EXTENT, PATTERNS, AND DRIVERS OF SMALLHOLDER WOODLOTS IN TANZANIA

By

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Abstract

Accurate tree cover maps are necessary for delineating forest habitat, quantifying terrestrial carbon stocks, and assessing timber stocks. Similarly, an accurate understanding of drivers of tree cover changes is necessary to slow deforestation and guide restoration efforts. Landscape and regional-level tree cover maps typically miss small woodlots[1]. These woodlots have a significant economic role for smallholders and in aggregate, may cover significant areas. Similarly, the drivers of fine-scale tree cover change are understudied, particularly in sub-Saharan Africa. Using a Tanzania as a case study, in this dissertation I: 1) test approaches for mapping woodlots, 2) study the actors in woodlots expansion, and 3) discuss the role of woodlots in global tree-planting policies. I used a mixed-methods approach of remote-sensing analysis for woodlot quantification, and field-based study for charting drivers of woodlot expansion. I identified woodlots via high- and medium-resolution imagery classification and compared the classification outputs to a hand-digitized woodlots dataset. I found that about half of woodlots are missed by the classifiers, particularly if they are both young (< 3 – 4 years) and small (< 0.4 Ha). This is a concerning limitation, since woodlots of < 1 Ha have proliferated recently in my study area, attaining a combined land cover equivalent to known large-scale government plantations. I also documented new actors in tree planting, namely urban-based associations of professionals looking for investment opportunities. In studying one such association (Maisha Shamba Association (MSA)), I documented a nascent pathway to rural land access by urbanites via associations, intermediary brokers, and online platforms. The scale of

[1] I define a woodlot as a small (< 5 Ha) uniformly aged patch of trees that is grown for timber, firewood, or fruits, and is clearly planted.

transactions is potentially significant, reaching 6937 Ha (~6% of total area) in one village. However, the tree-planting outcomes of the association members are difficult to discern via satellite imagery due to the newness of these enterprises and poor tree growth. The challenges of quantifying woodlots and the complexity of actors involved highlight the need for careful policies around tree-planting, particularly as global efforts turn to trees for landscape restoration, carbon sequestration, and for improving livelihoods.

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As they say – it takes a village.

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Introduction

We live in an interlinked world where the proverbial butterfly flapping its wings in one place causes a tornado in another. Those experiencing the tornado can hardly trace it back to the butterfly. Actions from one component of our world can have consequences in a distant, geographically separate place. My dissertation is an attempt to link the butterfly to the tornado in a specific context – that of changing land use in sub-Saharan Africa. I ask how we can measure the extent of woodlots and who are the contributors to this new land use. To address these complex questions, I use the range of tools available to land use change scientists, from satellite image analysis to field interviews.

Although land change science covers a range of land use and land cover dynamics from agriculture patterns to urban expansion, the field has come to focus heavily on tree cover due to trees' economic and ecosystem value (Crowther et al., 2015; Hansen et al., 2013). Land change science has tracked patterns of tree cover and looked for explanations for why they vary. Loss of forests has received the most focus because deforestation has adverse effects on climate, biodiversity, and ecosystem services (Curtis et al., 2018; Foley et al., 2005). Furthermore, tree cover change is much easier to discern from remotely sensed imagery than other forms of land use and land cover changes. While explanations for deforestation used to focus on local drivers, we now understand that forest loss is driven by diverse and even far-flung factors (Geist & Lambin, 2002). Like the butterfly and the tornado, deforestation patterns observed in one location can be due to factors that are seemingly removed from that locality (Guneralp et al., 2013; Seto et al., 2012). The complex factors contributing to deforestation are now summarized within a framework of 'proximate causes and underlying drivers' (Geist & Lambin, 2002).

The 'proximate causes and underlying drivers' framework is the result of decades of case-specific studies on patterns, drivers, and pathways to deforestation. These included studies on drivers of deforestation at multiple scales –from household level to regional level (Angelsen & Kaimowitz, 1999; Babigumira et al., 2014). Understanding deforestation drivers is also built upon increasingly fine-tuned abilities to quantify forest loss (Curtis et al., 2018; Hansen et al., 2013). And even after the Geist & Lambin's (2002) framework was developed, additional work was still necessary to improve region-specific explanations for drivers of deforestation (Ahrends et al., 2010; DeFries et al., 2010; Rudel et al., 2009).

Land change science also tracks patterns and drivers of tree cover gain. The trajectories of tree cover gain are summarized in forest transition theory, which predicts that landscapes can have a moment when they go from net tree cover loss to net gain (Rudel et al., 2010). However, the theory doesn't perfectly explain how or when a landscape would attain forest transition. Like many models of complex systems, forest transition theory is 'always wrong when applied to a particular case' (Rudel et al., 2010, p 96). Instead, forest transition events vary significantly over time, economic context, and by country. For example, after decades of deforestation, the northeastern United States began gaining forest in the 1920s, with significant forest regrowth starting in 1945, as large-scale agricultural production moved to the Midwest (Meyfroidt & Lambin, 2011). In the early 1990s, Vietnam had a turning point in extent of tree cover, achieved through native forest regeneration and tree-planting (Meyfroidt & Lambin, 2011; Nawir et al., 2007). Other countries like Chile, China, and India have increased tree cover via intensive private and government-supported tree planting (Ahrends et al., 2017; Heilmayr et al., 2016; Mather, 2007). Geographers and other land change scientists are still building models and methods to explain patterns, drivers, and pathways underlying forest transitions. Advancing 'forest transition science' will require work at multiple scales, improved precision in measuring tree cover gain, and complementary regional research, just as it did in the 'big sister' field of deforestation research.

To improve our ability to explain forest transitions, more research is needed, particularly in understudied, fast-changing world regions like sub-Saharan Africa. Sub-Saharan Africa stands out in meta-analyses in terms of the limited number of studies on drivers of tree cover changes (DeFries et al., 2010; Geist & Lambin, 2002). Experts point to an "African exception" (Fisher 2010), referring to the gap in knowledge on patterns and drivers of deforestation. This gap is wider still when it comes to our knowledge of tree cover gain. Part of the reason for lack of detailed studies of tree cover gain could be the dominance of dry biomes on the sub-continent. Another reason is the limited number of studies from sub-Saharan Africa. For example, in Meyfroidt & Lambin's (2011) review of global forest transitions that contains extensive information on trends in scores of countries, there are no examples from sub-Saharan Africa. The authors are unable to conclude whether the absence is from lack of studies, or from lack of forest transition processes (ibid). Furthermore, the dynamics of land use change as explained in other world regions do not seem to explain sub-Saharan Africa's trends (Rudel et al. 2009; Lambin & Meyfroidt 2011).

Part of the challenge in quantifying and explaining the trends in tree cover in sub-Saharan Africa seems to be the scale at which they take place (Fisher, 2010). The tree cover loss, for example, unfolds as localized, fine-scale degradation rather than conspicuous broad swaths of clearing (Ahrends et al., 2010). Tree cover loss documented in the humid parts of sub-Saharan Africa involves activities like selective logging and associated settlements (Brandt et al., 2016), tree-cutting for charcoal kilns (Naughton-Treves et al., 2007; Schure et al., 2014), or clearing for smallholder farms (Burgess et al., 2002). Accurate detection and quantification of such fine-scale tree cover trends is challenging, and precludes the use of coarse-resolution satellite imagery (Potapov et al., 2012).

Similarly, tree cover gain in the humid regions of sub-Saharan Africa occurs at a fine scale[2]. Tree cover gain has occurred as a result of fallowing of agricultural land (Carrière et al., 2002), planting of trees on farms to conserve soils (Tiffen & Mortimore, 1992), and development of small-scale woodlots for timber and firewood (Kimambo et al., 2020; Ngaga, 2011; Rudel, 2009). When the tree cover gain takes place as a result of agricultural land fallowing, the tree cover gain patches measured were < 1 Ha (Carrière et al., 2002). Similarly, planting trees on farms for soil conservation may increase tree cover at a landscape level, but it happens in diffuse, localized fashion (Miller et al., 2017). Smallholder woodlots, which are monocultures of trees planted on private land, also tend to average < 1 Ha in extent (Kimambo et al., 2020). Accurate quantification of such fine-scale tree cover via remote sensing is challenging (Gross et al., 2018). Mapping such fine-scale tree cover trends and identifying the drivers is the focus of this dissertation.

International climate change mitigation efforts have added a layer of urgency to the challenge of accurately measuring and predicting tree cover gain. Many global initiatives (e.g., Paris Accord, Aichi Targets, New York Declaration on Forests, REDD+) promote tree planting as a way to create ecological and economic benefits due to trees' capacity to sequester carbon, stabilize soils, and improve incomes (IUCN & WRI, 2014; Miller et al., 2017). The Paris Accord, for example, has spurred countries to set ambitious tree planting goals to mitigate climate

[2] Note that there are other processes that can lead to tree cover gain in dry biomes that dominate sub-Saharan Africa. Shrub cover can increase in grasslands from intensive grazing. Ligneous cover expands in 'greened' parts of the Sahel due to climatic-driven increase in wetness. Suppressing bushfires can also lead to tree cover increase in Savanna environments. While these are important tree cover gain processes, they are not the main focus of this dissertation which is more based on humid ecosystems.

change, reduce forest loss, and combat land degradation. It is unclear how countries will implement their tree planting pledges whether by government-run large plantations, or by large-scale NGO initiatives, or payments to individual woodlot owners. Moreover, how might the tree planting pledges dovetail with forest transitions or tree cover gain trends?

My goal is to provide an analysis of woodlot trends that can in turn be used to build towards a more comprehensive understanding of the drivers of tree cover gain trends. I will closely examine fine-scale tree cover in East Africa. Using a test-case of smallholder woodlots, I will test approaches for mapping fine-scale tree cover, explore the role of urbanization in rural tree cover change, and discuss the potential role of woodlots in global climate mitigation policies predicated on tree-planting. The following questions are addressed in each chapter:

Chapter 1: Is there a role for smallholder woodlots in global tree-planting pledges?

Resulting paper: Kimambo, N. E., L'Roe, J., Naughton-Treves, L., & Radeloff, V. C. (2020). "The role of smallholder woodlots in global restoration pledges – Lessons from Tanzania" *Forest Policy and Economics*, 115, 102-144. [Published]

This first chapter evaluates the potential synergies between fine-scale tree cover gain and global efforts to increase tree cover. In the past decade, concern for forest loss has spurred ambitious restoration goals for climatic, ecological, and livelihood benefits. Restoration activities typically rely on government-led or large-scale tree planting, but not spontaneous smallholder tree-planting, especially in Africa. Smallholder tree planting activities are harder to track than institutional efforts. In this chapter, I started with quantifying the extent of tree planting on smallholder woodlots in southern and eastern Tanzania, in comparison to large-scale plantations. The methods relied on visual interpretation of Google Earth Pro imagery in order to capture the fine-scale tree cover. Woodlots were digitized in randomly selected areas, and the resulting dataset used to estimate woodlots' area, distribution, and expansion rate. The results were surprising: as of the year 2018, woodlots in the smallest size class (<1 Ha) made up about half of the overall tree planting extent, covering an area equivalent to institutional (government + corporate) plantations. What's more, smallholder woodlots have been planted recently: 54% of the digitized samples were planted between 2012 and 2015, a sign of woodlots' rising prominence. The vast majority of the woodlots were non-native pine and eucalyptus species.

This chapter highlights a tension between such local tree-planting trends and global restoration goals. Thus far, Tanzanian smallholders are planting trees in response to regional timber demand, and not in response to global pledges, even as Tanzania pledged to restore 5.2M Ha. Though such tree-planting activities can count towards restoration goals, there is no explicit incorporation of extant smallholder tree planting in restoration plans. Subsidies or incentives linked to global restoration goals could encourage more diverse planting and longer harvesting cycles in the woodlots. Given African countries' recent restoration pledges that exceed 100M Ha, I recommend explicit incorporation of smallholder tree planting to maximize livelihood and governance benefits

Chapter 2: How can we best map woodlots of < 1 Ha using available satellite imagery?

Resulting paper: Kimambo, N. E., and Radeloff, V.C. "Mapping African smallholder woodlots of < 1 Ha across spatial resolutions." [Anticipated submission to *Remote Sensing the Environment*.]

This chapter addresses the challenge of quantifying fine-scale tree cover with remote sensing. Advances in remote sensing have increased available imagery of higher spatial, spectral and temporal resolution. Yet, world regions that have proven too difficult to study – where land use is at a scale too fine to detect by moderate spatial or temporal resolutions – still remain underexplored. In this chapter, I use woodlots as a case study and test the detectability of fine-scale tree cover. I compare detectability of woodlots across spatial resolutions of Landsat-8 and Sentinel-2, as well as when the imagery from the two sensors combined. I evaluate woodlot detectability by comparing classification results to a dataset of hand-digitized woodlots that distinguishes woodlots' age and patch size. The results show that woodlots are challenging to map, particularly when the trees are young, in very small patches (< 0.4 Ha), and mixed in with other land uses in a heterogeneous landscape. The overall accuracy of our maps ranged from 58 to 66%. However, an object-based approach for combining the Landsat-8 and Sentinel-2 had better user and producer accuracy compared to other approaches (51% and 72% respectively). Nevertheless, given that at best, our five maps could only detect up to half of the extant woodlots, mapping such fine-scale tree cover may require imagery of even higher spatial resolution. Without accurate quantification of woodlots, there is a risk of miscounting tree-cover gain from such fine-scale features.

Chapter 3: How do African urbanites gain access to rural land and do they significantly contribute to rural tree-planting?

