0 × 10⁶ US dollars for all of Tanzania. The numbers of plots in these designs for all of Tanzania are presented in Table 6, and for the Singida district in Table 7. Other sampling intensities, based on the other budget constraints, were also tested. The calculation is straightforward, using the tools constructed.

The area estimates of the classes wooded land and forest land (see section 3.2) for the re-classified Hunting map classes are 77.4 and 49.8 × 10⁶ ha, and the estimates of the corresponding total volumes for the same areas are 4 and 3 × 10⁹ m³. The equivalent area and volume estimates for the Singida district were 1.9 and 1.2 × 10⁶ h and 102 and 74 × 10⁶ m³ respectively.

The final estimates of NAFORMA after field measurements will be based on measured variables from the second-phase sample and total land area estimate of each stratum based on the first phase sample, including 346 256 plots. The efficiency of the stratification depends on many factors and the prediction errors. Unbiased estimates are, however, obtained despite the prediction errors. High errors in the estimates used for stratification decrease the effect of the stratification but do not cause biases in the estimates. One should also note that the plots in one cluster always belong to one stratum, owing to the definitions of the strata in question.

The cluster sizes and the land area estimates by the groups of the strata based on the first-phase sample are shown in Table 5.

Table 7. The number of the plots and the coefficient of variation for the Singida district for the stratified designs with the plot distances of 250 m corresponding the costs of 1.0, 2.5, and 4.0 × 10⁶ US dollars and non-stratified designs of 2.5 × 10⁶ US dollars for for all of Tanzania.

Cost (×10⁶)	1.0	2.5	4.0	2.5 (No stratif.)
Plots on land	228	544	887	469
Plots in wooded land	204	484	795	393
Plots in forest	139	334	561	252
Crew days	50	107	169	87
Exact cost (USD)	19 928	42 677	67 630	34 672
Coefficient of variation				
Area of wooded land	8.61	4.33	3.29	3.03
Area of forest	17.86	9.78	7.80	10.15
Mean vol. wooded land	7.88	4.75	3.86	9.54
Mean vol. forest	13.65	6.94	5.47	12.75
Total vol. wooded land	8.32	4.33	3.87	9.69
Total vol. forest	15.08	9.78	5.92	12.12

The numbers were selected in such a way that the plots in a cluster can be measured, on the average, in one day. A field crew consisted of seven people with an estimated daily cost of US $410 per person, including salary, daily allowance, and transportation. The number of the plots on land, on wooded land, and on forest land, as well as the total costs and coefficients of variation (CV) (relative standard error, 100 × error/estimate) for six different designs for the entire Tanzania, are given in Table 6. The costs of three stratified designs with a plot distance of 250 m are 1.0, 2.5, and 4.0 × 10⁶ US dollars, and the cost of the nonstratified design is 2.5 × 10⁶ US dollars. A cluster size of 10 plots was used for the nonstratified design. The error estimates are also presented for the design corresponding to 2.5 × 10⁶ US dollars, but with the plot distances of 200 and 300 m to demonstrate the effect of the plot distance on the sampling error estimates and costs. The equivalent values for the Singida district are in Table 7 without the plot distances of 200 and 300 m, and correspond to the designs and costs presented in Table 6.

The CV for the area estimate of the category forest land for entire Tanzania with field measurement budget of 2.5 × 10⁶ US dollars is 1.2% (Table 6). The similar errors for the budgets of 1.0 and 4.0 × 10⁶ US dollars are 1.9% and 0.8%. The CV for the mean volume for forest land for the budget of 2.5 × 10⁶ US dollars is 0.85% and for the total volume is 1.1%. Stratification particularly decreases the errors in the volume estimates (Table 6). The reduction of the plot distance to 200 m increases the sampling errors and the increase of the plot distance to 300 m decreases the sampling errors. There is an inverse relationship with cost. The distance of 250 instead of 200 m was preferred to get higher between-plot variation in the field data (elaborated in section 5.0).

The category of wooded land comprises almost the total land area, therefore it is more relevant to compare the errors (CVs) of the area estimates in the category of forest land.

The errors for small areas, e.g., districts, are naturally higher than for the entire country (Table 7). The final standard errors and CVs will be smaller than those in Table 7 when satellite images are used to enhance the estimates (see Section 5 of Tomppo et al. 2008).

