Participatory mapping of forest plantations with Open Foris and Google Earth Engine

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Abstract

Recent years have witnessed the practical value of open-access Earth observation data catalogues and software in land and forest mapping. Combined with cloud-based computing resources, and data collection through the crowd, these solutions have substantially improved possibilities for monitoring changes in land resources, especially in areas with difficult accessibility and data scarcity. In this study, we developed and tested a participatory mapping methodology utilizing the open data catalogues and cloud computing capacity to map the previously unknown extent and species composition of forest plantations in the Southern Highlands area of Tanzania, a region experiencing a rapid growth of smallholder-owned woodlots. A large set of reference data, focusing on forest plantation coverage, species and age information distribution, was collected in a two-week participatory GIS campaign where 22 Tanzanian experts interpreted very high-resolution satellite images in Google Earth with the Open Foris Collect Earth tool developed by the Food and Agriculture Organization of the United Nations. The collected samples were used as training data to classify a multi-sensor image stack of Landsat 8 (2013-2015), Sentinel-2 (2015-2016), Sentinel-1 (2015), and SRTM derived elevation and slope data layers into a 30m resolution forest plantation map in Google Earth Engine. The results show that the forest plantation area was estimated with high overall accuracy (85%). The interpretation accuracy of local experts was high considering general definition of forest plantation declining with increased details in interpretation attributes. The

results showcase the unique value of local expert participation, enabling the collection of thousands of reference samples over a large geographical area in a short period of time simultaneously building the capacity of the experts. However, sufficient training prior to the data collection is crucial for the interpretation success especially when detailed interpretation is conducted in complex landscapes. Since the methodology is built on open-access data and software, it presents a highly feasible solution for repetitive land resource mapping applicable at different spatial scales globally.

Keywords: Crowdsourcing, planted forests, open-source, multi-sensor, cloud computing, Tanzania

1. Introduction

Recent years have witnessed the practical value of emerging open-access Earth observation data catalogues and software in land and forest mapping. Data repositories provided by commercial vendors and public organizations, such as Google Earth and Global Land Cover Facility have diversified the opportunities to make remote sensing based observations at multiple spatial and temporal scales globally (Wulder and Coops 2014, Turner et al. 2015, Klein et al. 2017). Combined with cloud-based computing resources, these solutions have substantially improved possibilities for monitoring of environmental and land resource development in a changing world (Hansen et al. 2013, Dong et al. 2016, Xiong et al. 2017). The impacts have not only been on the lessening of previously laborious satellite data downloading and pre-processing phases of the work, but on the overall access to, and enabling of combined uses of multiple data sources simultaneously in a cloud-based environment. Access to open data repositories have enabled multi-sensor and multi-temporal image analysis essential to overcome the shortcomings related to land and forest mapping in the tropics such as spectral mixing between planted and natural forests, heterogeneous spectral characteristics of different tree species, dynamic land use patterns, and frequent cloud cover and moist conditions (Dong et al. 2013, le Maire et al. 2014, Fagan et al. 2015, Chen et al. 2016, Torbick et al. 2016).

At the same time new solutions to collect evidence-based information to support image processing have become widely accessible for the larger public. Collecting volunteered geographical information (VGI) based on, for example Google Earth images has been introduced for validating global and regional mapping of land cover (Fritz et al. 2009, Clark et al. 2010, Gessner et al. 2015, See et al. 2015a, See et al. 2015b, Tsendbazar et al. 2015, Estes et al. 2016), land conversion (Jacobson et al. 2015), cropland coverage (Fritz et al. 2015, See et al. 2015c) and forest cover (Song et al. 2011, Schepaschenko et al. 2015). These studies have shown the immense potential of crowdsourcing in creating large amount of geographical validation data with limited resource investment, particularly valuable in areas where such information did not previously exist.

However, the veracity and unknown quality and accuracy of the mapped data has been the major concern related to scientific applications based on VGI data (Comber et al. 2013, See et al. 2015b). The most important factors affecting the quality of collected information are related to lack of good quality images to support the decisions when collecting the data, and respondents' insufficient capacity for interpretation (See et al. 2013, Comber et al. 2016). In particular, studies which require specialized interpretation skills are sensitive to the quality of the collected data (Salk et al. 2016). In such cases, the quality of mapping can be improved by turning VGI approaches into structured participatory data collection campaigns by engaging groups of experts with local knowledge and providing sufficient background information and training for calibrating multiple interpretations (Verplanke et al. 2016). These participatory GIS (PGIS) solutions are promising combinations of open data catalogues, cloud computing capacity and motivated participants to tackle land and forest mappings (Brown and Fagerholm 2015). The integration of local knowledge and automated classification processes calibrate and contextualize land and forest information geographically (Hansen et al. 2014, Tropek et al. 2014).

The Food and Agriculture Organization of the United Nations (FAO) has developed an open-source software suite which enables the combination of participatory mapping with cloud-based image access and processing. One of these tools, Collect Earth, has been designed for structured, augmented data collection based on visual interpretation on Google Earth and other public sources of imagery (Bey et al. 2016). As a PGIS platform it offers a new generation of participatory image interpretation and classification environment, where easy-to-use elements of a public survey are combined with professionally structured visual image interpretation tasks.

In this study we have tested the quality and relevance of PGIS approach combined with the use of open-access image catalogues and software in mapping forest plantations at a regional scale in Tanzania, East Africa, where access to large amounts of data and computing power, as well as capacity of experts have previously prohibited efficient mapping and monitoring of land resources. We have developed a participatory mapping methodology, which utilizes open data catalogues and cloud computing capacity (Open Foris suite, Google Earth Engine) combined with participation of local experts. Our aim is to evaluate the role of participation in collecting reference samples, quality of the results and participant experiences as evidences of the suitability of the method for participatory land and forest mapping, and its possible generic uses and repetition for monitoring purposes. Furthermore, our aim is to test the suitability of this methodology in producing a high-resolution forest plantation map within our study area in the Southern Highlands of Tanzania, a region experiencing a rapid growth of smallholder-owned woodlots but where lack of spatially explicit estimates of the forest plantation coverage hampers the evaluation of environmental and socio-economic impacts of the land development.

2. Data and methods

2.1 Forest plantations in the Southern Highlands of Tanzania

The Southern Highlands area is located in Southwest Tanzania, roughly within the administrative regions of Iringa, Mbeya and Njombe (Figure 1). Overall, the terrain of the region is variable, with the altitude ranging from nearly 3000 m.a.s.l. of Mount Rungwe, to less than 300 m.a.s.l, in the floodplains of the Kilombero Valley. Unimodal rains start in November and continue until April and rainfall ranges from yearly average of 600mm in the North to over 2000mm in the Southwest (Mbululo and Nyihirani 2012). Due to its reliable and sufficient rains and mild temperatures the Southern Highlands is the most important forest plantation and silviculture area in Tanzania. The most common planted trees are pine (*Pinus patula*, *P. elliottii* and *P. caribaea*), several *Eucalyptus* spp., black wattle (*Acacia mearnsii*) and, in some areas, teak (*Tectona grandis*).