Resulting Paper: Kimambo, N.E. "The involvement of African urban dwellers in rural land sales and tree planting." [Anticipated submission *to Journal of Peasant Studies*]

This chapter explores land use change drivers and looks at a possible direct link between urban citizens and fine-scale tree cover gain in rural areas. Increase in population and growth of urban areas in sub-Saharan Africa have fueled demand for tree products like timber, construction poles, firewood, and charcoal. The demand partly explains the expansion of smallholder woodlots in rural areas. I continue to examine woodlots, by exploring a heretofore undocumented pathway to rural landscape change associated with urbanization, using a case study of an urban-based association participating in rural land acquisition and woodlot planting in Tanzania. By mapping the association's land parcels based on their purchase history and interviewing brokers and managers for absentee owners, I traced how urbanites purchase and manage rural parcels. I also tested whether the parcels belonging to the association members in my study have been disproportionately tree-planted using tree cover gain data generated from LandTrendr. I found that since 2007, individuals in the group (n = 435) have acquired parcels that range in size from 2 HA to 1214 HA, avg: 45.5 HA (n = 485) in 72 villages in 10 districts. To find and manage these rural parcels, the association members rely on a network of intermediaries via social media platforms (e.g., WhatsApp and Google Groups). From interviews, I learned that a third of the association parcels are tree-planted. Yet, parcels owned by urbanites did not show statistically significant difference in tree cover compared to the surrounding villages. Site visits showed that the apparent lack of trees in the urbanites' tree parcels is partly because some trees are young, and some parcels poorly managed. Additionally, the urbanites may be simply interested in acquiring the parcels but not farming them. I conclude associations and online platforms are enabling land transactions, creating unusual linkages between African urban investors and rural landscape changes. The direct role of urbanites in changing rural landscapes needs further elaboration. The role of urbanites needs to be better studied in order to be incorporated into any wider framework of tree cover gain drivers.

Contribution

The systematic observation of woodlots from multiple angles and at multiple scales is the connecting thread running through the individual chapters in this dissertation. The first chapter is the broadest, identifying the presence and significance of fine-scale woodlots across a third of Tanzania and reflecting on their significance in global environmental tree-planting campaigns. The second chapter compares different approaches for mapping woodlots with remote sensing and shows that woodlot detection is challenging with nearly half of extant woodlots missed. The third chapter is a fine-scale field study and introduces urbanites as possible direct shapers of rural landscapes. By undertaking this study, I hope to contribute to the growing field of research on understanding tree cover gain patterns and drivers and address a critical gap for sub-Saharan Africa. More such studies are needed given our hopes for the role of trees for solving the world's climatic, environmental and economic challenges.

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Chapter 1: The role of smallholder woodlots in global restoration pledges – lessons from Tanzania

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1.1 Abstract

In the past decade, concern for forest loss has spurred ambitious restoration goals for climatic, ecological, and livelihood benefits. Restoration activities typically rely on government-led or large-scale tree planting. A narrow focus on top-down initiatives could promote the recentralization of forestry activities and overlook important contributions by smallholders, especially in Africa. Smallholder tree planting activities are harder to track than institutional efforts. Here we quantify the extent of tree planting on smallholder woodlots in southern and eastern Tanzania, in comparison to large-scale plantations. In Google Earth Pro, we digitized all woodlots in randomly selected areas, and estimated woodlots' area, distribution, and expansion rate. We found that by year 2018, woodlots in the smallest size class (<1 Ha) made up about half of the overall tree planting extent, covering an area equivalent to the government and corporate plantations. What's more, smallholder woodlots have been planted more recently: 54% of the digitized samples were planted between 2012 and 2015, a sign of woodlots' rising prominence.

The vast majority of all planted trees were non-native pine and eucalyptus. Thus far, Tanzanian smallholders are planting trees in response to regional timber demand. Subsidies or incentives linked to global restoration goals could encourage more diverse planting and longer harvesting cycles. Given African countries' recent massive restoration pledges (e.g., Tanzania's 5.2M Ha), we recommend explicit incorporation of smallholder tree planting to maximize livelihood and governance benefits.

Keywords

tree planting; non-industrial tree plantations; small-scale tree plantation; smallholder forests; Bonn Challenge; global environmental policies

1.2 Introduction

Deforestation in much of Africa continues to adversely affect climate and ecosystem services (Curtis et al., 2018; Foley et al., 2005). Efforts to halt deforestation must address the wellbeing of local land users, particularly vulnerable smallholders (Adams et al., 2004). In fact, many global initiatives (e.g., Paris Accord, Aichi Targets, New York Declaration on Forests, REDD+) explicitly pledge to protect the rural poor while reducing deforestation (Laestadius et al., 2015). This concern for the poor persists as many global environmental initiatives shift their attention to landscape restoration and the re-establishment of forests' ecological functions (Fagan et al., 2020; Laestadius et al., 2015). Recent global restoration initiatives promote tree planting as a way to create ecological and economic benefits due to trees' capacity to sequester carbon, stabilize soils, and improve incomes (IUCN and WRI, 2014; Miller et al., 2017). Critiques for this approach warn that expanded tree-cover should not be equated with social or ecological improvements (Chazdon, 2008; Malkamäki et al., 2018; Veldman et al., 2015). Missing in the debate, particularly for Africa, is empirical evidence on how tree-planting in the name of landscape restoration affects local ecosystems and land users (Fagan et al., 2020). In this paper, we use Tanzania as a case study to look more specifically at how existing smallholder tree planting activities could align with global restoration goals.

Tree planting, including planting woodlots, is a core restoration pathway as stipulated by international landscape restoration guidelines (IUCN and WRI, 2014; Sabogal et al., 2015). Reported activities for initiatives like the Bonn Challenge have largely relied on broad-scale, government-led tree planting (Guariguata and Brancalion, 2014; Murcia et al., 2016). As of 2018, six tropical countries have reported performing restoration on a total of 12.6M Ha, with > 90%

done via large-scale tree planting led by governments and NGOs (Borah et al., 2018; Dave et al., 2017).

So far, most countries have responded to the global initiatives by making national restoration pledges in terms of land area (Fagan et al., 2020). Most national pledges do not explicitly define *where* the restoration will take place or *who* will perform the restoration of the pledged lands. African countries, for example, have pledged extensive areas for restoration, even exceeding AFR100 goal of 100M Ha (WRI, 2018). Reported activities thus far show that restoration via tree-planting unfolds in three ways. First, as any tree planting activity, at any scale, for example during a tree planting campaign or in government's public lands (IUCN and WRI, 2014). In this paper, we refer to this approach as *tree planting.* Secondly, a private corporation or an NGO could tap into restoration finances and undertake large-scale tree planting either on purchased land, or on land provided by the government, which we would call *plantations* (e.g., in India see Borah et al., 2018). Third, smallholders could plant trees for firewood, timber, or fruit on their private land, often in small landholdings (< 5 Ha) and we would call those *woodlots* (e.g., in Rwanda, see Dave et al., 2017). Even though all of these activities have taken place, the first and second approach are more common. Smallholder activities are more difficult to coordinate and monitor thus so far they have not been featured in reported restoration activities (e.g., Rwanda's report in Dave et al., 2017).

In short, restoration initiatives are unfolding in a way that will likely privilege larger actors thereby raising three governance concerns. First, the initiatives could promote forest governance recentralization, a setback after nearly three decades of transitioning to decentralized forest management to allow local citizens increased rights and responsibilities (Phelps et al., 2010). Second, large-scale tree planting by international companies has been associated with negative social outcomes including land alienation, loss of previous livelihood options, and disruption of social structures (Malkamäki et al., 2018); with additional criticism as land grabbing and 'carbon colonialism' when undertaken by organizations from the global north (Lyons and Westoby, 2014; also see response by Fischer et al., 2016). Third, tree-planting initiatives are presently inattentive to already ongoing bottom-up activities in the form of wide-spread smallholder woodlots, which, if better understood, may have the potential to support these broader goals (Nawir et al., 2007).

Smallholders in many parts of the world plant woodlots without global pledges in mind. There is presently a surge in woodlots in some developing countries (e.g., in Vietnam (Nawir et al., 2007), India (Mather, 2007), Indonesia (Torbick et al., 2016), Uganda (L'Roe and Naughton-Treves, 2016), and Ethiopia (Jenbere et al., 2012)).Some countries like India, Vietnam, and China have actively promoted smallholder tree planting (Borah et al., 2018; Frayer et al., 2014; Nawir et al., 2007). In other cases, woodlots have expanded simply in response to regional demand as forest resources become scarce (Mather, 2007; Rudel et al., 2005). In East Africa, the proximate driver of woodlot expansion is the increased demand for timber and fuel wood due to rapid urbanization and population growth (Held et al., 2017; Indufor, 2011; Jacovelli, 2009). The proportion of citizens living in urban areas in Sub-Saharan Africa nearly doubled between 1995 and 2015, and with it the demand for trees for construction timber, charcoal, and firewood (AfDB et al., 2016). In Tanzania, the increased tree products demand occurred while government tree plantations were facing reduced productivity (Ngaga, 2011). As a result, large-scale private plantations and smallholder woodlots have both expanded (Degnet et al., 2018). The recent expansion in woodlots in parts of Tanzania has been called a 'Timber Rush' to acknowledge how the growing timber demand has stimulated rural tree planting along with small-scale timber supply enterprises (Friis-Hansen and Pedersen, 2016; Koskinen et al., 2019). The increased demand for poles for rural electrification projects in In Uganda, Tanzania, and Kenya has also spurred entrepreneurial growing of large-diameter eucalyptus logs (FDT, 2015). As a result of these market forces, smallholders favor fast-growing species of pine, eucalyptus, cypress, or teak that have rapid returns (Arvola et al., 2019).

Despite these observations of increased smallholder tree planting activities, accurate quantifications of woodlot extent and expansion rates are uncertain. The estimates are uncertain because land use outcomes of many individual smallholders are harder to track than the actions of large institutional actors. For example, the Tanzanian government official reports estimated 0.15M Ha in smallholder woodlots (FBD, 2011) but others have estimated 0.18M Ha (Indufor, 2011) to 0.42M Ha, (Said, 2016). To generate these statistics, the government relied on municipal foresters' estimates (Ngaga, 2011) or extrapolations from market studies (Indufor, 2011). Newer studies after 2012 have used remote sensing and shown that smallholder woodlots could be between 0.23 – 0.33M Ha (FDT, 2013; Koskinen et al., 2019). These remote sensing maps are one-time observations from years 2013 and 2015. Due to the inherent limitations in spatial and temporal resolution of satellite data, the maps exclude young woodlots and do not describe temporal trends in woodlot establishment. Combined to a global level, it is therefore unsurprising that available statistics tend to underestimate the extent of smallholder woodlots (Torbick et al., 2016).

Enduring uncertainties in smallholder woodlots trends could mean missing opportunities for a more inclusive landscape restoration policies. Given the ambitious global targets for attaining climatic, ecological, and livelihood benefits via restoration and tree planting, the contribution of smallholders needs to be more explicitly considered. In this paper we present systematic data on the extent, spatial patterns, and temporal trends of smallholder woodlots in Tanzania. Specifically we ask:

1) How do smallholder woodlots compare with government and large-scale plantations in terms of overall extent and regional distribution?
2) Have smallholder woodlots expanded in the landscape in recent years?

We evaluate the results in the context of Tanzania's pledge of restoring 5.2M Ha of degraded lands by year 2030. We hope our findings inform the potential contribution of smallholder tree planters in national and international landscape restoration campaigns, especially in African countries.

1.3 Methods

Study area

We assessed the extent of tree planting in Tanzania, a country that has made a restoration pledge under the AFRI100 initiative of the Bonn Challenge to restore 5.2M Ha (WRI, 2018). Within Tanzania, our focal study area drew from samples in three regions: the Northern Zone, the Eastern Arc mountains, and the Southern Highlands (1 - 9°S; 33 - 38°E) (Figure 1. 1). We selected the three regions to represent diverse ecological characteristics (i.e., suitability for tree growth) and land use histories (i.e., legacies of tree planting). Ecologically, the selected regions have strong climatic gradients driven by elevation changes, with rainfall generally increasing with elevations (up to 2000 mm/yr in the Southern Highlands) (Fick and Hijmans, 2017). High rainfalls and moderate temperatures create suitable environment for tree establishment, with some locations capable of attaining rapid tree growth (mean annual increments up to 60 m^3/ha/yr (Jacovelli, 2009)). The potential for tree growth is evidenced by the presence of remnant montane forests (~ 0.5M Ha; ~ 3% of study area); some of which are strictly protected and important biodiversity hotspots (Burgess et al., 2007; Newmark, 1998). Even though some illegal logging still occurs in the strictly protected humid forests (Persha and Blomley, 2009) , widespread montane forest loss is not contemporary: the majority of the forest conversions that created present-day agriculture mosaics adjacent to the protected forests may have occurred in the past 200 – 300 years (Newmark and Mcneally, 2018).

The second reason for our site selection is the legacy of tree planting. The study areas share a history of tree planting by three types of actors: central government agencies, private companies, and smallholder residents (Ngaga, 2011). In fact, 65% of Tanzanian government tree plantations are located in our study area (Figure 1. 1), with the government plantations often abutting, and managed in conjunction with, adjacent natural forests (Jacovelli, 2014). The management of natural forests and government plantations in these humid ecoregions is thus different from the community-based or joint government-community forestry found in drier ecoregions like the miombo woodlands (Matose and Wily, 1996; Persha and Blomley, 2009; Wily and Mbaya, 2001). Additionally, In the past 30 years, private companies have established plantations as well, most of them in the Southern Highlands (Degnet et al., 2018; Indufor, 2011), a trend also seen in other African countries. Smallholder farmers have long established small woodlots, especially in areas located adjacent to the large-scale plantations and tea plantations (Ngaga, 2011), with empirical field studies suggesting additional expansion starting around year 2010 (Friis-Hansen and Pedersen, 2016).