The final sampling design selected together with the experts from Tanzania for the first National Forest Inventory of Tanzania, NAFORMA, included 36 592 plots of land. The number of the plots per cluster varied from 6 to 10 (Table 5). The distance between the plots was, in all strata, 250 m. The measurements were assessed to be a workload of about one year. The field measurement costs were estimated to be 2.6 × 10⁶ US dollars. It fulfilled the budget constraints. Estimates on a subnational level are possible using field data only, together with remote sensing data for district level and even village level. The locations of the clusters and field plots corresponding the selected design, double sampling for stratification, and a budget of 2.6 × 10⁶ US dollars are shown for all of Tanzania in Fig. 11 and for Singida district in Fig. 12.

Almost all the field plots were measured when this article was written, and it was possible to assess the real costs (see also section 5.0). It turned out that the costs per person, as well as the other costs, were somewhat higher than the estimated ones; for field personnel about 10% higher. The budget was increased respectively to complete the measurements.

5.0. Discussion

We have presented methods for constructing a sampling design for a forest inventory. The core ideas are sampling simulation on the detailed georeferenced maps of the variables of interest and landscape attributes for sampling error estimation as well as cost assessments. The error estimates and cost assessments are used for selecting the most cost-efficient design fulfilling the given constraints. The sampling errors of the basic volume and area estimates were used in evaluating the optional designs at country level and district level. The costs were assessed in terms of field measurement time. The methods have been demonstrated in a real setting, in constructing the sampling design for the Tanzania forest resource inventory, NAFORMA.

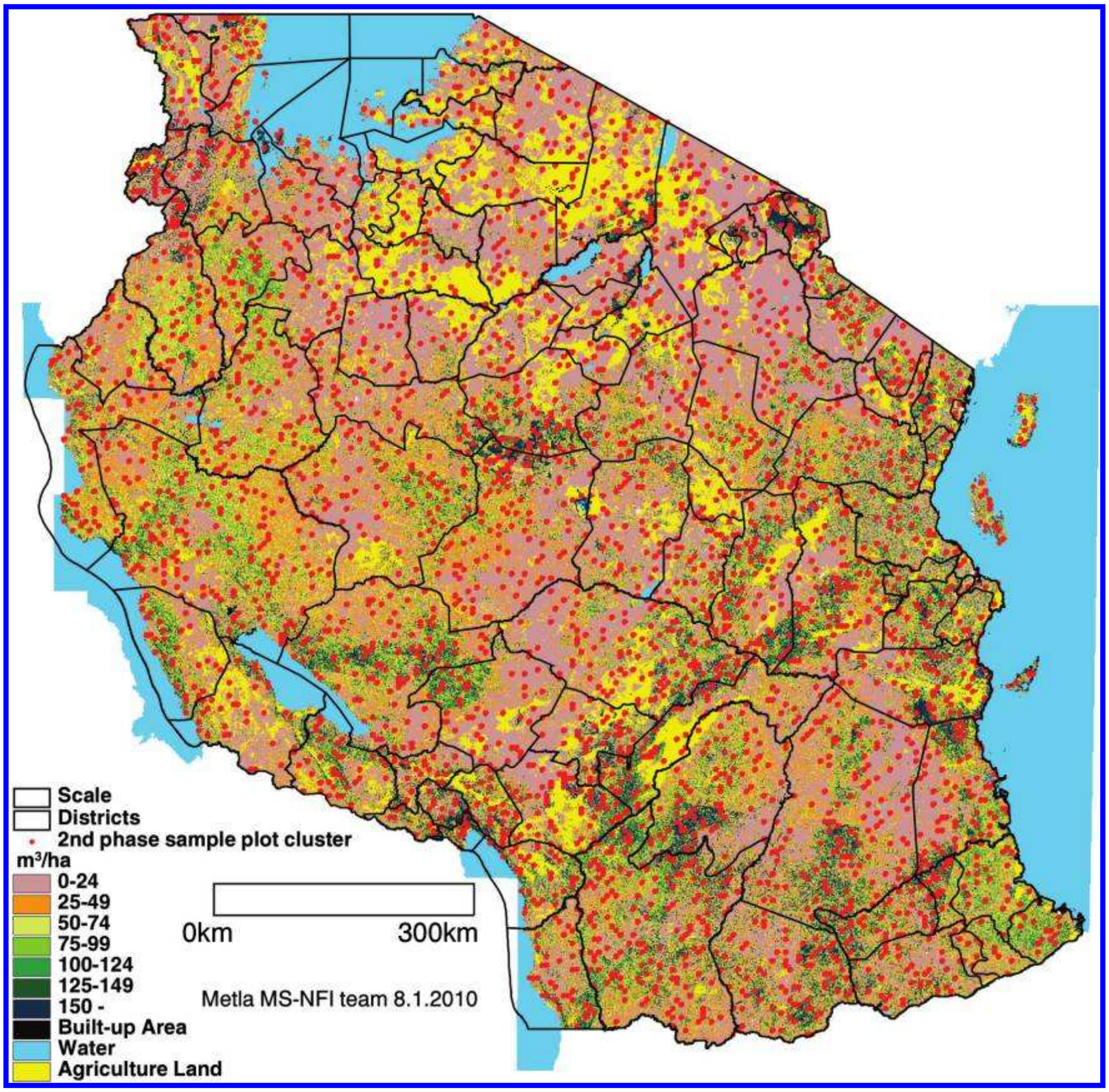
Digital land use and vegetation type information together with elevation variation and road network were employed in the sampling simulation, as well as the predicted volume of growing stock. The satellite image data used for volume prediction was from 2000. The quality of that data set was better than that of the other options available. To our understanding, the changes in volume and land use since 2000 do not essentially affect the optimality of the sampling design.