Currently the coverage of planted forests is unknown in Tanzania, with estimations ranging from 250,000 to 550,000 hectares (Ngaga 2011, MNRT 2015, FAO 2015). The most recent national estimates were produced in National Forest Resources and Monitoring Assessment (NAFORMA 2009-2014), which was the first field reference based national forest inventory in the country (MNRT 2015). NAFORMA produced two estimates on plantation cover for Tanzania. Based on the field samples the planted forest area was estimated to be around 555,000 hectares in the whole country, whereas according to the NAFORMA land cover map there are 147,000 hectares of planted forests in Tanzania and around 70% of those plantations are located in the area of the Southern Highlands (MNRT 2013). However, the mapping has not been explicit enough for deriving subnational estimates since only the large forest plantation areas are depicted in the national level maps. Recently, Southern Highlands has experienced a “timber rush” as many smallholders have established small scale private plantations for future investment ranging in size from smaller than an acre to a couple of hectares (Ngaga 2011). These non-industrial private forestry establishments have been particularly promoted in this area through various donor-funded incentive schemes, such as Hifadhi ya Mazingira (HIMA 1990-2002), and more recently Private Forestry Programme (PFP, since 2014), and Forestry Development Trust (FDT, since 2013) (Danida 2007, FDT 2016, PFP 2016). There is an urgent need to produce a baseline map of forest plantations for the area, and also introduce a methodology of systematic, repeatable and open-access forest plantation cover mapping with open data.

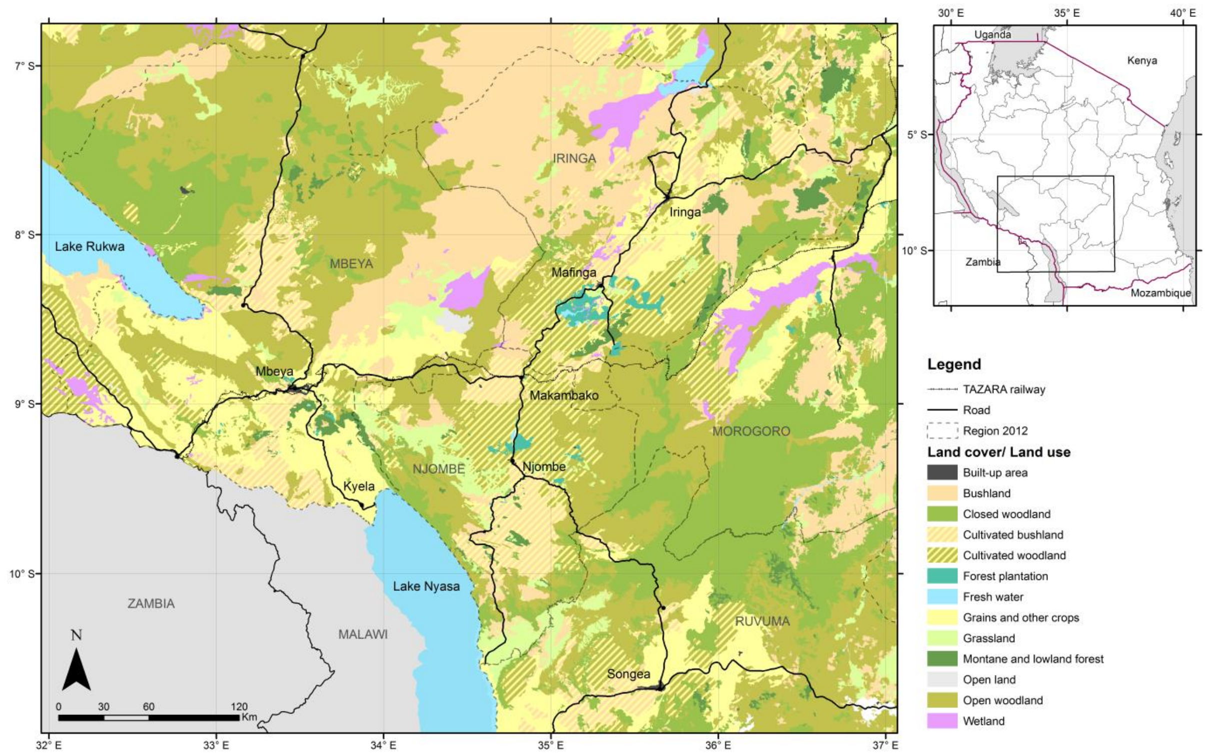

Figure 1. The study area is located in the Southern Highlands in the south-west corner of Tanzania lying in between 6.8°S and 10.9°S and 32°E and 37°E covering area of ca 202,770 km^2. The land cover is dominated by woodlands, bushlands and agricultural area. The largest forest plantations are concentrated in the vicinity of Mafinga and Njombe (MNRT 2013).

2.2 Design of the participatory mapping methodology

The forest plantation mapping was based on freely available global geospatial datasets and satellite images combined with participatory reference data collection, use of the Open Foris suite, Google Earth and Google Earth Engine (Figure 2). Both optical [Landsat 8 OLI (Operational Land Imager) best-pixel mosaic from 2013-2015 and Sentinel-2 MSI (Multispectral Instrument) median mosaic from 2015-2016] and synthetic aperture radar [SAR; ALOS PALSAR (2010) and Sentinel-1 (2015)] satellite data sets were used in the mapping, as the combined use has proven to be more effective in detecting forest covered areas (Dong et al. 2013, Fagan et al. 2015, Torbick et al. 2016). The optical datasets were accessible through Google Earth Engine (GEE) as pre-processed and geo-referenced image collections, facilitating straightforward utilization of the images in the GEE code editor platform to create cloud-free best pixel mosaics. We found this especially feasible in our case as frequent cloud cover over the study area necessitated using the best available pixels from multiple image acquisitions to create cloud-free composites suitable for classification. At the time of our analysis, the ALOS PALSAR imagery was not accessible through GEE and analysis-ready Sentinel-1 SAR data on GEE still lacks the radiometric normalization along slopes. Due to the missing metadata, respective correction routines couldn't be applied in GEE. For that reason, both ALOS PALSAR and Sentinel-1 data were pre-processed with the Open Foris SAR toolkit (Vollrath et al. 2016) that provides fully-automated pre-processing routines for analysis-ready SAR data. Detailed description of the datasets and the pre-processing steps prior the extraction of spatial variables is included in the supplementary material.

The methodological approach was divided into 3 stages preceded by the acquisition and pre-processing of the geospatial datasets (Figure 2). In the first stage, a preliminary forest plantation/non-plantation layer was created. In the second stage, a reference data set of 7500 sample points was generated and stratified based on the first stage land cover classes and the sample locations were interpreted and assigned to land cover classes by local experts in a two-week participatory mapping campaign (Mapathon). In the third stage, final forest plantation map was created and the accuracy of the map was assessed.