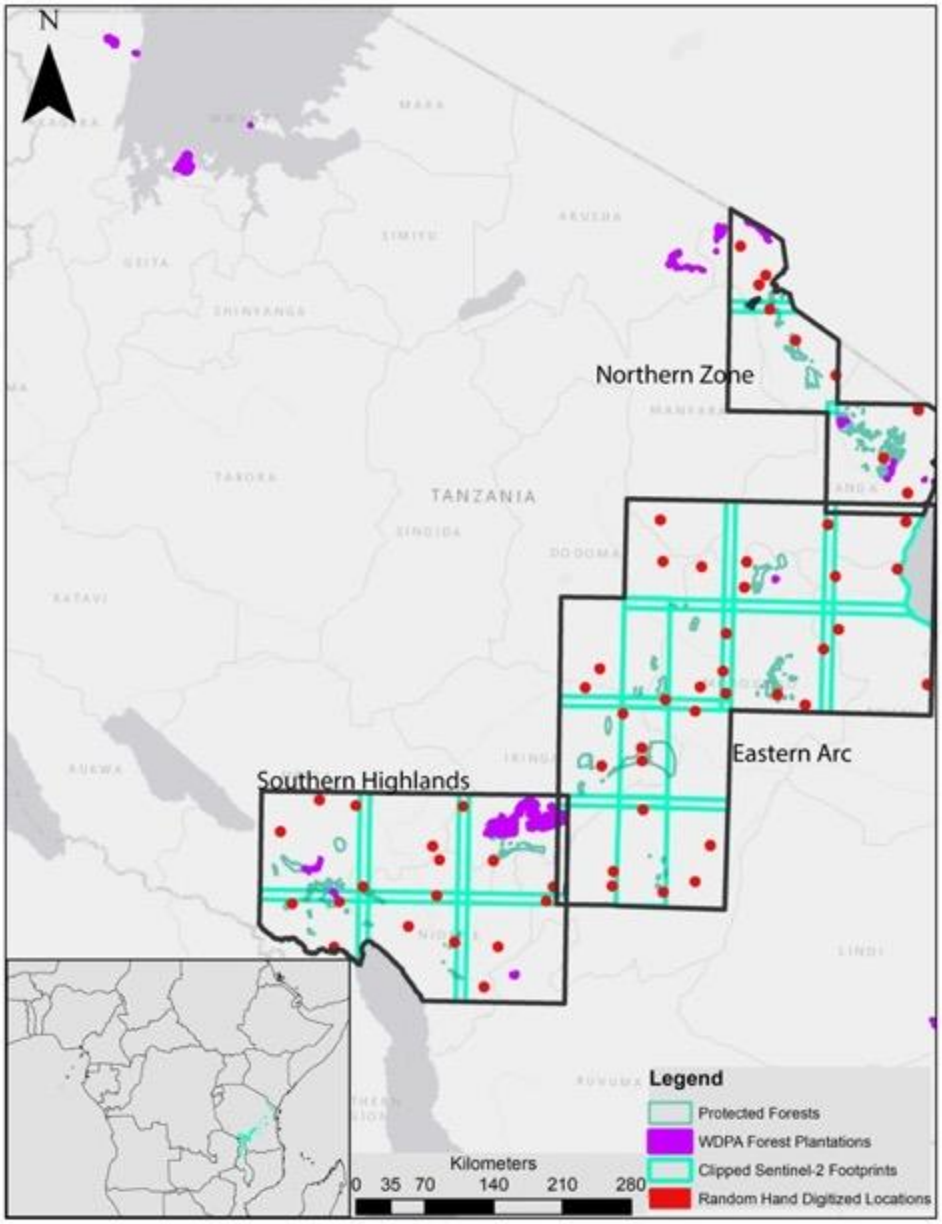

Figure 1. 1: a) Context map showing Tanzania and the Rift ecoregion. b) Study site indicating woodlots digitization locations. Three randomly placed circles, each measuring 100 km^2 are in each Sentinel – 2 footprint. We digitized all woodlots in each sample using Google Earth Pro. The site covers the Southern Highlands, the Eastern Arc Mountains, and the Northern Zone to optimize for ecoregions that are suitable for trees.

Data

Hand-digitized woodlots in randomly selected locations

To estimate the extent and distribution of woodlots, we generated a random sample of the study area, and digitized all woodlots within the sampled area via image interpretation on Google Earth Pro. Our visual interpretation method is similar to Petersen et al., 2016 since both rely on woodlots' distinct characteristics from natural forests in terms of color, texture, and the regular shape of man-made land cover. Visual interpretation of Google Earth imagery, is commonly used for collecting training points for classification (e.g., Koskinen et al., 2019). However, some studies have used Google Earth Pro for tree cover quantification in hard to classify areas like drylands (Bastin et al., 2017). In our method, we combined the visual interpretation with random sampling design to be able to estimate overall woodlot area. Definitions of 'woodlot' vary: here we used a commonly accepted one in the East African context that refers to a small (< 5 Ha) uniformly-aged patch of trees that is grown for timber, firewood, and/or fruits, and is clearly planted (Kimambo and Naughton-Treves, 2019; Ngaga, 2011). We did not digitize natural forests.

The random sampling locations were selected using QGIS Random sampling tool, generating three random points per footprint for 20 Sentinel-2 footprints (to be used in a future analysis). This created a total of 60 sampling circles of 0.01M Ha each centered on the random point, for a total sample area of 0.6M Ha, or 3.2% of the study area.

In each random circle, we hand-digitized all woodlots visible in the most recent Google Earth Pro imagery at the time of digitization (year 2018). The availability of up-to-date high-resolution Google Earth images varied by location, with some areas' most recent image dating back to the early 2000s. Thus, we recorded the date the image was acquired and the age category for the woodlot. A unique woodlot was delineated by visual evidence for borders such as fire breaks and farm boundaries (See S 1. 1 for woodlot digitization and age category protocol). Additionally, we placed areas of uniform age and uniform tree texture in unique woodlots and assigned the woodlot an age measure of: “Young”, or “Intermediate”, or “Mature”, based on the tree density. The “Young” category are woodlots with sparse tree density in which round tree crowns and the linear planting texture is still visible; while the “Mature” category indicates dense woodlots where the tree canopy has closed.

Large-scale institutional (government, private corporation) plantations

To quantify the extent and characteristics of the institutional plantations in our study area, we relied on previous publications, the World Database of Protected Areas, and the Tanzania Forestry Services (TFS) GIS department (TFS, 2012). The published reports and the databases, and TFS records each give slightly different acreage for the extent of large-scale institutional plantations. The different acreages result from conflating the extent of the entire management area of a plantation which can include tree-planted areas and areas that are not actively planted with trees. We distinguish these values whenever possible and put together actual extent of large-scale plantation tree cover in the study site.

Analysis

How do smallholder woodlots compare with government and large-scale plantations in terms of overall extent and regional distribution?

To compare patterns of smallholder woodlots to those of large-scale plantations, we first determined the spatial patterns of smallholder woodlots, and then compiled statistics for large-scale plantations in the study area. We calculated the mean woodlot area for the digitized samples. To check for robustness of our area estimate, we calculated the confidence interval of the mean woodlot area for a probability of 95% by bootstrapping, using the “boot” package from R (Canty and Ripley, 2017). The bootstrap generated 2000 replicates of the same sample size as our data and calculated the mean statistic for each. We calculated the confidence intervals for the mean woodlot area from the bootstrap; using the bias-corrected and accelerated (BCa) method (See S 1. 2 for R code for replication). We report the mean, the upper-bound, and the lower-bound estimation of woodlot area for the samples, then proportionally scale the values to the rest of the study area.

We calculated the size class distribution of the digitized woodlots to infer the possible actors involved in tree planting (eg: smallholder, or medium-scale, or large scale). We group the digitized woodlots into 4 size classes: < 1 Ha, 1-5 Ha, 5 -10Ha, and > 10 Ha. We report the contribution of each of the size classes to tree planting extent.

Evaluating the spatial distribution of woodlots is helpful for identifying locations with tree planting momentum, and those where the activity has just begun. Since woodlots may be clustered at a regional scale, we evaluated the spatial distribution of the woodlots within regions. We report the density of woodlots (measured as number of woodlots in per sample) by region: Northern Zone, Eastern Arc and Southern Highlands. We use the density and the distribution of woodlots within samples to describe spatial distribution patterns of the planted trees.

Large-scale plantations: To compare the relative contribution of smallholders versus the large-scale institutional plantations to tree planting in the study area, we generate the extent of these institutional large-scale tree plantations by compiling literature values. We report the range of literature values for the extent of large-scale plantations in the study area. We identify the specific locations in our samples that are the large-scale institutional plantations. We compare characteristics (average woodlot size, age, and woodlots distribution) between smallholder samples and institutional samples.

Have smallholder woodlots expanded in the landscape in recent years?

To determine if woodlots are an emergent trend, we characterized the present-day age-composition of the digitized woodlots. Google Earth Pro images do not have the same observation date, so the digitized woodlots were a one-time snapshot of various woodlots at different ages and different years. First, we describe the distribution of the woodlot ages by year and by sampling circles. Then, we adjust each woodlot's assigned age class to what it would be if observed in year 2018. Using imagery observation, we estimate that it takes two calendar years for a woodlot to transition from the "Young" to "Intermediate" or "Intermediate" to "Mature" categories (See S 1. 3 for time-lapse). We report the adjusted age composition of the woodlots for the entire sample, and at the regional level (Northern Zone, Eastern Arc, and Southern Highlands).

To estimate the rate of expansion of smallholder woodlots area by year, we estimate planting date and calculate the proportion of woodlots planted in that year. We use the mean annual expansion rate as a possible increase in woodlot area per year, and project the expansion for the duration of the Bonn Challenge pledge (2018 – 2030).

1.4 Results

Smallholder woodlots < 1Ha cover an area equivalent to institutional plantations

We found 7372 woodlots in our sample of 60 randomly selected circles of 0.01M Ha each. The total area and number of digitized woodlots was not normally distributed (Figure 1. 2), and 45% of the samples had no woodlots in them. Samples had a total amount of woodlots that ranged from 0 - 9%. (Figure 1. 2). Mean woodlot coverage in the samples was 0.6 % (95% CI: 0.3 - 1.2%), thus the study area's woodlot extent was 0.11M Ha (95% CI: 0.06 - 0.22M Ha) (Table 1. 1).

The majority of the digitized woodlots (91%) were < 1 Ha (Mean woodlot size is 0.5 Ha; range: 0.005 Ha to 75 Ha). The woodlots < 1 Ha contribute more to the overall tree planted extent than other size classes (mean: 0.3%; 95% CI: 0.1-0.6%) (Table 1. 1). Woodlots > 10 Ha and those between 1-5 Ha each contribute at most 0.35% to the overall tree planting (mean: 0.12%, 95% CI: 0.03 - 0.35%) (Table 1. 1).

Woodlots tended to be clustered at a regional level. The Eastern and the Northern Zones have samples with low density of woodlots, and some with no woodlots (average 11.8 and 19.6 woodlots per sample respectively; 47% and 25% of samples with no woodlots, respectively), while the Southern region had high-density of woodlots (average: 306.5 woodlots per sample, 45% are samples with no woodlots). The 7 samples that contribute 90% of all digitized woodlots were all in the Southern region (Table 1. 1).

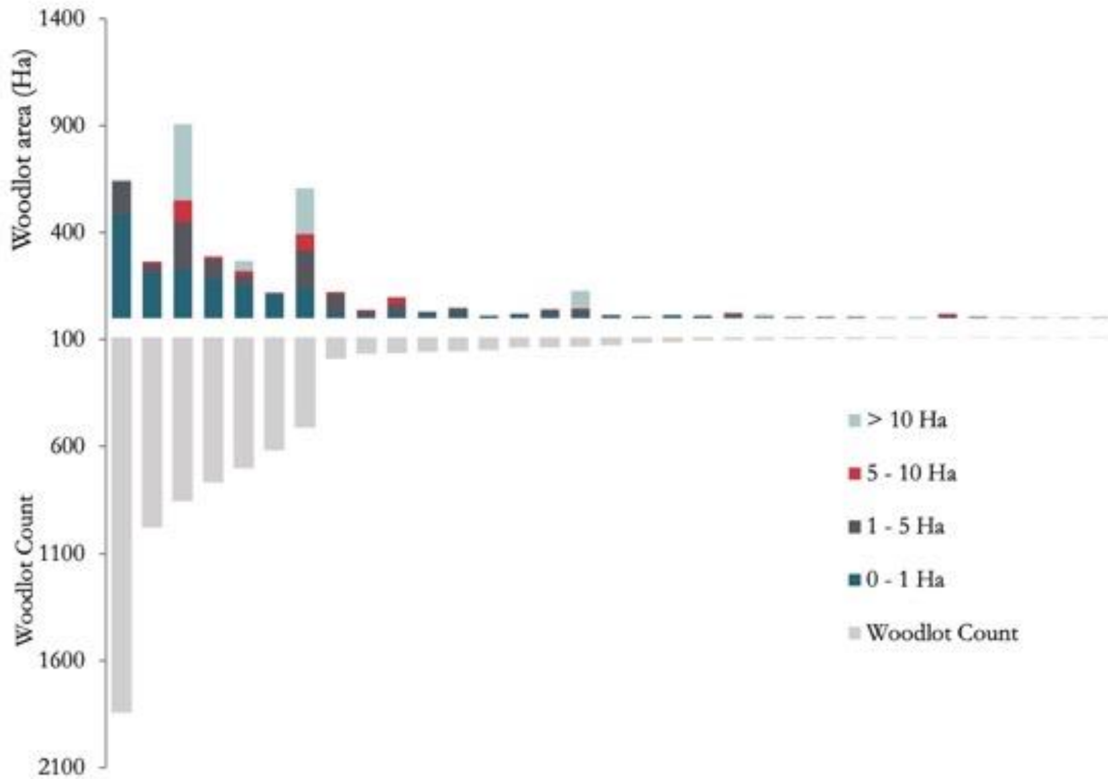

Figure 1. 2: Contribution of different woodlot size classes to each sampling location's planted tree area. Top bar chart: Contribution of different woodlot size classes to the total tree planted area within a sampling location. Different colors represent different woodlot size classes [< 1 Ha, 1-5 Ha, 5 -10Ha, and > 10 Ha]. Bottom bar chart: woodlot count in each sampling location.

From government reports and literature values, we found fifteen large-scale plantations in our study area (Figure 1. 1, Table 1. 2) Eight belong to the government, and seven belong to private companies. The government overall plantation landholding covered a total of 0.11 M Ha, while the private companies' plantation landholding covered between 0.07M Ha and 0.15M Ha (Table 1. 2). The government plantations in our study area represent 65% of all government plantations in Tanzania. The tree-planted areas differ from overall landholding size of the institutional plantations, since the overall landholdings also include: 1) areas for future expansion that have not been planted with trees yet, and 2) native forest patches that are managed alongside with the plantations. The actual tree-planted area ranges from a total of 0.1M Ha to 0.13M Ha (0.4% to 0.7% of the study area) with the government plantations accounting for 0.06M Ha to 0.08M Ha and private companies covering 0.04M Ha to 0.05M Ha (Table 1. 2). Our upper-bound estimation of the proportion of the landscape with woodlots < 1 Ha (0.11M Ha; 0.6%) is equivalent to the landscape proportion of the government and corporate plantations combined (0.13M Ha; 0.7% of the study area).