The key elements of the design are:

- Double sampling for stratification: a stratum includes the land area represented by the clusters of the stratum when the areal representation of a cluster is calculated from the first phase sample.
- Predictions of the volume of growing stock and costs assessments of the field measurements were used: the real volumes may deviate from the predictions. Despite this fact, the final estimates are unbiased.
- Every fourth cluster was marked to be remeasured in the coming inventories. Note that also the temporary plots are accurately geolocated, making it possible to remeasure those too, and use like the permanent plots for those parameters for which the variables are measured on the temporary plots.
- The current strata can be used for the permanent plots. Alternatively, the permanent plots may be allocated into the new strata. A new stratification can be constructed for the temporary plots (discussed later).
- The approach taken uses some input data, in this case volume predictions, and some land use/land cover area information (Hunting maps in this case). These data sets can be replaced by other similar data sets in other possible applications of the method presented.
- Other than the above, the procedure can be repeated in quite a straightforward way.

The design with stratification and optimal allocation of the plots into each stratum optimises the design for the current status of the forests. The design is no longer optimal if the forests change significantly. This is one reason that only 1/4 of the plots were marked to be remeasured in the coming inventories. The first inventory also provides more accurate information of the spatial variation of the forests than what was available when constructing the current design. A new design can be argued also for this reason. A small number of permanent plots was selected for immediate measurements to estimate the changes more accurately in the next inventory. In the next inventory, the locations of the

Fig. 11. The location of the clusters and plots using double sampling for stratification.



permanent plots of the first inventory and their stratification can be kept, and the locations of the new temporary plots optimised conditionally on the given locations of the permanent plots. In the long run, the permanent plots should be replaced gradually. It is possible to add new permanent plots in the next inventory. The question of the proportion of the permanent plots versus temporary plots is really multidimensional and far from a trivial problem. The answer depends on, e.g., the parameters of interest, the current state estimates versus change estimates, and the temporal correlation of the variables that are used for parameter estimation. However, in a country such as Tanzania, where the variation of forests and land use in different parts of the country is high, the advantages of stratification are obvious.

After the field measurements, we also noticed that the number of strata could be lower than the one used in the first NAFORMA. This could be taken into account in the coming inventories.