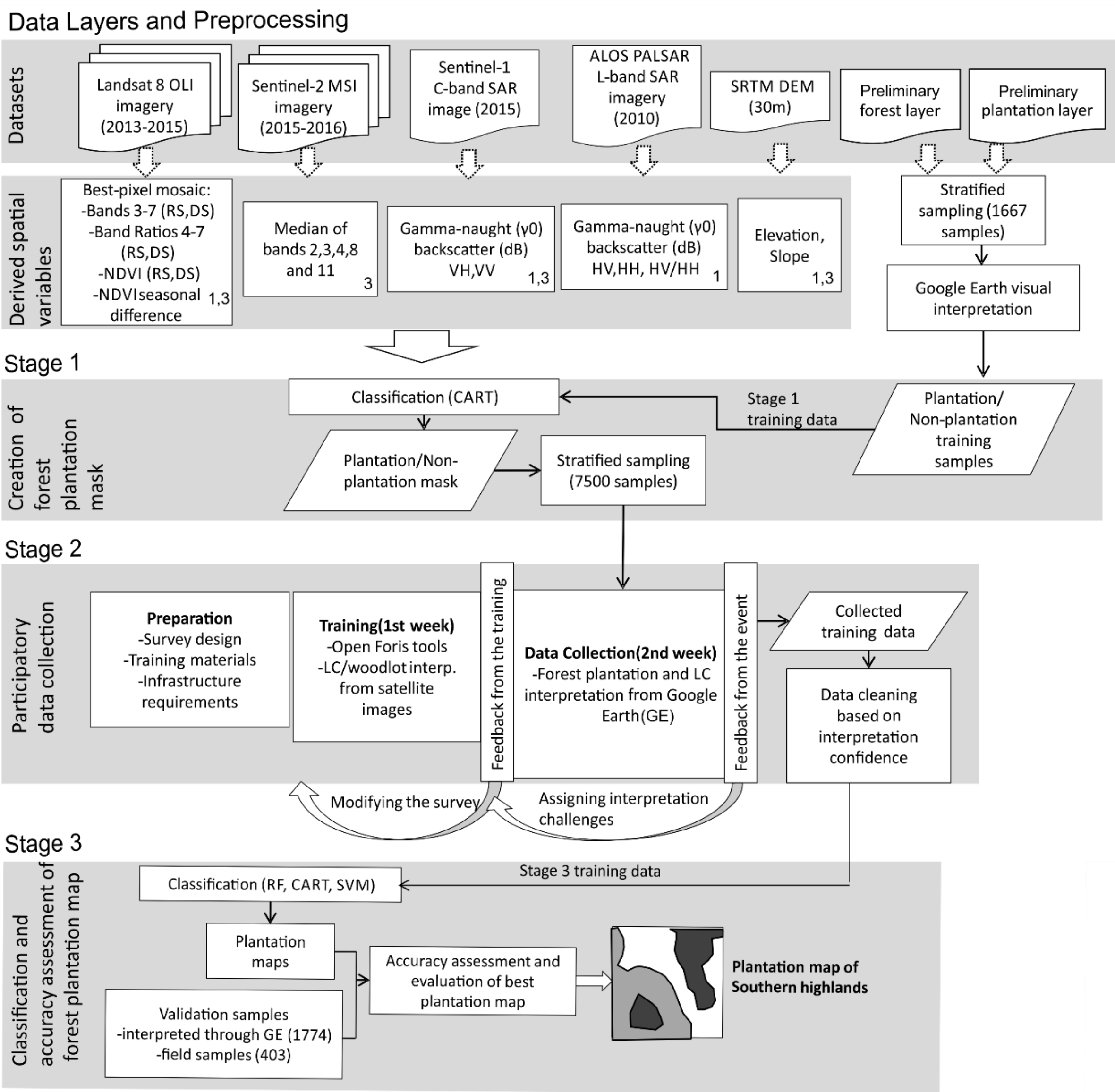

Figure 2. The overall study design was based on three stages. RS and DS marked in the derived variables of Landsat 8 OLI best pixel mosaic refer to rainy season and dry season, respectively. Numbers 1 and 3 in the down-right corner of derived layer boxes refer to the classification stages in which the layers were used. The classifiers used in the third stage were Random Forest (RF), classification and regressions tree (CART), and Support Vector Machine (SVM).

2.3 Creation of forest plantation mask (Stage1)

A sample point data set was stratified based on preliminary forest plantation and forest area estimates. The total amount, geographical distribution and extent of the sample points for the survey were constructed with the Open Foris Accuracy Assessment tool (https://github.com/openforis/accuracy-assessment). We used an adjusted number of points with a minimum sample size of 150 points to ensure enough points represent forest plantations. Altogether, 963 sample points were created with 150, 361 and 452 points falling on forest plantation, forest and other land strata, respectively.

The Collect Earth tool of the Open Foris suite was used to collect land cover information from the sample locations. Collect Earth bridges Google Earth, Bing Maps and Google Earth Engine and allows online visual interpretation of very high to medium resolution satellite imagery including DigitalGlobe, SPOT, Sentinel-2, Landsat and MODIS (Bey et al. 2016). In Collect Earth, the user fills the survey form for the sample locations with relevant land cover information based on visual interpretation (Figure 3). The Collect Earth survey, simple at this stage with binary plantation/non-plantation classes, was created using the Collect tool of the Open Foris suite that enables the construction of a structured survey form.

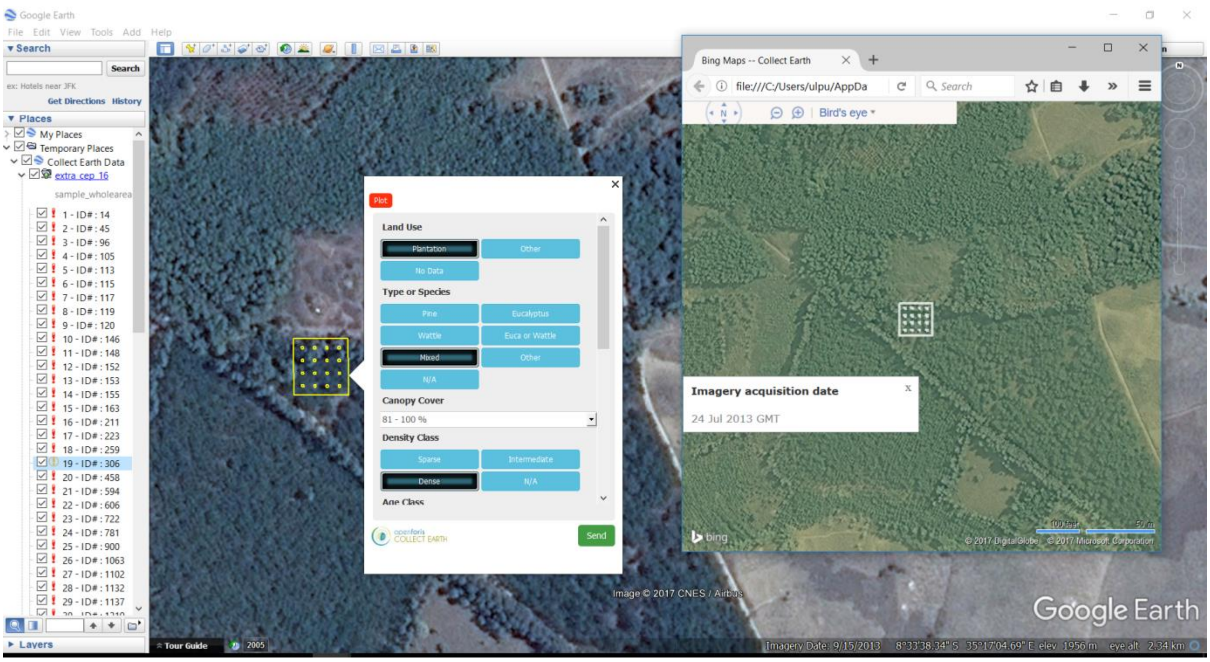

Figure 3. Collect Earth allows easy filling of the structured survey form and viewing the plot area in different data repositories (Google Earth and Bing Maps in this example).