Digitized samples in areas with institutional plantations had larger, more contiguous tree planting areas than the samples that were in smallholder areas. Institutional plantations areas had woodlots in the largest size class, averaging 22.26 Ha per woodlot. The institutional woodlots also tended to be in the oldest size class (77% as "Mature"). The institutional plantations whose establishment dates are known were started several decades ago, with some dating to 1930s (Table 1. 2). Within a sample, the institutional woodlots tended to be spatially contiguous; only separated by demarcated roads or fire breaks (the mean separation distance is ~ 86 m, which is 5 times smaller than the average width of the institutional woodlots, ~ 396 m). Smallholder woodlots < 1 Ha are on average 66 m apart; but the average width of each woodlot is 47 m. The smallholder woodlots tend to be separated by other land uses, creating a more heterogeneous landscape (Figure 1. 3).

Table 1. 1:Estimated extent of woodlots for the entire study area, by each of the three sub-regions (Southern Highlands, Eastern Arc, Northern Zone) and by size the class of the woodlots. The range for each category (upper and lower bound values) is estimated by bootstrapping at a 95% confidence interval

	Average woodlot count	Tree planting extent (Ha; (%))	Extent of woodlots <1 Ha (Ha; (%))	Extent of woodlots 1-5 Ha (Ha; (%))	Extent of woodlots 5-10 Ha (Ha; (%))	Extent of woodlots > 10 Ha (Ha; (%))
Overall (n = 60)	120.9	114,863; (0.6%)	52,615; (0.3%)	32,662; (0.2%)	9,096; (0.05%)	22,224; (0.12%)
Overall Range (min-max)	0 - 2006	55,585 – 224,892 (0.3% – 1.2%)	26,810 – 110,880 (0.1% - 0.6%)	16,600 – 61,971 (0.1% – 0.3%)	4,080 – 21,057 (0.02% – 0.11%)	5,021 – 64,490 (0.03% – 0.35%)
Southern Highlands (n = 22)	306.5	86,513; (1.5%)	40,378; (0.7%)	23,090; (0.4%)	6,784; (0.11%)	16,242; (0.28%)
Southern Highlands Range	0 - 2006	43,005 – 168,823 (0.75% - 3%)	18,492 – 80,333 (0.3% - 1.4%)	10,959 – 42,976 (0.19% - 0.75%)	2,564 – 16,117 (0.04% – 0.28%)	1,490 – 50,698§ (0.03% - 0.9%)
Northern Zone (n = 8)	19.6	5,696; (0.2%)	1,198; (0.04%)	1,529; (0.06%)	174; (0.006%)	2,787; (0.1%)
Northern Zone Range	0 - 56	1,034 – 18,286† (0.04% – 0.68%)	370 – 2,521 (0.01% - 0.09%)	505 – 4,104† (0.02% – 0.15%)	0 – 349 (0% – 0.01%)	0 – 8365 (0 – 0.3%)
Eastern Arc (n = 30)	11.8	8,878; (0.08%)	3,395; (0.03%)	3,618; (0.03%)	997; (0.01%)	403; (0.003%)
Eastern Arc Range	0-80	4,592 – 14,420 (0.04% - 0.13%)	1,899 – 6,356 (0.02% - 0.06%)	1,730 – 7,385 (0.02% – 0.07%)	307 – 2,281 (0.002% - 0.02%)	0 – 1,167 (0% - 0.01%)

§ Bootstrapping confidence intervals are unstable due to small sample size

Table 1. 2: Extent and location of large-scale government and corporate plantations found in the study area

Name of Plantation	Region	Year Established	Planted Area (Ha) (FDB, 2011)	Planted Area (Ha) (Ngaga, 2011)	Expansion Area (Ha) (Ngaga, 2011)	Planted Area (Ha) (Said, 2016)	Expansion Area (Ha) (Said, 2016)	Overall Area (WDPA, 2018)	WDPA Outline
				Government Plantations					
Sao Hill	S.Highlands	1939	41,604	45,000	41,000	57,574	28,429	52,605	YES
Kiwira	S.Highlands	1960	2,637	2,784	45	2,756	28	1,782	YES
Longuza	E.Arc	1952	2,450	2,450	200	2,073	267	2,808	YES
Mtibwa	E.Arc	1961	1,410	1,410	75	2,341	28	901	YES
Lusungulu	E.Arc	Proposed	--	--	--		9,000	2,236	YES
North Kilimanjaro (Rongai)	N.Zone	1926	6,200	6,754	200	6,489	1,075	8,124	YES
Shume	E.Arc	1907	3,804	4,591	140	4,353	72	15,637	YES
Kawetire	S.Highlands	1937	1,956	1,956	520	2,911	798	4,077	YES
Total (Government)			**60,061**	**64,945**	**42,180**	**78,497**	**39,697**	**88,170**	
Proportion of study area (%)			**0.3**	**0.3**	**0.2**	**0.4**	**0.2**	**0.5**	
				Corporate Plantations					
Green Resources LTD	S.Highlands		12,000	12,000	70,000	18,352	18,420	--	NO
Kilombero Valley Teak Company	S.Highlands		8,000	8,150	1,500	8,200	7,360	--	NO
New Forest Company	S.Highlands		1,400	1,500	4,000	1,500	9,000	--	NO
Tanganyika Wattle Company	S.Highlands		14,000	14,500	--	14,656	904	--	NO
Mufindi Paper Mills	S.Highlands		3,500	3,600	30,000	6,000	28,980	--	NO
Matelekeza Chang'a	S.Highlands			--	--	6,000	520	--	NO
Unilever Tea (Tz) LTD	S.Highlands			--	--	--	--	--	NO
Total (corporate)			**38,900**	**39,750**	**105,500**	**54,708**	**65,184**	--	

Overall Total institutional	**98,961**	**104,695**	**147,680**	**133,205**	**104,881**
Proportion of study area (%)	**0.4**	**0.6**	**0.8**	**0.7**	**0.6**

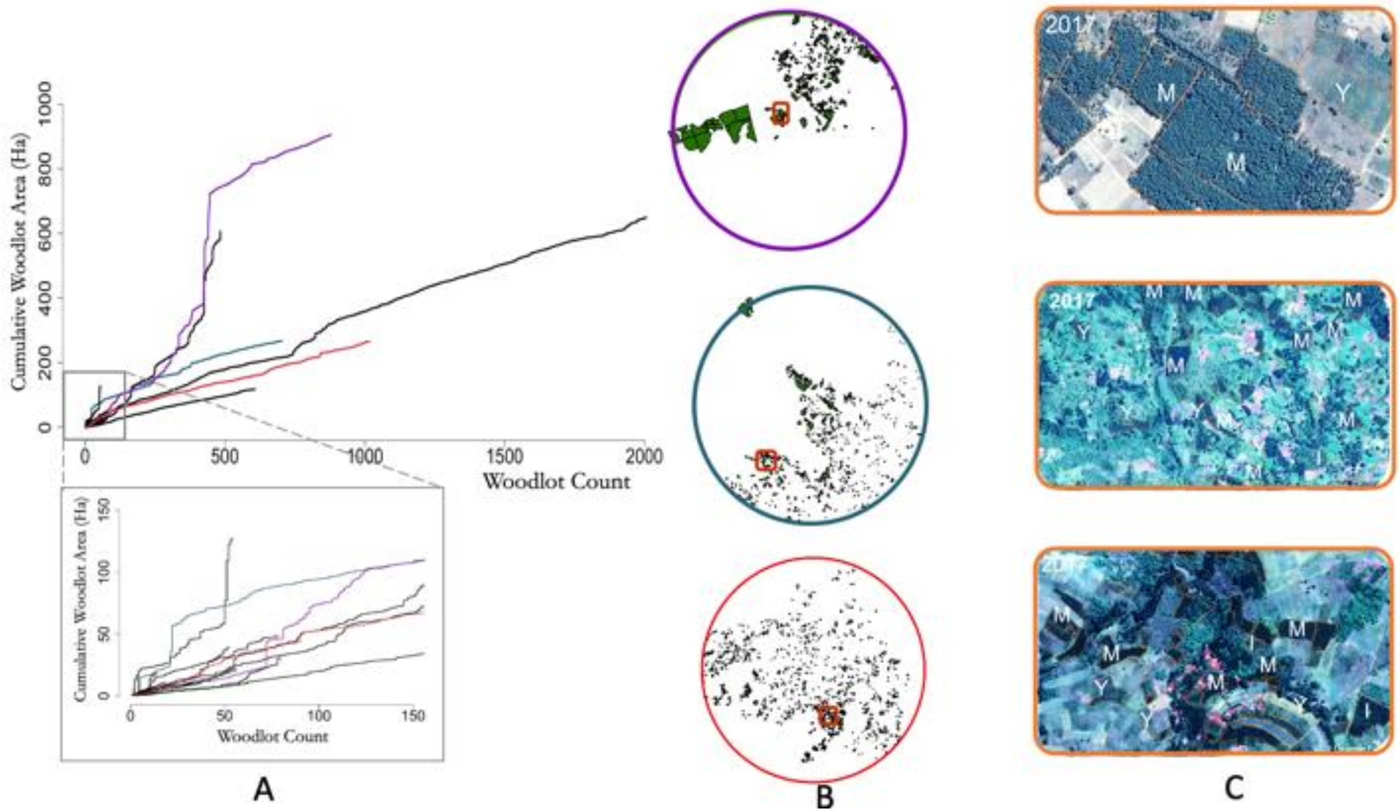

Figure 1. 3: A) Percent cumulative area curves for each of the randomly selected sampling circles. The curves are not normalized but describe within-sample woodlot size distribution; showing how different woodlot sizes contribute to total tree planted area. Plot inset shows sampling circles with few woodlots. B) Three examples (corresponding to the purple, the cyan and the red cumulative area charts) indicating how the digitized woodlots are distributed within sampling locations. C) Digitized woodlots corresponding to the indicated squares in the sampling locations. “Y” indicates sparsest, youngest woodlots, “I” woodlots of intermediate age, and “M” densest, mature woodlots.

Smallholder woodlots are rapidly expanding, with 54% of the digitized woodlots planted between 2012 and 2015.

To estimate woodlot planting date, we adjusted the age of the woodlots based on the Google Earth Pro's image date. Without adjusting the woodlot age to the year in which we did the digitizing (2018), it is still evident that most tree planting is recent. 75% of the digitized woodlots came from imagery dated after year 2016, therefore the woodlot ages in those samples are reported as observed (Table 1. 3). For those age-unadjusted woodlots, the age compositions are: Young: 27%, Intermediate: 31% and Mature 40% (Table 1. 3, also see S3 for sample-by-sample distribution of imagery dates).

We estimate that more than half of the digitized woodlots were established after 2012 (Table 1. 3). For woodlots < 1 Ha, this is proportionally equivalent to 0.08M Ha in a period of three years (2012 -2015). If we assume that smallholders will continue to plant trees at these observed rates, they may plant another 0.02M Ha to trees in the duration of the Bonn Challenge (2018 – 2030), for a total woodlot extent of 0.4M Ha. Thus, smallholder woodlots could contribute 7% to the country's overall restoration target, unaided. As the digitized woodlots averaged 0.5 Ha per woodlot, this expansion could represent 0.75M individual woodlots, and thus potentially represent activities of hundreds of thousands of farmers.

Table 1. 3: The age of woodlots based on the observed image date on Google Earth Pro, and the observed age class for the digitized woodlot. The ages of woodlots from imagery after 2016 are reported as observed.

Observed Google Earth Image Date	Observed Age Class	Adjusted Age Class (to YR 2018)	Number of Woodlots	Estimated Planting Date
2008	Young	Mature	16	< 2011
2010	Young	Mature	2	< 2011
2011	Intermediate	Mature	3	< 2011
2011	Mature	Mature	6	< 2011
2011	Young	Mature	79	< 2011
2012	Intermediate	Mature	199	< 2011
2012	Mature	Mature	132	< 2011
2012	Young	Mature	286	< 2011
2013	Intermediate	Mature	17	< 2011
2013	Mature	Mature	65	< 2011
2013	Young	Mature	33	< 2011
2014	Intermediate	Mature	3	< 2011
2014	Mature	Mature	8	< 2011
2014	Young	Mature	34	< 2011
2015	Intermediate	Mature	19	< 2011
2015	Mature	Mature	29	< 2011
2015	Young	Intermediate	161	2012-2014
2016	Intermediate	Mature	74	< 2011
2016	Mature	Mature	129	< 2011
2016	Young	Intermediate	420	2012-2014
2017	Mature	Mature	2193	< 2011
2017	Intermediate	Intermediate	999	2012-2014
2017	Young	Young	2270	2015-2017

2018	Mature	Mature	1	< 2011
2018	Intermediate	Intermediate	4	2012-2014
2018	Young	Young	78	2015-2017

1.5 Discussion

Smallholders are active and emerging tree planters in Tanzania. The majority of the woodlots in the study area at the time of our study (year 2018) were < 1 Ha and planted between 2012 and 2015. The total extent of smallholder woodlots (0.6% of study area) is equivalent to that of institutional tree plantations (government + corporate: 0.7% of study area).

Estimating woodlots extent and expansion rate

Our mean estimate of the extent of tree planting exceeds acreages from earlier reports (e.g., Ngaga, 2011) but is smaller than in other recent studies, partly due to differences in scale and scope of analysis (Koskinen et al., 2019; Said, 2016). In terms of scale, our study randomly sampled a broad area, as opposed to targeting areas where tree planting is concentrated. Given that tree-planting at present is spatially clustered, and relatively rare, random sampling followed by a confidence interval calculation is the most robust approach even though the many null observations result in wide confidence intervals and risk underestimating the phenomena (McGarvey et al., 2016). We calculated that 0.6% of the study area was planted in trees, with an upper-bound estimate of 1.2%. Other studies (e.g., Koskinen et al (2019)) have estimated woodlot and plantations extent of up to ~ 1% (0.24 ± 0.09M Ha) in the southern Highlands of Tanzania. Our study area and Koskinen et al (2019) differ slightly in scope, with a spatial overlap of 53%. The concordance in woodlot area estimates corroborates the approximate extent of tree planting activities in the region, while the differences highlight the sensitivity of landcover analyses to scale and scope.

The majority, 54%, of the woodlots were planted within a half-decade of our study year (2018). Smallholders have planted woodlots smaller than one hectare at an average rate of 20,000 Ha/year during 2012-2015. Ours is apparently the first attempt to measure the rate of woodlot expansion in the region by age and at a resolution < 1 Ha. Our analysis assumes that the young woodlots are newly established as opposed to being part of a harvesting-and-replanting cycle. Our assumption and our finding that woodlots are expanding rapidly are corroborated by field studies that document these trends (Friis-Hansen and Pedersen, 2016; Said, 2016). Nevertheless, the rate of woodlot expansion could still be an underestimate due to the difficulty of detecting very young and intercropped trees, as well as woodlots in locations with low image quality, and the lack of recent imagery in some locations (See S 1. 4 for imagery acquisition years). The high-resolution Google Earth Pro imagery provided us an easily accessible data source for quantifying this fine-scale land use change, but the varied image acquisition date presented analytical challenges in terms of data gaps (Bastin et al., 2017).