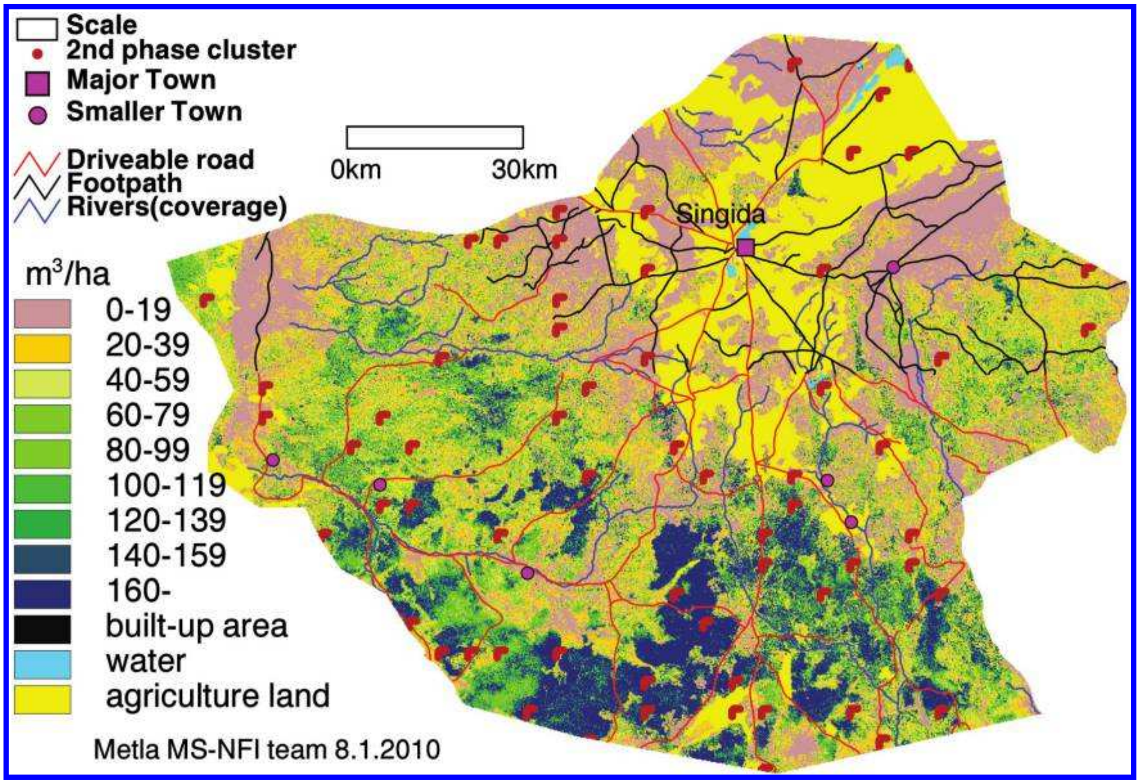
Double sampling with stratification has the advantage of allocating the resources optimally with respect to the parameter estimates used in optimisation. A further problem, in addition to the possible change of design, is that this sampling method entails a somewhat complicated estimation procedure. Separate stratification for the permanent plots and temporary plots presume two sets of estimates with error estimates. The estimates can be merged using the error estimates (Ware and Cunia 1962).

Additional measurements were carried out on the permanent plots, e.g., measurements of the trees with breast height diameter <1 cm (Fig. 8), and the soil measurements.

In the tests carried out, the stratified design significantly improved the efficiency compared with the nonstratified alternatives (Tables 6 and 7). Stratification on the basis of managed versus nonmanaged forests was also considered. The area of nonmanaged forests was not significant, therefore this option is not relevant in Tanzania and was left out of the analyses.

An exact comparison of the traditional NFMA design (Saket et al. 2010; FAO 2013) and the design proposed would have required detailed information about the proportion of large trees and small trees for cost and error assessments. This information was not available when the methods were developed. A rough idea about the efficiency of the NFMA design in another type of forests is given in Tomppo and Katila (2008) where the NFMA design was compared to a stratified cluster sampling and strata composed by regions. The costs for the NFMA design were four times those of the alternative design with the same errors.

Fig. 12. The location of the clusters and plots using double sampling for stratification, the Singida district.



The relative sampling error of the estimate of the land category called here forest land with the stratified design presented and with a total field measurement budget of 2.5×10^6 US dollars is 1.2%. The similar errors for the mean and total volumes of the growing stock were 0.9% and 1.1% respectively.