The collected samples were used as training data for image classification. The Landsat 8 OLI, ALOS PALSAR, Sentinel-1 and SRTM elevation and slope data sets were used as inputs. A classification and regressions tree (CART) classifier was chosen to carry out the classification experiments in GEE. Additional samples (704) were added to the training dataset to improve classification performance in forest plantation and natural forest classes, as these were often mixed in initial classification results. Adding these points, a total of 1667 reference points were used for the first stage forest plantation mask.

2.4 Participatory data collection (Stage 2)

The objective of the second stage was to increase the accuracy and precision of the first stage forest plantation mask by collecting a large amount of reference points through the participation of local experts. 2,500 sample points (7500 in total) were allocated to each stratum (forest plantation, forest, and other land cover) based on the forest plantation mask and tree cover layer of stage 1. The size of the sample plot was adjusted to 30x30m equivalent to the pixel size of the imagery used in the classification stage. The survey was broadened from the first stage to include also other land cover classes than forest plantations. Systematic grid of 16 sample points within each plot was used to estimate the coverage of land use and land cover (LULC) elements within the plot area, guiding the respondent in the selection of the land cover class. For woodland, bushland, grassland, and open land the coverage proportions of LULC elements were defined by the NAFORMA land cover system (MNRT 2015) but apart from those, the precept was to define the dominant LULC class inside the plot. In cases where the plot area was shared equally by two or more land cover classes, a previously agreed hierarchy was used (Martinez and Mollicone 2012) (Figure 4). For forest plantations, the species, canopy cover and age class were recorded along with information on the year of establishment and latest clearing whenever possible. Also ‘no data’ and low interpretation confidence options were included in the survey and later used with the image date to indicate the quality of the data.

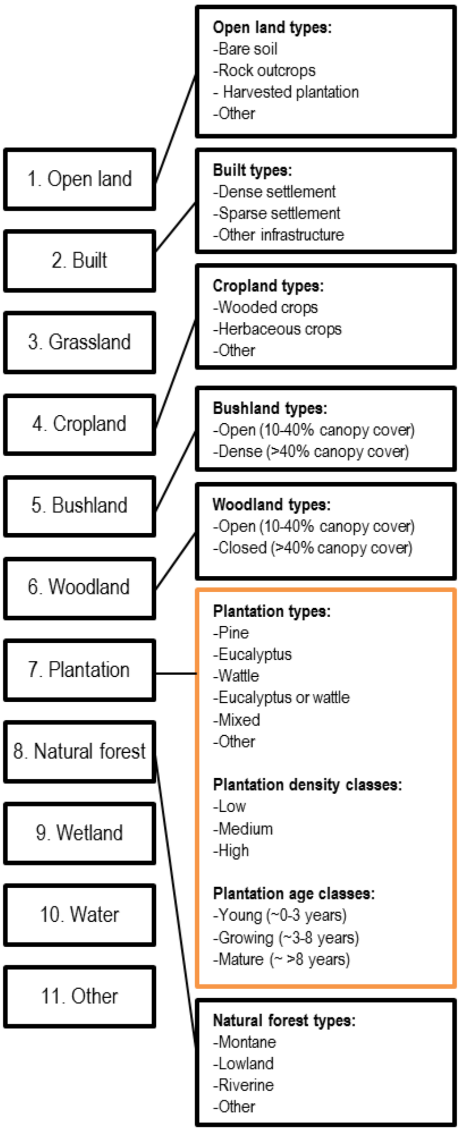

Figure 4. Land use and land cover (LULC) classes and their hierarchy for interpretation.

Making the process of a large reference sample data collection through participation feasible, a PGIS data collection campaign, Mapathon, was organized at the University of Dar es Salaam (UDSM) Department of Geography HEI-GIS lab in October 2016. A total of 22 participants took part in the Mapathon: eight forestry, remote sensing and mapping experts from the University of Dar es Salaam (UDSM), Ardhi University (ARU), Private Forestry Programme (PFP) and Tanzania Forest Service (TFS), and 14 MSc and BSc students from UDSM and University of Bagamoyo (UOB) Geography Departments.

During the first four days, the participants were trained on using Open Foris Collect Earth and on interpreting land cover and forest patterns of the Southern Highlands based on high-resolution satellite imagery. The focus of the training was on separating forest plantation types (species and estimated age class). After the first week's experience and based on the participants' feedback on the challenges of the interpretation, the survey was slightly modified: 'harvested plantation' class was added in the open land cover classes due to its spectral characteristics, and a choice of 'eucalyptus or wattle' was added in the forest plantation types, since the respondents often had difficulties in distinguishing between these two species.

During the second week of the Mapathon, the participants interpreted LULC information visually on individually assigned batches of plots through Collect Earth. In addition to the Google Earth and Bing Maps imagery, the participants were offered a possibility to use previously downloaded auxiliary data in QGIS to support the interpretation: the Landsat 8 OLI 2-season mosaics, SRTM digital elevation model (Jarvis et al. 2008) and WorldClim average temperature and mean annual rainfall (Hijmans et al. 2005). These layers can be accessed through the GEE extension of Collect Earth but were downloaded in advance to avoid problems caused by the instabilities in the internet connection.

During the Mapathon the participants collected information for 6,871 samples including 387 'no data' observations. 23% (1,587) of the interpreted samples had low confidence, poor accuracy or insufficient marking and were modified by the research team, resulting in 6,866 sample points available for the supervision of the land cover and forest mapping. Out of all points, 1,534 were forest plantation reference points (Figure 5, Table 1). Most of the plantation plots were interpreted as eucalyptus or wattle by species and growing (3 to 8 years old) by age.