Smallholders as an increasingly important actor in the tree-planting landscape

Across East Africa, woodlots are becoming more prevalent because of increased urban demand for timber, electric poles for rural electrification programs, firewood, and charcoal (Arvola et al., 2019; Kimambo and Naughton-Treves, 2019). Tanzania, for example, is forecast to have a deficit of 3.2 million m^3 in round-wood equivalent by 2035, a shortfall which will necessitate the tripling of extant plantations (Indufor, 2011). Market experts predict that these deficits will be met by smallholder woodlots, thus woodlots' extent will likely continue to increase (Arvola et al., 2019; Held et al., 2017). Woodlot expansion is likely to be concentrated in the regions' highlands and lake zones where ecological conditions are suitable for tree growth (Jacovelli, 2014).

Although we could not differentiate among actors planting woodlots less than one hectare in size, we note that the blanket term of 'smallholder woodlots' conceals complex dynamics of who is planting woodlots. Sub-Saharan Africa is experiencing rapid changes in land ownership and distribution, in part due to the emerging land markets and new commercializing African farmers (Deininger et al., 2015; Hall et al., 2017; Jayne et al., 2015). Accordingly, citizens' ability to participate in tree planting depends on land access. Among rural farmers, those with more land and more off-farm income are more likely to establish woodlots (Jenbere et al., 2012; Kimambo and Naughton-Treves, 2019; L'Roe and Naughton-Treves, 2016). Furthermore, local institutions such as churches and schools as well as urban-based entrepreneurs also look to woodlots as an economic opportunity and contribute to the expansion of rural tree planting (Lusasi et al., 2019). There is more heterogeneity in the motivations and actions of the woodlot planters than is suggested by the small woodlot sizes.

What is the role of smallholder woodlots in international landscape restoration initiatives?

Thus far, local markets, not international initiatives, are spurring Tanzanian smallholders to plant woodlots. Nonetheless, it is worth exploring the means by which pledging countries could benefit from, and support smallholder activities. Of the set of international initiatives promoting tree-planting, the Bonn Challenge is best suited for incorporating smallholders in Tanzania and other sub-Saharan Africa countries. Thus far, Africa's 54 countries have together pledged 170M Ha to restoration (FLR and IUCN, 2017). Tanzania has pledged 5.2M Ha (6% of its territory). If present-day expansion rates continue in Tanzania, smallholder woodlots would cover ~0.4M Ha by 2030. Adding existing government and corporate plantations sums to only ~12% of Tanzania's restoration pledge. How and where the country expects to meet the remaining 88% of the pledged goal is an open question. Many different actors and types of landscapes will need to be incorporated to ensure goals are met equitably and effectively (Fagan et al., 2020). Thus far, in their pledges, countries rarely specify what kinds of landscapes will be restored, who will be undertaking the work, and where it will take place (FLR and IUCN, 2017). In the process of determining how the restoration pledges will be met, countries have an opportunity to incorporate smallholder woodlots.

From an ecological perspective, woodlots have an uncertain role for habitat restoration. In general, ecologists have cautioned against equating tree planting with restoration, especially when non-native trees are planted in monocultures (Veldman et al., 2015; Wood et al., 2014). However, several countries focus on tree-planting to measure restoration achievements (e.g., number of seedlings planted (35 million seedlings across 20,000 Ha in Brazil (Dave et al., 2017)) or total area planted in trees (e.g., 9.8M Ha in India (Borah et al., 2018)). Furthermore, Forested Landscape Restoration guidelines, and the Bonn Challenge 'best practices' documents emphasize tree planting as a core feature of restoration of deforested or agricultural lands (FLR and IUCN, 2015; IUCN and WRI, 2014), including non-native woodlots or agroforestry where appropriate (Sabogal et al., 2015). The emphasize on tree planting in restoration programs justifies attention to woodlots, but the woodlots will have different restoration implications depending on the land cover and land use they replace (Veldman et al., 2015). Smallholders in countries such as Tanzania generally have short-term investment horizons, which is why they prefer to plant fast-growing, easily marketed trees like pine and eucalyptus (Arvola et al., 2019). Promoting native forest restoration on smallholder lands is thus difficult and likely requires special incentives (Nawir et al., 2007).

From an equity perspective, expanding the smallholder tree planting could be a way for African countries to advance their ambitious tree-planting goals while minimizing displacement. India, for example, reports planting trees on 9.8M Ha since 2011, 94% via government-led efforts (Borah et al., 2018). However, such a centralized approach runs counter to long-standing efforts to decentralize natural resource management in Africa (Persha and Blomley, 2009; Phelps et al., 2010). Large-scale tree planting undertaken by government agencies or corporations has adverse socio-economic impacts (Lyons and Westoby, 2014; Malkamäki et al., 2018). Working with smallholder tree planters may be a more promising and less heavy-handed approach.

Finally, there is the vexing question of whether supporting ongoing woodlot trends attains additionality. Some programs, such as REDD+, required evidence that the funds invested (e.g., in tree planting) spur an outcome that would not have been achieved otherwise (Wunder, 2007). Additionality has been less central to the Bonn Challenge, because credit has mostly gone to organizations able to demonstrate that their activities count towards fulfilling restoration goals (Hagmann et al., 2018). This is true even when agencies' activities were undertaken before the country made its Bonn Challenge pledge (Borah et al., 2018; Dave et al., 2017), and even when activities were originally based on initiatives unrelated to restoration (Pistorius et al., 2017). In pledge fulfillment accounting so far, there is no clear distinction between activities that have occurred independent of the restoration pledges and those that occurred because of it. Thus, smallholders should be similarly considered for restoration funding even when they develop their woodlots independent of the global restoration pledges, especially given that restoration initiatives wish to promote desired landcover trends while also improving livelihoods.

Additional considerations for incorporating smallholder woodlots into global tree-planting pledges

Supporting existing smallholder woodlots requires organizing many distributed actors and nudging them toward closer alignment with restoration goals. Organizing smallholders can be achieved via existing village- and district-level timber associations (Tirivayi et al., 2018). These organizations could subsidize and distribute tree seedlings from species that have strong economic potential and are more ecologically desirable (Nawir et al., 2007). Locations where tree planting already occurs can be provided with extension support for nurturing and protection of native tree species in order to enrich the diversity of woodlots (Nguyen et al., 2014). Smallholders could even be paid subsidies to encourage longer rotation times, which would improve carbon sequestration, and improve timber yields (Indufor, 2011). Such subsidies could also be used to encourage ecologically appropriate zoning. For example, woodlots could be subsidized in certain areas such as formerly cultivated lands that are undesirable for food crop production (L'Roe and Naughton-Treves, 2016; Telila et al., 2015).

A practical concern for how to incorporate woodlots into landscape restoration would be where funds for such an endeavor would come from, and what would happen if the local demand for tree products collapsed. Identifying funding sources is beyond the scope of this paper but there are many precedents of financial assistance for smallholder-based tree planting from central governments, NGOs, and the European Union (Jacovelli, 2009; Komaza, 2016). Relying solely on external payments to incentivize tree-planting comes with risk. REDD+ payments in Tanzania, for example, created high local expectations followed by disappointment when the payments were not sustained (Massarella et al., 2018). Other similar payments-based environmental management programs face frequent interruptions and shocks (Etchart et al., *submitted manuscript*). Given market forecasts for timber demand and the likely role of smallholders in meeting them, it may be more tenable to tether broad-scale tree-planting efforts to the woodlot expansion trend.

1.6 Conclusion

Smallholders are active and emerging tree planters in Tanzania and beyond, and deserve consideration in international restoration initiatives. Smallholder woodlots already cover an extent equivalent to government and corporate plantations, and they are rapidly expanding. Given that woodlots average <1 Ha, the coverage we measured reveals the actions of thousands of farmers, and thus signals an opportunity for wide-spread smallholder incorporation. Farmers already undertaking tree planting could benefit from restoration financing by receiving woodlot establishment subsidies and extension support for better tree farm management. Woodlots can meet restoration and carbon sequestration goals if they are established in appropriate location and use sound management practices. Most importantly, leveraging existing trends and momentum among a broad range of actors that include smallholders could be a more socially viable option for meeting ambitious national tree-planting goals rather than relying solely on large-scale projects. Though the woodlots are individually small, they can play a large role in African forestry policy.

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Chapter 2: Mapping African smallholder woodlots of < 1 Ha across spatial resolutions

Resulting paper: Kimambo, N. E. and Radeloff, V.C. Mapping African smallholder woodlots of < 1 Ha across spatial resolutions. Anticipated submission to Remote Sensing the Environment.

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2.1. Abstract

Accurate tree cover maps are necessary for delineating forest habitat, quantifying terrestrial carbon stocks, and assessing the economic value of trees. Global tree cover maps miss small woodlots. Our goal was to assess approaches for overcoming this limitation using imagery of higher spatial resolution and increased observation frequency. We mapped smallholder woodlots of < 1 Ha in Tanzania. We created statistics-based image stacks for Landsat-8 (30-m) and Sentinel-2 (10-m) using imagery gathered between 2016 and 2018. Then we tested two approaches for increasing observation frequency by combining the Landsat-8 and the Sentinel-2 image stacks. First, we simply combined the pixel-based Landsat and Sentinel image stacks. Second, we generated objects from Sentinel-2 and used them to summarize the Landsat-8 image stack. Using a random forest classifier, we produced five woodlot maps: 1) pixel-based Landsat-8, 2) pixel-based Sentinel-2, 3) object-based Sentinel-2, 4) pixel-based combined Landsat-8/Sentinel-2, and 5) object-based combined Landsat-8/Sentinel-2. The overall accuracy of our maps ranged from 58% to 66%. For the woodlot class, we obtained producer accuracy from 37% to 51% and user accuracy from 64% to 73%. Combining the Landsat-8 and Sentinel-2 using spatial objects resulted in the best user and producer accuracy (51% and 72%, respectively). We compared the five maps with hand-digitized woodlots and noted that about half of the extant woodlots were missed across all five maps, particularly if the woodlots were young or very

small (< 0.4 Ha). Our results suggest that using an object-based combination of Landsat-8/Sentinel-2 has the most promise for mapping fine-scale tree cover in our study area. However, given that, at best, our five maps could only detect up to half of the extant woodlots, mapping such fine-scale tree cover may require even higher spatial resolution.

Keywords

plantations, google earth engine, tree cover map, SNIC, OBIA, data fusion

2.2. Introduction

Mapping tree cover has been a core effort for remote sensing because of trees' economic and ecosystem values (Crowther et al., 2015; Hansen et al., 2013). Approaches for tree cover mapping have greatly advanced since the beginning of the satellite era as the number of sensors and their spatial resolution continually improve (Sexton et al., 2016). However, capturing small woodlots is a challenge even in state-of-the-art global tree cover maps (e.g., Hansen et al., 2013, thus limiting the maps' local veracity (Sexton et al., 2016). Small woodlots in Africa and southeast Asia contribute to those regions' timber needs (Jacovelli, 2014; Mather, 2007; Rudel, 2009), and their extent has increased in recent years (Kimambo et al., 2020; Payn et al., 2015). Capturing fine-scale and emerging tree cover is also important for globally emerging efforts to foster tree planting for carbon mitigation and landscape restoration (Dave et al., 2017; Fagan et al., 2020; Veldman et al., 2015). Here, we use smallholder woodlots as a test case for the effect of improved image spatial resolution and object-based image analysis methods in mapping fine-scale tree cover.

Higher spatial resolution of input imagery can increase overall map accuracy and estimations of total area of tree cover (Grainger, 2008; Sexton et al., 2016). Global tree cover maps are continually updated when higher resolution imagery becomes available (Hansen et al., 2013, 2003; Sexton et al., 2013). However, global tree cover maps continue to have limited local accuracies particularly limited in heterogeneous areas or in dryland ecosystems (Bastin et al., 2017; Fisher et al., 2016), wherever tree cover patches are small or mixed in with other land uses. This is a concern given the global prevalence of tree cover patches that are < 0.5 Ha (Sexton et al., 2016; Thompson and Gergel, 2008). Thus, regional approaches to mapping tree cover are necessary, particularly ones that go beyond presently available global tree cover products that use Landsat's 30-m resolution (Bastin et al., 2017; Rahman et al., 2018; Salajanu and Olson, 2001). Smallholder woodlots are a good test case for how spatial resolutions beyond Landsat's 30-m affects tree cover mapping accuracies and area estimation.

The free availability of ESA's Sentinel-2 10-m resolution imagery presents an opportunity for improving fine-scale tree cover mapping beyond Landsat's 30-m resolution. On one hand, Sentinel-2 imagery has been successfully used to map heterogeneous tree cover, including distinguishing different kinds of plantations in south Asia. Those studies improved on previous Landsat-based studies (Hurni et al., 2017; Nomura and Mitchard, 2018). On the other hand, Sentinel-2 imagery has several pre-processing challenges, particularly cloud-screening (Fisher et al., 2016; Salajanu and Olson, 2001). Sentinel-2 cloud-screening algorithms perform poorly due to the lack of a thermal band, resulting in pixels that contain clouds and cloud shadows even after cloud-masking (Zhu et al., 2015). Some studies have suggested that these challenges limit accuracy gains when comparing Landsat-8 and Sentinel-2 maps (Carrasco et al., 2019; Salajanu and Olson, 2001). More comparisons are necessary to test whether increased spatial resolution improves tree cover maps in heterogeneous landscapes.

Much like improving spatial resolution, increasing the number of observations used in a classifier can also generally improve the accuracy of tree cover maps. Multi-date observations of a location increase chances of a cloud-free image and can capture phenological changes that are useful for distinguishing different kinds of land cover (Carrasco et al., 2019; Hurni et al., 2017; Senf et al., 2015). Comparisons of land maps produced from a single-date versus a multi-date approach show that resulting accuracies are comparable when the single-date image is well-timed seasonally (Carrasco et al., 2019; Grabska et al., 2019). However, well-timed and cloud-free images are often unavailable, particularly for the humid biomes of sub-Saharan Africa (Ju and Roy, 2008). To produce analysis-ready imagery without clouds, observations from multiple dates can be used to generate pixel-level statistics (e.g., mean, median, and standard deviation

(SDEV)). These statistics are also useful for distinguishing tree cover properties, tree cover properties, like species type and patch age (Hurni et al., 2017; Pasquarella et al., 2018; Yin et al., 2017). Sometimes, these distinctions can be achieved with reasonable accuracy even when the constituent imagery are partially cloudy (Sheeren et al., 2016; Turlej, 2018).