When assessing the costs presented, one should note that some remote clusters take a long time to reach. In the cost calculations, each cluster is assumed to be visited separately. However, in practice, nearby remote clusters could be measured by staying in the neighbourhood of the clusters overnight, which would reduce the total costs compared with the ones presented in this work.

The selected design allows the use of NAFORMA as the basis for UNFCCC greenhouse gas reporting of and for REDD purposes. The NAFORMA field plots cover all land categories, making assessment of the areas and area changes of all IPCC land categories and carbon pools and their changes related to the areas of the land categories and land area changes possible (IPCC 2003, 2007). The final relevance of NAFORMA for GHG reporting depends on the availability of the other data and models needed for carbon pool estimation. Soil data were also measured in NAFORMA. Biomass models are under constructions.

The accuracy of the estimates and the estimate of the changes for small areas can be enhanced with additional information, such as remote sensing based information (Tomppo et al. 2008). A sound statistical approach is also highly recommended when using remote sensing data as additional information.

FAO FRA definitions and harmonised definitions given in Tomppo et al. (2010*a*) were employed throughout when relevant, making the estimates applicable in international reporting.

Preliminary data were available by NAFORMA to carry out rough comparisons with the error estimates. The data were still somewhat incomplete, as some inaccessible plots were yet to be measured. This should be taken into account when comparing the error estimates. The volume models were the most simple ones employing a simple form factor.

The area, volume, and error estimators given by Tomppo et al. (2011) and adapted to double sampling for stratification were used. The stratum level estimates were first calculated with the total area estimate of each stratum calculated from the first-phase sample.

The CV of the estimate of forest land area (Hunting map land categories 1–3) in our sampling study with about 35 000 plots on land was 0.87% (Table 6). The similar error estimate calculated with the preliminary field data was 0.84%. The area estimates were 49.8 and 48.2×10^6 ha respectively. The difference in the area estimates can be caused by the different definitions of the combined land categories 1–3 of the Hunting map and NAFORMA. Another reason could be due to the inaccuracies of the locations and boundaries of the land patches on the Hunting map. The difference does not cause bias to the final estimates based on the stratification. The stratification is only less efficient if it is based on inaccurate data. The error estimates for the average volume of the growing stock on forest land were 1.1% in the sampling study and 2.30% in the field data. The error estimates for the total volume on forest land were 1.4% in the sampling study and 2.3% in the field data. The lower error estimates of the sampling study compared with real estimates, known from earlier experiences, were taken into account when making the decision concerning the sample. The practical error estimates could be decreased by using a multisource approach and, e.g., post-stratification.

A few things should be remembered when comparing the error estimates of the two methods. (*i*) In the sampling study, the land categories were based on the map data and may deviate from that of the field inventory. (*ii*) Owing to different definitions, the spatial distribution of the land patches may be different, thereby affecting the error estimates. (*iii*) The volume estimates of the sampling study were based on pixel level predictions, based on a simple regression model in this case. In these predictions, there is always a "tendency towards mean" effect that decreases the volume variation and also the error estimate of the mean and total volumes. However, the error estimates of the land classes are similar in both methods. As expected, the error estimates for volumes are lower in the sampling study.

The purpose of the sampling study was to compare the efficiencies of the different sampling designs, not to estimate the true errors. We believe that the sampling method presented works for this purpose.

When planning the application of the methods to another country or area, accurately georeferenced data for error and cost estimation are needed. The application is quite straightforward after this. However, the number of the strata should be decided thoroughly. The preliminary result calculations showed that the number of strata could be decreased to make the estimates also for district level in all districts. The use of ancillary data, such as remote sensing data, helps in this task with the current design. Reducing the number of the strata could be considered in the possible revision of the method for the next round of the inventory in Tanzania.

One should also note that this article presents the methods for constructing a sampling design and the direct field measurement costs only. An entire forest inventory includes a significant amount of other cost pools, such as the planning of the inventory, crew supervision, quality control and assurance work, crew training time and costs, equipment and supply costs, lodging, administration, data processing, and reporting. These costs should also be taken into account in planning the total budget.

Finally, finding an inventory design that fulfils the optimality criteria simultaneously for several parameters is an extremely demanding task and presumes detailed and representative information throughout the country as well as valuation of the error estimates of different parameters. Therefore, designing an efficient inventory is a long process and the solution can be improved through consecutive inventories.

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