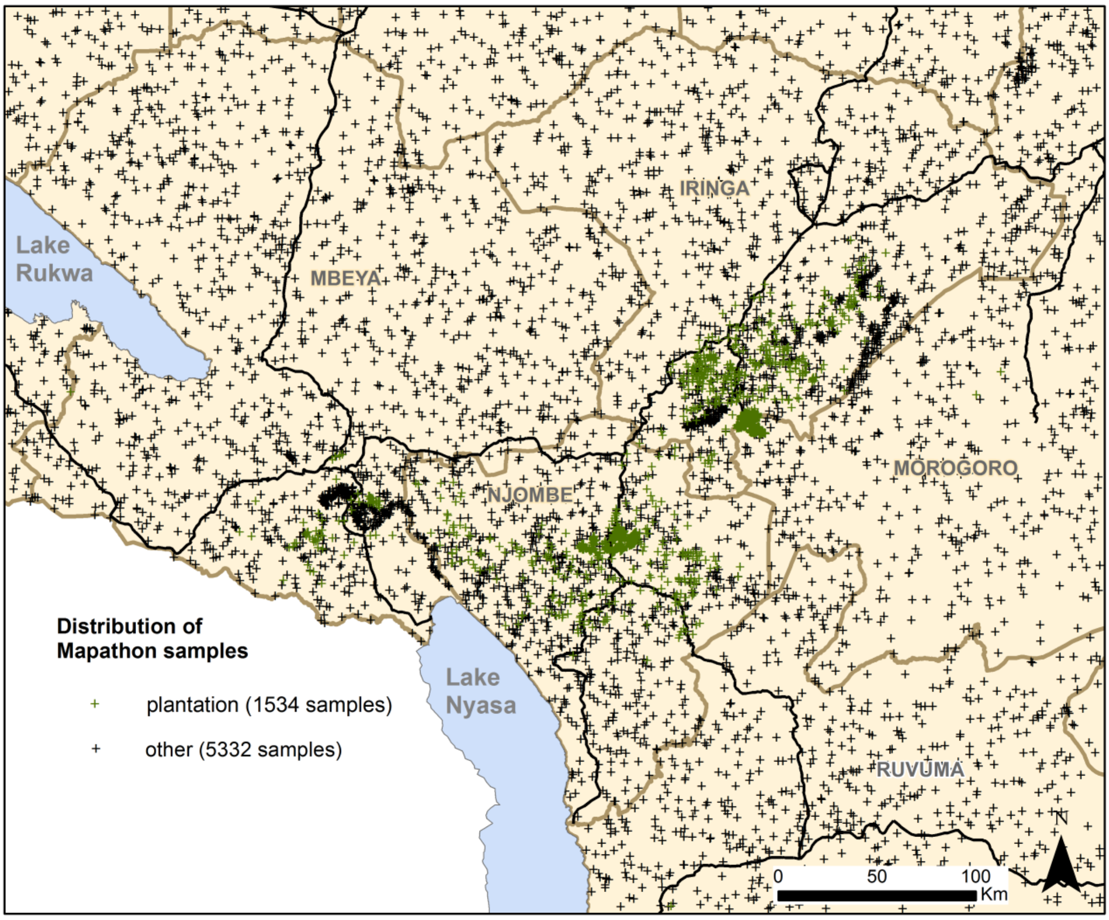

Figure 5. Distribution of the samples collected by the local experts during the Mapathon. The sample distribution is denser in forest plantation and forest areas because of the stratification based on the 1st stage classification.

Table 1. Number of collected samples during the Mapathon by forest plantation species and age, and other land cover classes.

Plantation species	P	E/W	Mix	N/A
	604	862	44	24

Plantation age	Rp	Gr	Mat	N/A						
	150	318	263	803						
Land cover	**Bu**	**Bl**	**Cr**	**Fn**	**Gl**	**Ol**	**Otl**	**Wa**	**Wt**	**Wl**	**N/A**
	26	1039	815	727	479	177	26	5	184	1746	108

P = Pine, E/W = Eucalyptus or wattle, RP = Recently planted, Gr = Growing, Mat = Mature, Bu=Built up, Bl=Bushland, Cr=Cropland, Fn=Natural forest, Gl=Grassland, Ol=open land, Otl=Other land, Wa=Water, Wt=Wetland, Wl=Woodland

The accuracy of the interpretation was evaluated against ground data collected during field visits in 2015 and 2016. 147 known reference samples were interpreted by local experts and research team members during the Mapathon, and the accuracies were tabulated. Furthermore, the confidence of all of the collected samples was evaluated by randomly choosing 300 forest plantation points and 300 other land cover points (in total 8% of all points), to be interpreted by the research team members. The interpretation agreements of local experts and research team members were calculated and tabulated.

To evaluate the learning experiences of the local experts during the Mapathon we collected systematic feedback using a form with specified learning statements and open-ended questions. The statements allowed participants to assess the quality of the event and personal learning experiences by marking their agreement related to the statements on a scale from 1 to 5. The open-ended questions allowed participants to describe their key skills after the completion of the Mapathon campaign. We asked which skills the participant felt they specifically learned though the Mapathon, in which remote sensing skills they felt the most confident after the event, and which skills they felt they still needed more practice in.

2.5 Classification and accuracy assessment of forest plantation map (Stage 3)

The training data collected through the participatory GIS campaign was used to produce the final forest plantation and planted tree species maps. We left out the ALOS PALSAR 2010 from the data layers at this stage to ensure a uniform temporal coverage of the data sets. By the time of the stage 3 classification, Sentinel-2 imagery from the dry season had become available and was added to the datasets. Due to having most of the data sets in 30m resolution, the classification target resolution was set to the same pixel size in GEE, which means that the data being classified gets automatically resampled to 30m resolution with nearest-neighbour method.

Three different classifiers (CART, Support Vector Machine and Random Forest) were tested for the final classification in GEE. All of these classifiers have a well-established methodological base and are widely used in land cover and forest mapping applications (Fagan et al. 2015, Khatami et al. 2016, Torbick et al. 2016, Zhao et al. 2016). The accuracies were compared using a reference data set. Based on the best accuracy, Random Forest with 150 trees was selected for creation of the forest plantation area and planted species distribution maps.

Due to the heterogeneity of the study area landscape, forest plantations that consisted of only 1 or 2 pixels were erased from the output prior the accuracy assessment. Altogether 900 validation samples were created with the Open Foris Accuracy Assessment tool and stratified based on the three land cover classes used (forest plantation, natural forest and other land cover). The amount of samples for each stratum was fixed following the guidelines of Olofsson et al. (2014) leading to 100 samples for forest plantations and 328 and 472 for forest and other strata, respectively (Figure 6). The land cover information of these samples was interpreted through very high-resolution imagery in Google Earth and Bing Maps by the research team, and used to estimate the accuracy of the forest plantation map. In addition, 357 field observations samples were collected during visits to the Southern Highlands in February 2015, February 2016, and November 2016. These samples were used to estimate the accuracy of the plantation species map.