Objects can be used as a way can be useful for fine-scale tree cover mapping because object-level analysis may improve classification accuracy. Comparisons between object-based and pixel-based image analysis sometimes conclude that there is no difference in mapping accuracies (Duro et al., 2012), but other times object-based analysis outperforms pixel-based analysis (Peña-Barragán et al., 2011). Object-based methods can result in accuracy gains in heterogeneous areas when they reduce the spatial heterogeneity of features that result in noisy classification outputs (Li et al., 2016; Toure et al., 2018). Furthermore, objects can provide additional information for classification by generating object-level metrics like texture, shape index, and patch area. These metrics can improve tree cover classifications (Li et al., 2014).

Objects can be used as a way to combine information from different imagery (Pohl and Genderen, 2017; Zhang, 2010). If multiple observations are helpful for distinguishing tree cover properties, then combining data from multiple sensors could further increase the observation frequency, particularly for cloudy locations (Claverie et al., 2018). Two sensors that can be useful in combination for land cover mapping are Landsat-8 and Sentinel-2 (Carrasco et al., 2019; Mankinen et al., 2017). These studies combined imagery from the two sensors, but that can introduce classification errors since Landsat-8 and Sentinel-2 images have a mis-registration of ~1 pixel (Yan et al., 2016). However, stacking Landsat-8 and Sentinel-2 images at an object level, instead of at a pixel-level, can alleviate the pixel offset challenge, because the objects contain several pixels that describe one feature. More work is needed to assess whether there is a difference in the classification results of tree cover when Landsat-8 and Sentinel-2 imagery are combined at a pixel level versus at an object level.

Ultimately, accurate mapping of a woodlot depends on whether the woodlot is separable from the surrounding context (Lu and Weng, 2007; Ozdogan and Woodcock, 2006). Characteristics like the age and size of a tree cover patch can affect the separability of the patch; patches that are bigger, spatially contiguous, and spectrally contrasting with surrounding landscape are easier to detect. These characteristics can further explain detectability of tree species (Fassnacht et al., 2016; Grabska et al., 2019; Sheeren et al., 2016). Because woodlots come in a wide range of characteristics (including age and size), we can test how those characteristics affect overall mapping accuracies.

Using smallholder woodlots as a test case, our overall goal was to determine whether improved image spatial resolution and observation frequency affects the accuracy and total area of fine-scale tree cover maps. Our objectives were:

1. To compare the accuracy and total mapped area of woodlots between a Landsat-8 (30-m) map and a Sentinel-2 (10-m) map;
2. To compare the accuracy and total mapped area of woodlot maps produced from combining Landsat-8 and Sentinel-2 images at a pixel-level and at an object-level;
3. To determine how a woodlot's age and patch size affects its detection.

2.3. Methods

Study area

We assessed the extent of woodlots at a site in the Southern Highlands of Tanzania centered on a Sentinel-2 grid number 36LYR (8.9148°S, 34.6857°E)(Figure 2. 1). The region has high rainfall (up to 2-m per year at 2000-m asl), and moderate temperatures (Fick and Hijmans, 2017), making the area suitable for tree planting. We selected the study location because it was the site of substantial tree planting, particularly on smallholder land (Indufor, 2011; Kimambo et al., 2020; Ngaga, 2011). Smallholder woodlots are mostly planted with pine and are sold for timber, firewood, and construction poles (Arvola et al., 2019; Koskinen et al., 2019). The woodlots average 0.45 Ha and are of variable age, with the majority established between 2012 and 2015 (Kimambo et al., 2020). These smallholder woodlots have very short rotation cycles (7 – 10 years), as smallholders harvest the woodlots early to meet pressing cash needs (FDT, 2015).

Data and Methods

Our approach consisted of five steps, all of which we carried out in Google Earth Engine (Figure 2. 2) (Gorelick et al., 2017). First, we created two statistics-based stacks: one for the Landsat-8 (30-m) imagery and another for the Sentinel-2 (10-m) imagery, using imagery from 2016 to 2018 to capture the woodlots planted between 2012 and 2015. Second, we generated spatial objects from the Sentinel-2 (10-m) statistics-based stack. Third, we combined the statistics-based stacks from Landsat-8 and Sentinel-2 at a pixel level into one stack. We also combined the stacks at an object level by summarizing the Landsat-8 imagery with the Sentinel-2 objects. Fourth, we mapped woodlots in each imagery stack with a random forest classifier and the same training data. These steps produced five woodlot maps: a Landsat-8 map at 30m resolution, a Sentinel-2 map at 10m resolution, an object-based Sentinel-2 map, a combined Landsat-8/Sentinel-2 map at a pixel-level, and a combined Landsat-8/Sentinel-2 map at an object-level. We validated the five woodlot maps with an independent validation dataset. Last, we used a hand-digitized woodlots dataset to analyze woodlot detection patterns across the five maps, given each patch size and age.

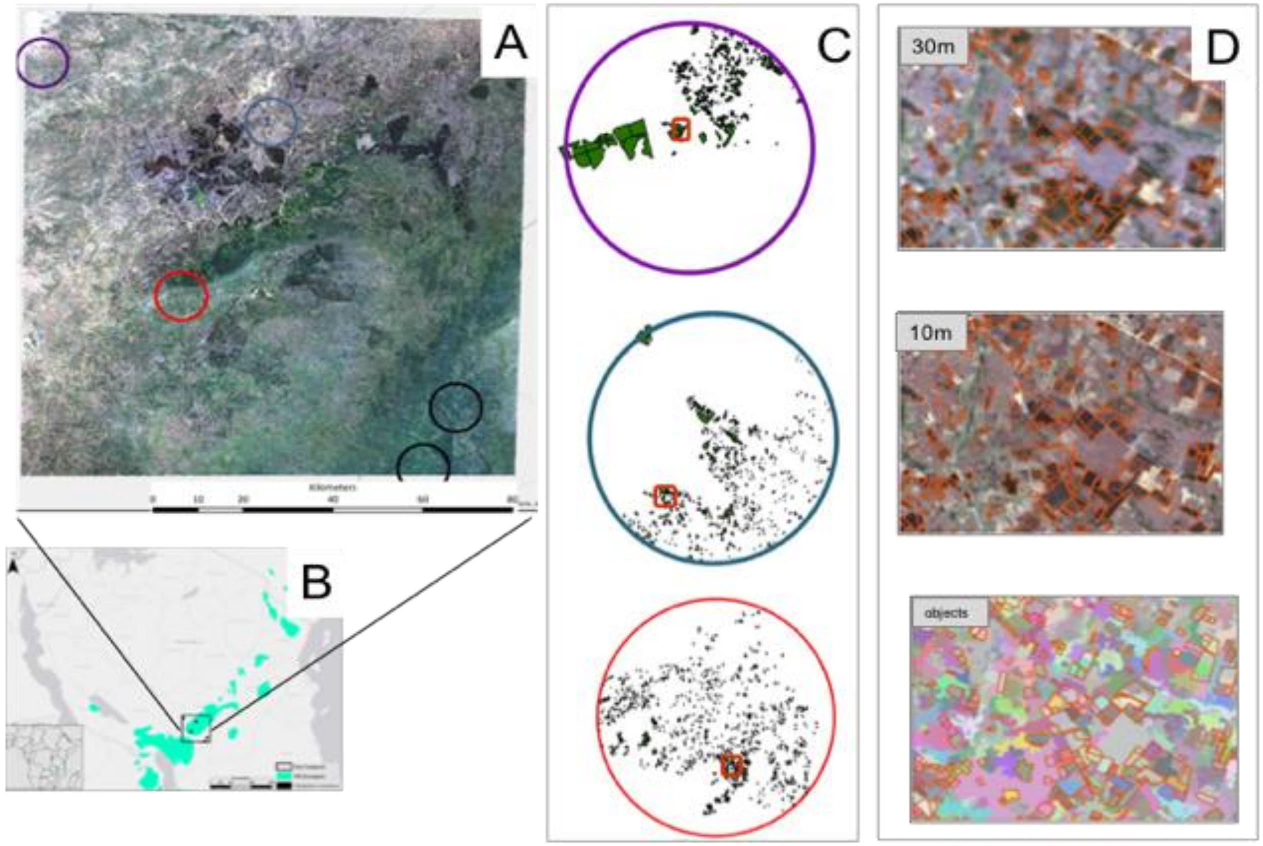

Figure 2. 1: A) The study area footprint, including hand-digitization locations. The underlying image is Sentinel-2's median pixel statistic over a 3-year period (Jan 2016 – December 2018), with an RGB combination of Bands 4, 3 and 2. B) Context map showing Tanzania and the study area footprint. C) Three examples (corresponding to the purple, the dark blue and the red circles in panel A) indicating how the digitized woodlots are distributed within sampling locations. D) Hand-Digitized woodlot images from the indicated square in the top circle in panel C. The digitized woodlot images are overlaid on the 30-m resolution statistics imagery (top square), the 10-m statistics imagery (middle), and with the image objects created from segmentation (bottom).

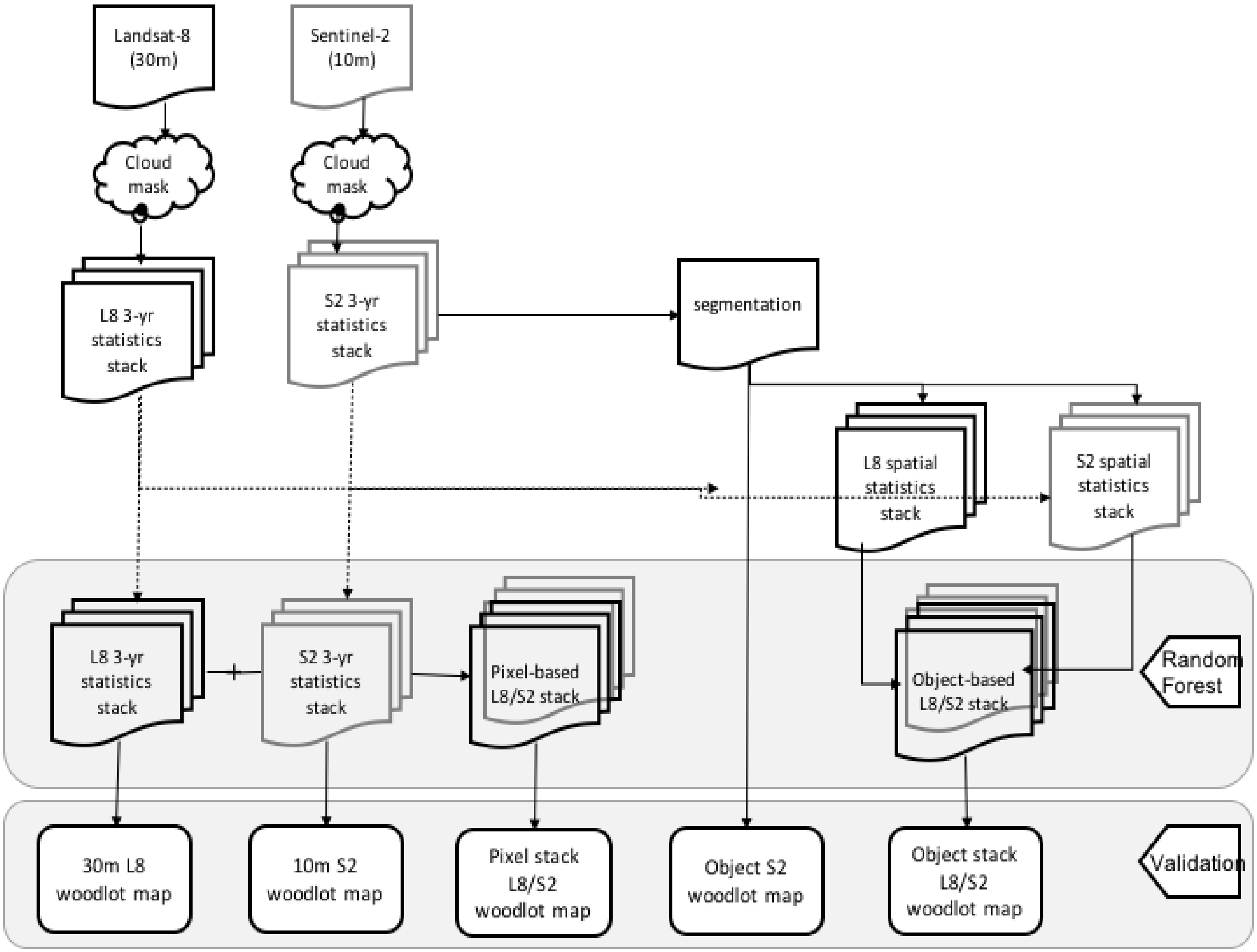

Figure 2. 2: Flowchart of band statistics generation, segmentation, cross-resolution data combination, classification, and validation.

Data

Landsat-8 and Sentinel-2 imagery statistics stacks

To generate the Landsat-8 statistics-based input data, we analyzed all available Landsat-8 Level 1 Surface Reflectance imagery from January 2016 to December 2018, which consisted of 232 scenes. We masked clouds using the pixel quality information band and applied an additional cloud filter based on pixel brightness. For each image, we calculated three indices: the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI) ((B3 – B5)/(B3 + B5)), and Bare Soil Index (BSI). We summarized the indices and six bands (B2, B3, B4, B5, B6, and B7) by calculating the mean, median, and pixel values at the 20th percentile. The resulting Landsat 8 statistics image stack contained 27 bands used for woodlot mapping at 30-m resolution.

We performed similar steps to generate the Sentinel-2 statistics-based input data. We processed imagery from Level 1C Sentinel-2 that contains both Sentinel 2A and 2B acquisitions and covered the study period (January 2016 to December 2018). We had 1531 individual images in our study area; many more than the Landsat-8 product because of the Sentinel-2's tiling system that led to partial image segments. For each input image, we masked clouds using a publicly available custom tool that implements Sentinel's STEP cloud masking in Google Earth Engine (Principe, 2019). We selected the 10-m bands (B2, B3, B4, B5, and B8) and a 20-m band (B11) and calculated the same three indices we used with Landsat-8 (NDVI, NDWI, BSI). We summarized the bands and the indices into mean, median, and 20th percentile values, and refer to these as 'statistics' in remainder of the manuscript. The resulting Sentinel-2 statistics stack contained 24 bands used for woodlot mapping at 10-m resolution.

Training and validation data

We generated 778 points across 12 land cover classes (cropland, forest, grassland, tea, urban, wetland, woodland, water, woodlot intermediate, woodlot mature, woodlot young, and woodlot harvested. See S 2.1 for detailed class definitions). To collect training and validation data points, we interpreted high-resolution Google Earth Pro imagery (see examples in S 2.1). Google Earth Pro is missing recent imagery for some locations, thus we performed an additional cross-check for each point with the Sentinel-2 10m statistics imagery to ensure that the land cover recorded was accurate for the year 2018. For the four woodlot classes (woodlot young, woodlot intermediate, woodlot mature, and woodlot harvested), we confirmed woodlot cover, and distinguished woodlots from other classes, by additional interpretation of the temporal signature of the training pixels. We used a Landsat-based, publicly available custom tool (Yin, 2019) that charts temporal spectra over a given time window (See S 2.2 for examples). Checking the woodlots points against the input imagery and the temporal information was important since woodlots are a dynamic and newly emerging land cover in the study area.

To separate training and validation datasets, we randomly split the points into training and validation datasets for each class (75% training, 25% validation). The training dataset contained 246 points for the four woodlot classes and 341 points for all the other seven classes. The validation dataset contained 81 points for the four woodlot classes, and 110 points for the other seven classes.

Woodlot patch-size and age data from hand-digitization

To obtain data for patch-level woodlot characteristics, we generated four random samples of equal area (10, 000 Ha each) that covered 4% of the study site. In each sampled location, we hand-digitized all woodlots visible in the most recent Google Earth Pro imagery at the time of digitization (year 2018). The availability of up-to-date high-resolution Google Earth images varied by location, with some areas' most recent image dating back to the early 2000s. Thus, we recorded the date the image was acquired and the age category for the woodlot. A unique woodlot was delineated by visual evidence for borders such as fire breaks and farm boundaries (See S 1. 1 for woodlot digitization and age category protocol). Additionally, we placed areas of uniform age and uniform tree texture in unique woodlots and assigned the woodlot an age measure of: "Young", or "Intermediate", or "Mature" category based on the tree density. The "Young" category are woodlots with sparse tree density in which round tree crowns and the linear planting texture is still visible; while the "Mature" category indicates dense woodlots where the tree canopy has closed.

Object generation

We created a single layer of spatial objects of the study area. We created objects of varying sizes by iteratively segmenting and masking the image stack. In Google Earth Engine, we used Simple Non-Iterative Clustering (SNIC) (Achanta and Susstrunk, 2017) and segmented the Sentinel-2 10-m statistics stack. First, we segmented the image at a coarse scale (seed: 36, zoom: 14), summed the standard deviation (hereafter SDEV) of all bands, and masked the large, homogeneous objects (lowest 10^{th} percentile in summed SDEV and highest 10^{th} percentile in area). Second, we segmented the unmasked sections of the image at a finer scale (seed: 20, zoom: 7), assessing the correspondence of the resulting objects to landscape features by visual inspection. Finally, we combined the objects generated at coarse and fine segmentation levels into a single layer. We use the objects layer to calculate per-object mean and SDEV for the Sentinel-2 and the Landsat-8 imagery stacks.

Combining Landsat-8 and Sentinel-2 at the pixel-level and at an object-level

To increase the observation frequency at each location, we combined the Landsat-8 and the Sentinel-2 statistics stacks in two ways: (a) at the pixel level, and (b) at the object level. At the pixel-level, we combined the two stacks such that the combined had 51 bands, and the resolution of the Sentinel-2 image (Figure 2. 2). At the object level, we took the SNIC segmentation results and calculated per-object mean and standard deviation for each band in the Sentinel-2 and the Landsat-8 stacks. We also calculated additional object properties (area, perimeter, width, and height). The resulting object-based image stack had 109 bands and the resolution of the segments (Figure 2. 2). Combining the statistics stacks increased the number of cloud-free pixels for all locations. For the cloudiest areas (e.g., < 5 cloud-free pixels in Landsat 8) the number of cloud-free pixels increased to 40 - 63 when Sentinel-2 observations were included.

Woodlot classification

To identify woodlots in the study area, we first mapped land cover generally, with 12 land cover classes (cropland, forest, grassland, tea, urban, wetland, woodland, water, woodlot intermediate, woodlot mature, woodlot young, and woodlot harvested). We used the same training data and a random forest classifier to classify 1) the Landsat-8 30m resolution stack 2) the Sentinel-2 10m resolution stack 3) the object-based Sentinel-2 stack, 4) the Landsat-8/Sentinel-2 stack combined at a pixel level, and 5) the Landsat-8/Sentinel-2 stack combined at an object-level.

Validation

To assess the overall accuracy, we combined the six non-tree classes (cropland, grassland, tea, urban, wetland, and water) into an 'other' class and three woodlot classes (woodlot intermediate, woodlot mature, woodlot young) into a 'woodlots' class. We performed validation among five classes (other, forest, woodland, woodlot harvested, woodlots). We evaluated the maps based on the overall accuracy of the classification. We also assessed whether the accuracies of the five classified maps were statistically significantly different using Cochran's Q test, which is an extension of the McNemar test beyond a binary comparison (Foody, 2004). The Cochran's Q test determined whether any of the five maps accuracy was different from the rest. We calculated accuracy-adjusted areas with a custom tool in Google Earth Engine (Bullock et al., 2019). For the 30-m and the 10-m resolution maps, we report the overall accuracy and total area. We report the total area and accuracy of woodlot maps created from higher frequency of observations at a pixel level and at an object level. We also report which woodlots are best captured by the five maps based on the woodlot's age and size characteristics.

2.4. Results

The five maps produced by this study have overall accuracies ranging from 58.3% to 66.1% (Table 2. 1). The maps' overall accuracies are not statistically significantly different from one another (Cochran's Q test: Q = 4.268, df = 4, p-value 0.37, Table 2. 2). The maps show that woodlots cover are about one quarter of overall land cover (23±2%). Increasing spatial resolution from Landsat-8's 30-m to Sentinel-2's 10-m did not significantly improve detection of woodlots. The woodlot class had the highest user and producer accuracy when mapped with combined Landsat-8/Sentinel-2 imagery at an object level (producer accuracy: 50.9%, user accuracy 71.6%, Table 2. 1). Furthermore, for the subset of woodlots that were both young and small (< 0.4 Ha), only ~ 25% were captured across the five maps.

Table 2. 1: Overall accuracies of the five maps, the proportion of tree cover and woodlots, and the user and producer accuracies of the woodlot class

Classification Map	Overall Accuracy (%)	Proportion Tree cover (Forest and Woodland) (%)[1]	Proportion Woodlot (%)[2]	Woodlot Producer Accuracy (%)	Woodlot User Accuracy (%)
Landsat-8 (30-m)	66.1 ± 6.9	25.8	22.3	42.0	67.7
Sentinel-2 (10-m)	61.8 ±7.4	26.9	25.0	42.3	72.9
Sentinel-2 Object	58.3 ± 7.8	27.2	24.7	36.7	63.8
Landsat-8/Sentinel-2 Pixel	64.2 ± 7.5	28.2	23.6	40.5	71.0
Landsat-8/Sentinel-2 Object	63.9 ± 7.2	26.5	20.6	50.9	71.6

[1]The proportion of study area that is forests and woodlands as calculated by area-adjusted and accuracy-dependent metric

[2]The proportion of study area that is woodlots of all ages (excluding harvested areas) as calculated by area-adjusted and accuracy-dependent metric

Comparing woodlot mapping accuracy and total area between Landsat-8 30 m resolution map and Sentinel -2 10 m resolution map

As expected, the overall commission and omission error patterns were similar across the Landsat-8 30-m and the Sentinel-2 10-m maps. Generally, woodlots tended to be confused with other tree covers, particularly less-dense woodlands (Table 2. 3 and Table 2. 4). The most confusion was between harvested woodlots and active woodlots, followed by active woodlots and forests. However, the Sentinel-2 10-m map had slightly higher producer and user accuracy (0.3 and 5.2 percentage points higher, respectively) for the woodlot class compared to the 30-m resolution map (Table 2. 3 and Table 2. 4). The two spatial resolutions were not statistically different in terms of their overall accuracy (McNemar's chi-squared = 0.08, df = 1, p-value = 0.7).

Table 2. 2: Cochran's Q test comparing whether the five maps differ in their accuracy when all the classes are merged together (Woodlots vs Other Classes), when woodlots and harvested classes are combined (Woodlots + Harvested vs Other Classes) and for all five classes altogether. The maps are not statistically significantly different in their accuracy.

	Cochran's Q	degrees of freedom	p-value
Woodlots vs Other Classes	4.3	4	0.4
Woodlots + Harvested vs Other Classes	8.0	4	0.1
All Five Classes	4.3	4	0.4

Table 2. 3: Accuracy matrix for Landsat-8 30-m map. The rows are the classifier-assigned class labels, while the columns are the validation points class labels. 'Other' combined six classes that were not tree-related.

	Other	Forest	Woodland	Harvested[1]	Woodlots
Other	**76.5**	0	7.1	23.5	7.8
Forest	1.5	**44.4**	7.1	0	1.5
Woodland	9.3	27.7	**67.8**	11.7	17.1
Harvested	4.6	0	3.5	**23.5**	4.6
Woodlots	7.8	27.7	14.2	41.1	**68.7**

[1]This class denotes recently harvested woodlots in the study area

Table 2. 4: Accuracy matrix for Sentinel-2 10-m map. The rows are the classifier-assigned class labels, while the columns are the validation points class labels. 'Other' combined six classes that were not tree-related.

	Other	Forest	Woodland	Harvested[1]	Woodlots
Other	**82.8**	0	22.2	35.5	7.8
Forest	0	**50.0**	18.5	0	3.1
Woodland	3.1	27.7	**40.7**	11.7	15.6
Harvested	10.9	0	0	**23.5**	6.25
Woodlots	3.1	22.2	18.5	29.4	**67.1**

[1]This class denotes recently harvested woodlots in the study area

The Landsat-8 30-m map had a total woodlots area of 22.3% of the study area (2.8% standard error Figure 2. 3), equivalent to 0.26M Ha (0.06M Ha CI), while the Sentinel-2 10-m map had a total area of 25% (3.1% standard error), equivalent to 0.30M Ha (0.07M Ha CI). The Sentinel-2 map showed the highest area proportion of woodlots compared to the other maps.

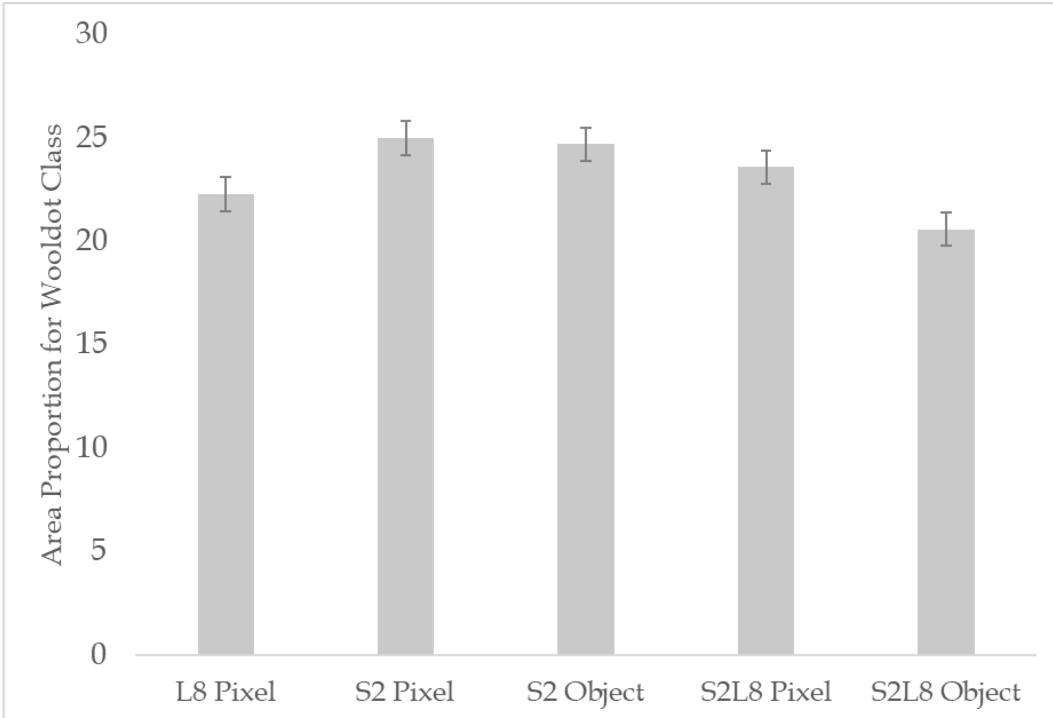

Figure 2. 3: Area proportion of woodlots across the five maps, with standard errors. The Sentinel-2 map estimated the highest proportion of the site as woodlots.

Woodlot identification accuracy and area mapping for pixel-level and object-level combined Landsat 8 and Sentinel-2 images

Overall accuracy for the combined Landsat-8/Sentinel-2 maps were similar to the accuracy of the stand-alone Landsat and Sentinel maps. However, in the Landsat-8/Sentinel-2 maps, the user and producer accuracies were higher for the woodlot class (Table 2. 5 and Table 2. 6). The object-based and pixel-based Landsat-8/Sentinel-2 maps were also not statistically significantly different from each other (McNemar's chi-squared = 0.11, df = 1, p-value = 0.7).

Table 2. 5: Class-level accuracy for pixel-based combined Landsat-8/Sentinel-2 woodlot map.

The rows are the classifier-assigned class labels, while the columns are the validation points class labels.

Class	Other	Forest	Woodland	Harvested	Woodlots
Other	**87.5**	0	25.0	35.3	6.3
Forest	0	**55.5**	14.2	0	1.6
Woodland	3.1	22.2	**42.8**	5.8	15.6
Harvested	3.1	0	3.5	**23.5**	7.8
Woodlots	6.2	22.2	14.2	35.2	**68.7**

Table 2. 6: Class-level accuracy for object-based combined Landsat-8/Sentinel-2 woodlot map.