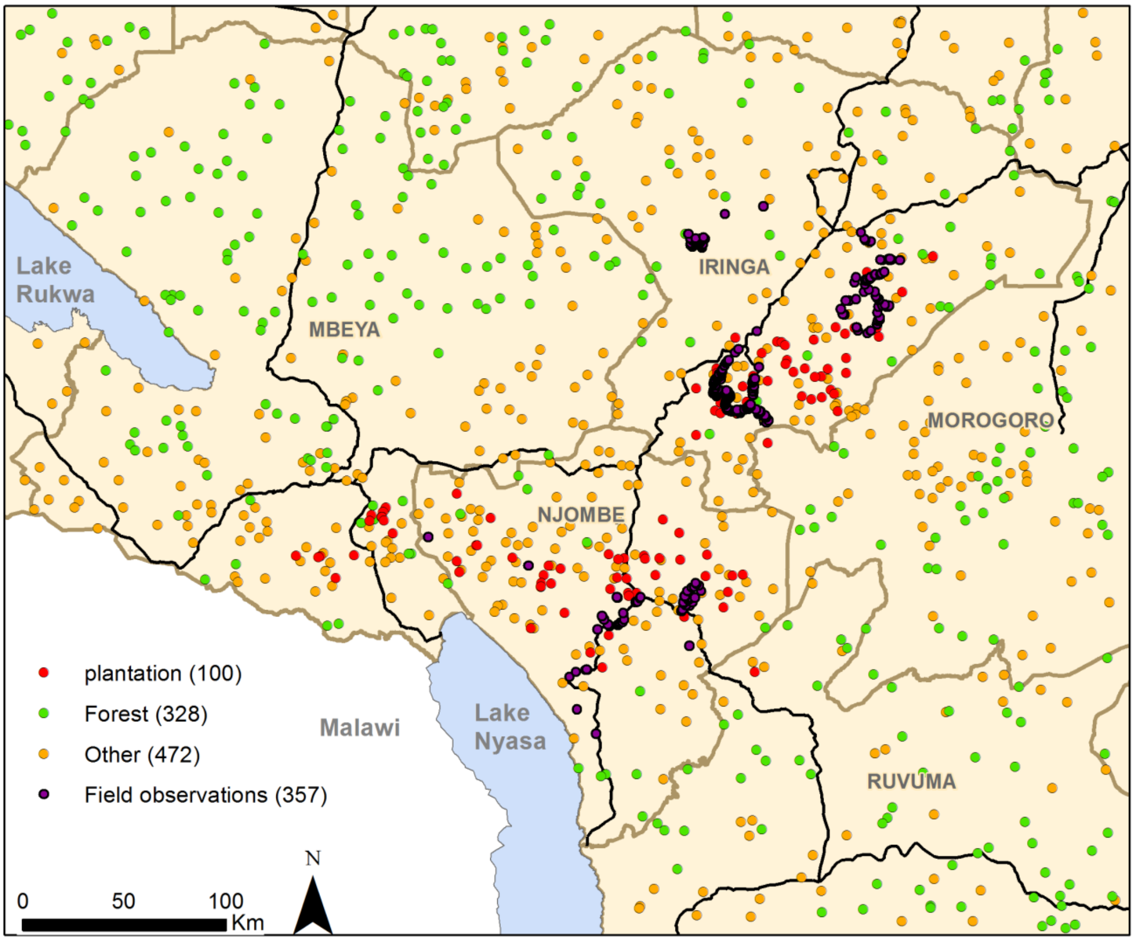

Figure 6. Distribution of the validation samples.

3. Results

3.1 Success of participation in reference sample collection

The participants had a varying degree of similarity in their interpretations (Figure 7, Table 2). The local experts had an average agreement of 84% for distinguishing between forest plantation and other land covers based on the field reference data. For the research team members the average agreement was 97%. In some areas, inaccuracies were overestimated since not all of the reference points were detectable from the Google Earth images due to the time discrepancy between the field observations and the visual interpretation based on older image date. Thus, some of the differences may have been actual changes in land cover. Generally, the interpretation agreements with reference data were higher for those local experts who stated being proficient with remote sensing (Figure 7). Pines were detected with high accuracy by local experts (86%) and research team members (100%). Since the amount of Eucalyptus and Wattle samples in the reference data was small, we did not calculate the agreements for these attributes.

The confidence assessment of the collected sample points resulted in similar findings as the comparisons against field samples (Table 2). The agreement of interpretation between local experts' and research team members' observations was high regarding the forest plantation samples (94%). This means that forest plantations could be recognized from other land cover types with relatively high confidence using visual interpretation. The agreements were lower but still relatively high for plantation species. Pine plantations were identified with 72% agreement and eucalyptus and wattle plantations with 55% agreement. These figures show that pines are more easily detected in the study area while the canopy shape of eucalyptus and wattle resembles that of natural forest causing more classification errors. Different age classes were identified with overall agreement of 60%.

Overall, between local respondents and research team members the LULC interpretation agreements were highest with forest class (69%) and lower with the other classes (50% agreement or less). This may be due to the heterogeneity character of the landscape which made it difficult to label single land cover information for a plot. Also, interpretation based on poor-quality images could have caused some of the disagreement: among the 600 cross-referenced samples the authors identified 22 images that were not suitable for interpretation due to cloud coverage or blurry images on both Google Earth and Bing, although these images had been interpreted by the respondents with high confidence.

Table 2. The upper part of the table shows the agreements of local experts and research team members' interpretation of 147 reference points collected from the field. The local expert data includes all of the interpretations made by 16 respondents. The research team member data includes interpretations from 2 experts. The lower part of the table shows the results of the confidence test of 600 interpreted samples.

	Plantation interpretation agreements		Species interpretation agreements		Age class interpretation agreements		
Field Reference Data	Plantation	Other LC	P	E/W	Rp	Gr	Mat
Number of samples	68	79	52	-			
Correctly classified by local experts	84%	55%	86%	-			
Correctly classified by research team members	97%	79%	100%	-			
Visual Interpretation Data							
Number of samples	300	300	155	124	55	136	68
Agreements between local experts and research team members	94%	86%	72%	55%	64%	63%	56%

P = Pine, E/W = Eucalyptus or wattle, RP = Recently planted, Gr = Growing, Mat = Mature

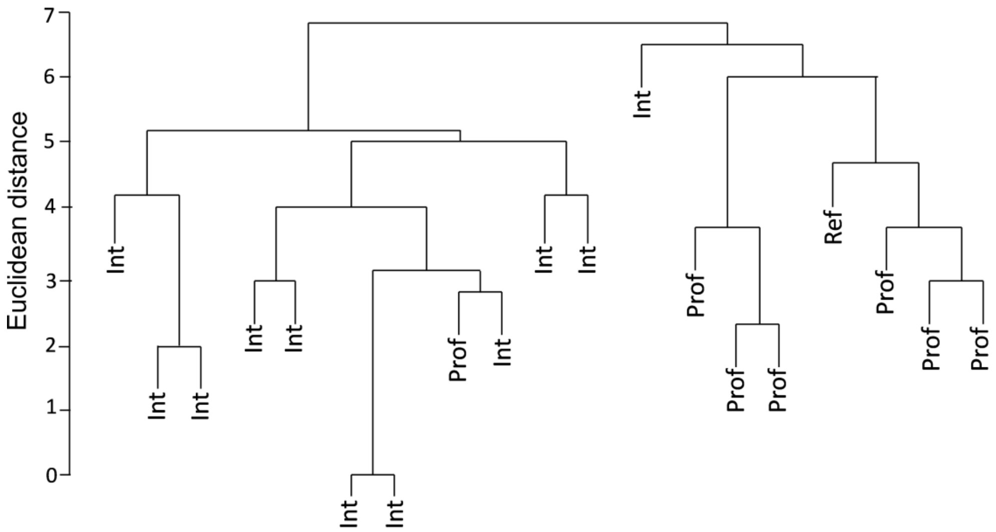

Figure 7. Hierarchical clustering of the expert interpretation of 147 known field reference points clustered based on their Euclidean distance against the reference points. Interpretations conducted by experts, proficient (Prof) with remote sensing have smaller distance to field reference (Ref) compared to interpretations of intermediate (Int) skills on remote sensing.

3.2 Capacity building of the Mapathon event

Based on the feedback collected from the local experts, the participants felt that they were substantially benefiting from the Mapathon experience. Only two experts had previous experience with Open Foris tools, but most had been using Google Earth in their studies or professional work. They all felt that the experience was positive in general and that they were highly motivated to take part (avg. score 4.9/5.0). Although the working process required training and some of the interpretation tasks were challenging, the participants felt that their understanding of the exercise was high (avg. score 4.3/5.0). They felt that their skills in remote sensing and image interpretation became much better than before (avg. score 4.7/5.0). On top of learning remote sensing and image interpretation, the participants also felt that they learned organising and time-management issues, in addition to which their understanding of the applications of remote sensing are now wider and more real-world based.

The orientation week was considered necessary in providing the participants with required skills for interpretation and to share knowledge to modify the survey. According to the participants, still more practice would have been needed in analytical image analysis skills, in software skills and in demanding image interpretation tasks. We also received plenty of feedback about a need for a follow-up training on how to create a survey for Collect Earth. Such training was organized as part of the results dissemination and discussion event arranged for the participants after the mapping work had been finished.

3.3 Forest plantation cover and distribution

Based on our participatory mapping methodology, using Random Forest classifier there are 240,000±87,000 hectares of planted forests in the Southern Highlands area and the overall accuracy of the plantation map is 85±2% (Table 3). These plantations cover approximately 1% of the study area. The relatively large confidence interval area of the forest plantation area is explained by its relatively small coverage and misclassifications with the dominant land cover classes. These new forest plantation cover estimates in the Southern Highlands are

50-200% higher than the previous estimates made in the National Forest Inventory NAFORMA Land Cover map (MNRT 2013). Although these figures are not explicitly comparable due to the national scope of NAFORMA Land Cover map, the difference suggests that the previous estimates of forest plantation coverage were underestimates.

In the Southern Highlands, the forest plantations are concentrated in the highland range, in the regions of Iringa, Mbeya and Njombe (Figure 8A). The majority of the planted forest landscape is characterized by numerous small and scattered woodlots (Figure 8B). In contrast, there are concentrations of high-intensity planted forests close to Mafinga, Njombe and Mbeya. These areas are characterized by large industry-scale dense forest patches (Figure 8C).

At the species level the forest plantation map overall accuracy was 65±4% with pines having the highest classification accuracies (Table 4). The eucalyptus and wattle classes were combined due to their problematic interpretation in the samples. Pines are the most dominant plantation species covering 69% of all the forest plantations (Figure 8). The share of eucalyptus and wattle in the classification output is 31%.

Table 3. Error matrix populated by the estimated proportion of area for each category. Rows represent map categories and columns represent reference categories. Accuracy measures are presented with 95% confidence interval.

	Forest plantation	Natural Forest	Other	Total	Map area (ha)	Estimated area (ha)	User's accuracy	Producer's accuracy
Forest plantation	0.0075	0.0006	0.0008	0.0089	180011	239842 ± 87023	0.84 ± 0.07	0.96 ± 0.04

Natural Forest	0.0044	0.3399	0.1100	0.4542	9200524	7132229 ± 425063	0.75 ± 0.04	0.95 ± 0.02
Other	0	0.0116	0.5252	0.5369	10874033	12882496 ± 420410	0.98 ± 0.01	0.76 ± 0.04
Total	0.0118	0.3521	0.6360	1	20254568			
Overall Accuracy	0.85 ± 0.02							

Table 4. Error matrix populated by the estimated proportion of area for each category. Rows represent species map categories and columns represent reference categories. Accuracy measures are presented with 95% confidence interval.

	Pine	Eucalyptus or Wattle	Natural Forest	Other	Total	User's accuracy	Producer's accuracy
Pine	0.0050	0.0008	0	0.0003	0.0061	0.82 ± 0.06	0.68 ± 0.07
Euca or Wattle	0.0006	0.0020	0.0002	0.0000	0.0028	0.71 ± 0.07	0.67 ± 0.07
Natural Forest	0	0.1339	0.2096	0.0349	0.4542	0.46 ± 0.08	0.56 ± 0.08
Other	0.0405	0.0304	0.2026	0	0.5369	0.49 ± 0.11	0.65 ± 0.10
Total	0.1218	0.1671	0.4124	0.2987	1		
Overall Accuracy	0.65 ± 0.04						

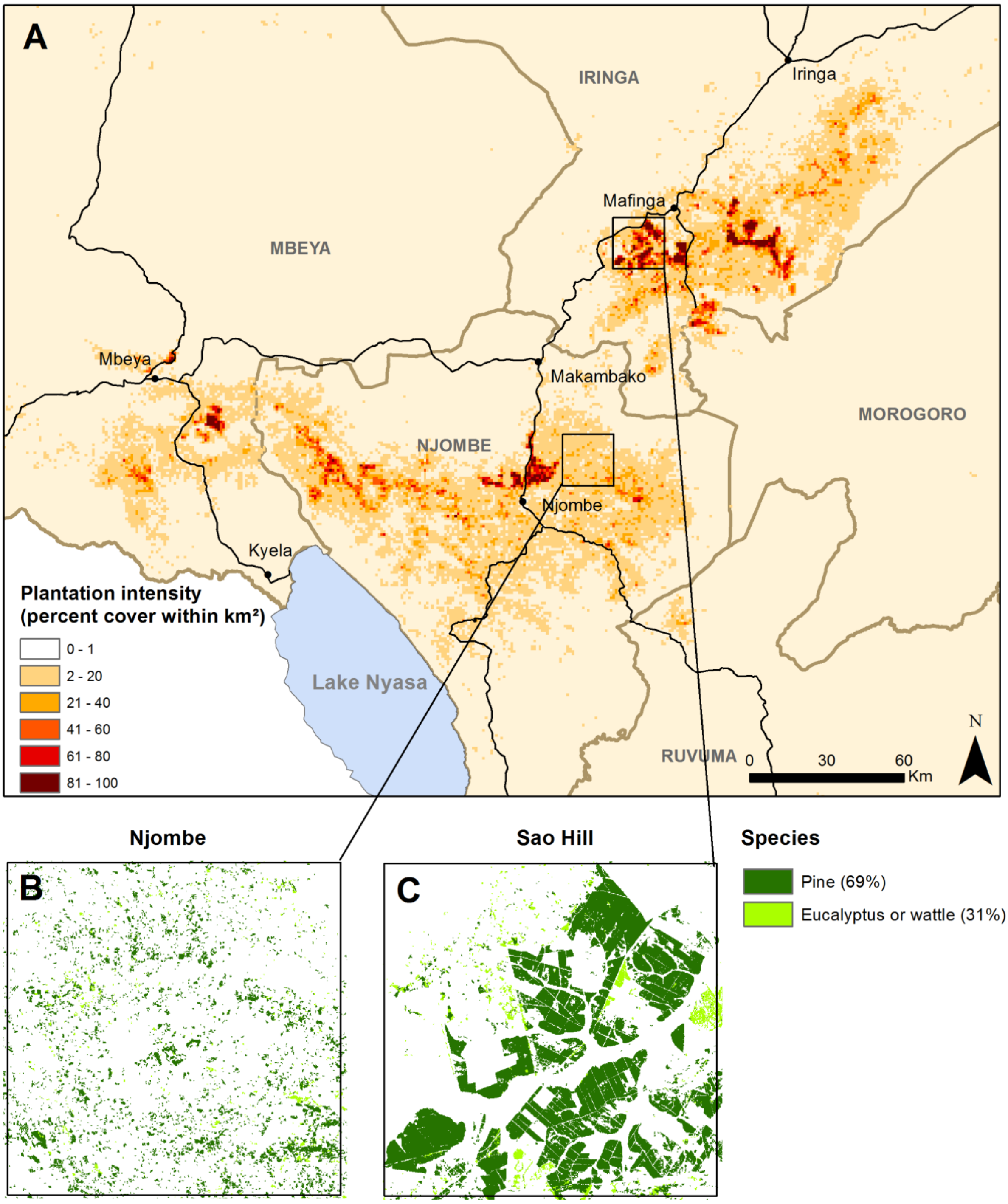

Figure 8. A) Spatial distribution and composition of the forest plantations in 2015 in the study area. Most of the areas are dominated by smallholder woodlots (B, Njombe) while some areas are dominated by industry-scale plantations (C, Sao hill) visualized in 20x20km example areas.

The created plantation map of the Southern Highlands and the reference and validations samples are freely available at PANGAEA (https://doi.pangaea.de/10.1594/PANGAEA.894892), and the GEE script is available at GitHub (https://github.com/utu-tanzania/sh-plantations).

4. Discussion

Recent development of open-access data catalogues and cloud computing capacity have improved possibilities for monitoring land resources in areas with data scarcity and difficult field accessibility. Our aim was to test the relevance of participatory GIS approach combined with the improved access to data and software in providing locally calibrated and spatially detailed forest and land cover information. A carefully planned and conducted participatory mapping campaign resulted in a high quality forest plantation reference sample set for the extensive study area of the Southern Highlands, which was further classified to a high-resolution spatially explicit forest plantation map. Furthermore, the mapping campaign increased the capacity of the local experts to conduct rigorous mapping of land cover based on open-source data and software they all have access to. Our research shows that this methodological set-up is a feasible approach to produce locally fixed land cover information with limited resource investment especially in areas where previous information of such spatial data is generic or non-existent.

One of the main challenges in participatory reference data collection is the quality and consistency of the collected samples (Comber et al. 2013, See et al. 2015b). Despite the challenges that participants had in the image interpretation process in our study, the forest plantations were interpreted with relatively high confidence, comparable to previous studies with similar methodology (Clark et al. 2010). Carefully planned, structured and visually attentive survey eases participants' interpretation work technically and leave more room for the actual interpretation of the images. With the Open Foris suite, the development of guided surveys with nested questionnaire and easy access to auxiliary data sources is available (Bey et al. 2016). The approach can greatly simplify otherwise rather challenging interpretation tasks. Recent studies relying on crowdsourcing have stated that the expert opinion depends on the case, having low influence on simple interpretation tasks and more influence on challenging tasks (Salk et al. 2016). Also, the familiarity of the study area has been reported to have influence, depending however on the tasks and the geographical scope of the survey (Comber et al. 2014). Our results are in concordance with these findings clearly showing that when dealing with complex landscapes and challenging interpretation, methods and tools that enable interpreters to focus more energy on the classification task improve decision-making and ultimately improve results.

A structured survey and carefully adjusted level of interpretation details can effectively reduce the misinterpretations. In our study, the interpretation agreement declines when details are increased from forest plantation coverage to specific plantation quality attributes. This demonstrates that, at least in complex environments, it may not be realistic to expect good accuracy on detailed level information such as tree species or age derived from visual interpretation of optical data and this should be noted when planning the purpose and methods of the survey. Successful participatory mapping campaigns require a well-designed practice of participation with simple data collection set-up, embedded user motivation and realization of benefits of participation to the users (Verplanke et al. 2016). These elements are especially crucial, when participatory mapping approaches are taken into those parts of the world where professional remote sensing practices and experiences working with image interpretation are less established, but where mapping processes are crippled without well-conducted participation and access to local knowledge.

Involving local expertise through participation has a significant potential in facilitating forest and land resource mapping when large amounts of training data are needed, when field-based data collection is too laborious and costly, and when local knowledge in general is needed to obtain relevant information of the forest and land features (Clark et al. 2010). Gathering participants for an intensive data collection campaign allows learning from each other, incorporating better control over the reliability of the collected information and strengthening the remote sensing expertize of the participants. These elements are all vital for the success of the mapping results and additionally they empower developing societies with better access and opportunities for natural resource mapping and management (McCall et al. 2015; Verplanke et al. 2016).

Our results show that organized training is a fundamental element in conducting participatory image interpretation and classification efforts. The extensive training period prior to the actual mapping increased the motivation and capacity of the local experts particularly to interpret differences between forest plantations and natural forests, and acted as an important preparation for the challenging interpretation task. Participants' pre-training ensures that essential skills are mastered and the semantics of interpretation are calibrated between the experts (Comber et al. 2016, Salk et al. 2016). The training period also allows research team members to learn from local experts and use that knowledge to modify the survey with respect to the skills of the respondents, the complexity of the landscape and the interpretation procedure.

In light of the fact that spatially explicit forest plantation estimates were previously missing from the Southern Highlands, the forest plantation map developed in this research gives access to one of the most fundamental baseline datasets to base regional forest management decisions on and to assess the sustainability of land development. Compared to recent similar scale plantation mapping studies conducted in the tropical regions, the achieved accuracy of our forest plantation map is somewhat lower (Dong et al. 2012, Petersen et al. 2016, Torbick et al. 2016). However, the mapping of rubber, oil and eucalyptus planted as spatially extensive monocultures is not comparable with the heterogeneous landscape of our area of interest where the majority of the forest plantations are smallholder woodlots. The complex landscape structure of the Southern Highlands with multifunctional agroforestry land uses and detailed topographical variation affects the classification performance of small plantations by generating mixed pixels. Furthermore, technical restrictions for detecting young plantations and regenerating forests have been reported also in previous studies (Dong et al. 2013, le Maire et al. 2014). Therefore, the map is a conservative representation of the forest plantations and most likely an underestimation of the forest plantation area as indicated also by larger plantation cover estimates generated based on the reference data. Repetition of the mapping every 2-3 years would not only enable identification of the dynamics of forest plantation cover, but also increase the reliability of the baseline map.

This research was conducted foremost at regional level, but the overall approach and the methodology used are applicable at different scales and in different regions. The Open Foris survey tools facilitate visual interpretation of very high-resolution satellite images, especially useful for collecting a large number of training samples in a cost-effective way. Combined with learning-based expert participation, a constantly updated global harmonized catalogue of satellite imagery and geospatial datasets and cloud computing resources of GEE, this set-up is a promising approach for environmental remote sensing in the next years to come (Teluguntla et al. 2018). GEE is especially suitable for repeatable multi-temporal and multi-sensor approaches due to the capabilities of image collection filtering and reducing mechanisms in a user-friendly JavaScript environment, providing a powerful tool for dynamic land cover mapping over large geographic areas (Patel et al. 2015, Xiong et al. 2016, Chen et al. 2017, Teluguntla et al. 2018). At present, GEE hosts the most significant open satellite image collections and the algorithm functionalities are constantly updated to meet the needs of user community (Gorelick et al. 2017). However, there are still limitations in available datasets (e.g. GEE's pre-processing routine for Sentinel-1 ingestion does not include radiometric slope correction necessary for land cover classifications), algorithms (e.g. lack of readily available pixel-based sun-sensor geometry correction), functionalities (e.g. Boosted regression trees classification (BRT)), control over the results, user memory and storage capacity. In many studies this leads to data transfer between GEE and other software e.g. R statistics, meanwhile losing some of the key benefits of conducting all the methodological steps from data acquisition to result output at a single platform.

Remote sensing as a professional discipline has crossed an important border from a rather restricted expert-based science to broader citizen-supportive practice and discourse. These changes have been and will continue to be enlarging societies' general capacities in data driven decision making, creating ownership, responsibility and commitment to resource governance, and empowering citizens to spatial decision-making and dialogue which follows from those decisions (See et al. 2015b, Fritz et al. 2017).

5. Conclusions

Spatially explicit information on the extent of forest plantation cover is essential to estimate the environmental and socio-economic impacts of the forest dynamics and to support sustainable forest management, particularly in regions that experience a rapid expansion of forest plantations. This study demonstrated the power of combining local expertise with the opportunities created by the recent development of free and online data repositories and cloud computing capacity in producing credible spatial estimates on forest plantation cover and species distribution in complex and heterogeneous landscapes. The participatory approach was found particularly suitable as it creates ownership and builds capacity enabling the repetitive monitoring of the plantations. Since the methodology is based on open source applications it is applicable in all parts of the world at various scales, driven however by the locality of sampling design. This set-up is a promising approach for environmental remote sensing in the next years to come.

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