The rows are the classifier-assigned class labels, while the columns are the validation points class labels.

Class	Other	Forest	Woodland	Harvested	Woodlots
Other	**78.1**	0	22.2	17.6	7.8
Forest	0	**50.0**	11.1	0	1.6
Woodland	10.9	33.3	**40.7**	11.8	9.3
Harvested	7.8	0	0	**29.4**	6.2
Woodlots	3.1	16.6	25.9	41.17	**75.0**

Effect of patch size and age on woodlot detection

When comparing the classified map with the hand-digitized data, we found that the five woodlot maps (from Landsat 8, Sentinel 2 pixel-level, Sentinel-2 object level, Landsat-8/Sentinel-2 Object, Landsat-8/Sentinel-2 Pixel) captured up to half of the woodlots that were actually present in the landscape (49 – 53%) (Figure 2. 4). On the other hand, approximately 4 - 10% of sampling locations that did not have woodlots in them were identified as woodlots (Figure 2. 5). In other words, based on the hand-digitized samples, the five woodlot maps missed considerably more of the woodlots (high error of omission) in the landscape than they falsely included in the overall woodlot category (error of commission).

The detectability of a woodlot patch varied with the age of the woodlot (Figure 2. 6). Young woodlots were the hardest to detect, and when detected they were often confused with intermediate-age woodlots. Between the five maps, young woodlots were best detected by Sentinel-2 pixel-based maps. Intermediate-aged woodlots were surprisingly the ones that were detected the most. When mis-classified, the intermediate-aged woodlots were most likely to be placed in the 'harvested woodlots' class. Landsat-8/Sentinel-2 object-based map detected the largest proportion of intermediate-aged woodlots. The Landsat-8 map detected the largest proportion of mature woodlots compared to the other datasets. When mature woodlots were misclassified, they were often placed into a non-woodlot class or in the intermediate-age woodlot class (Figure 2. 6).

When controlling for the age of the woodlot, larger woodlots tended to be more easily captured across the five maps. For young woodlots, patches > 1 Ha, were detected three times more than patches smaller than the median patch size of 0.4 Ha. For mature woodlots, a patch size increase from < 0.4 Ha to > 1 Ha doubled the detection of the woodlots (Figure 5). Landsat-

8/Sentinel-2 combined worked best for woodlot detection for intermediate-aged and mature woodlots that are larger than 0.4 Ha.

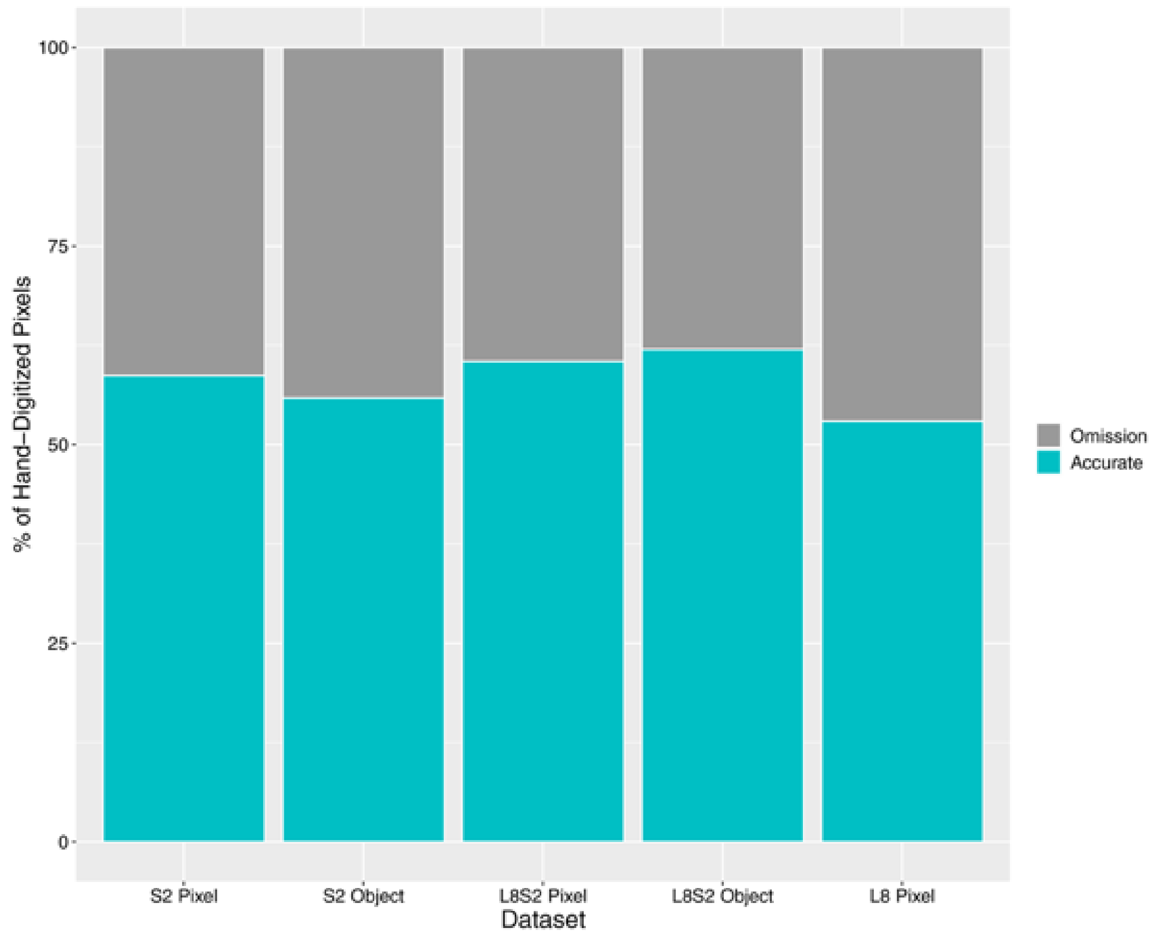

Figure 2. 4: The proportion of hand-digitized woodlots accurately captured in the classified map (aqua) and omission errors (grey). 100% represents all the hand-digitized woodlots. Abbreviations: S2 = Sentinel-2, L8S2 = Landsat-8/Sentinel-2, L8 = Landsat-8

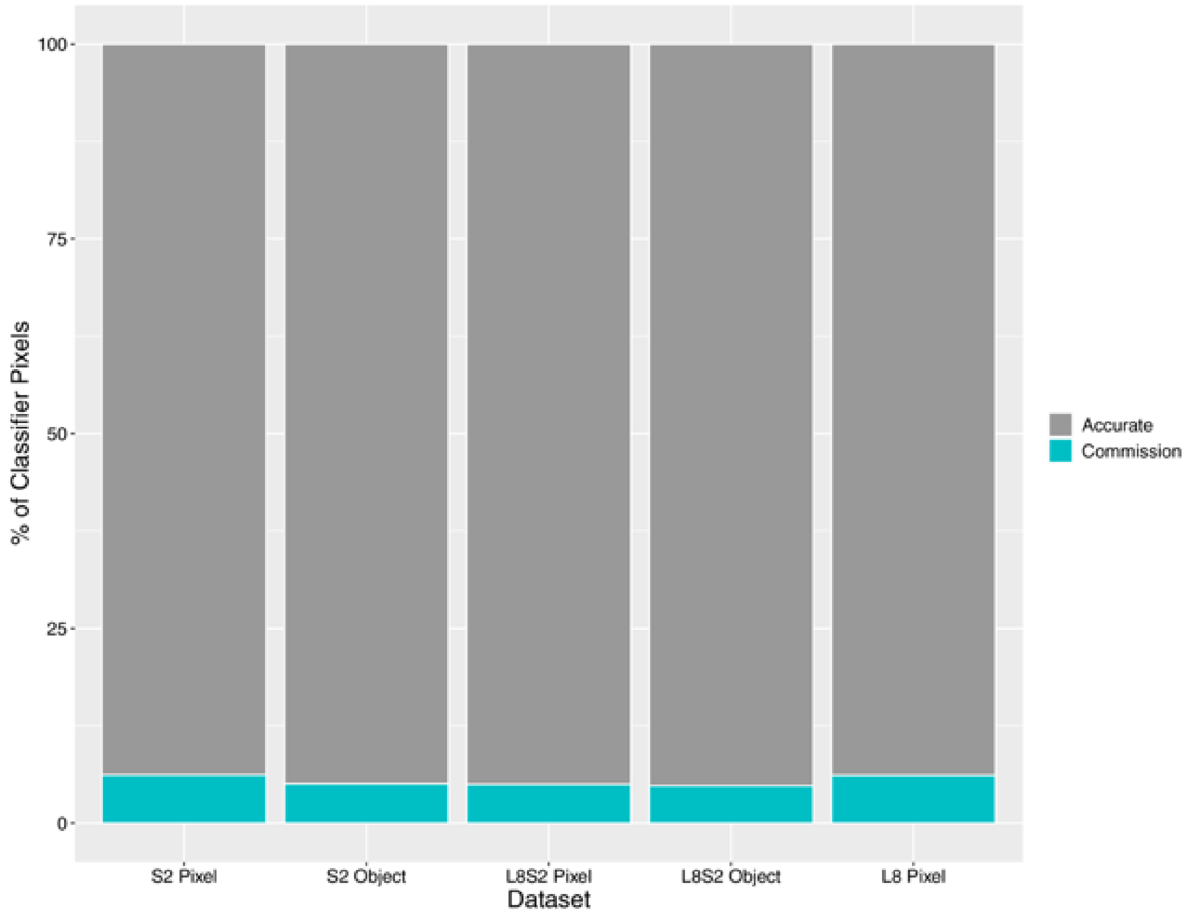

Figure 2. 5: The proportion of commission errors (i.e., proportion of sampling locations without woodlots in them that was classified as containing woodlots) (aqua) and accurate absence (i.e., proportion of locations in the sampling area that did not have hand-digitized woodlots and were not classified as woodlots of woodlots) (grey). Abbreviations: S2 = Sentinel-2, L8S2 = Landsat-8/Sentinel-2, L8 = Landsat-8

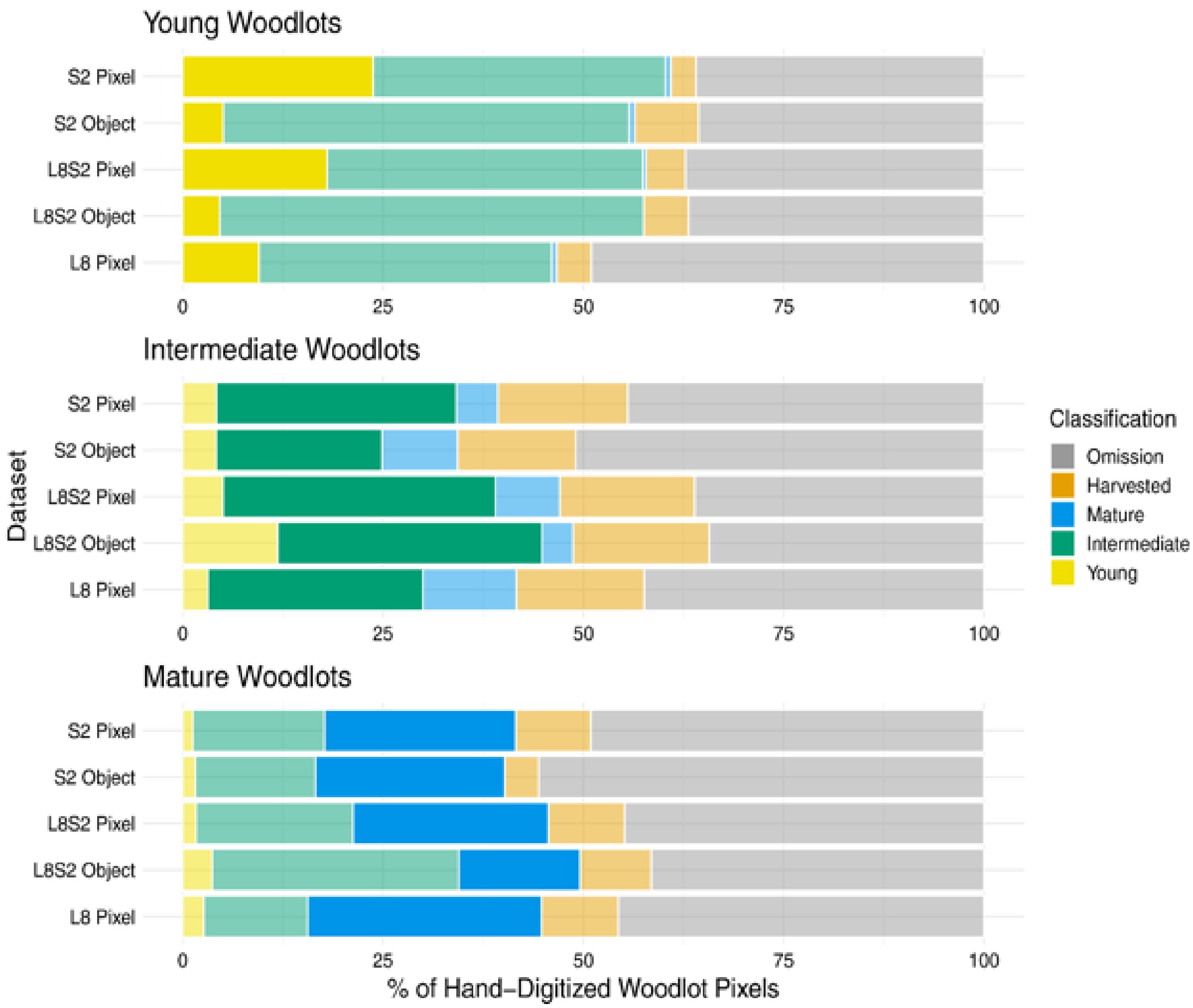

Figure 2. 6: Errors of omission and commission between woodlot age classes (young, intermediate, mature). Each chart shows how the woodlots in that age class were classified by the given map. The first panel shows that young woodlots tend to be assigned to the intermediate and young age classes. The second panel shows that intermediate-aged woodlots are often accurately assigned to the intermediate age class. The third panel shows that mature woodlots tend to be assigned to the mature or intermediate age class. Across age classes, the largest proportion of woodlots are unclassified, and if misclassified they tend to be assigned to the intermediate age category. Abbreviations: S2 = Sentinel-2, L8S2 = Landsat-8/Sentinel-2, L8 = Landsat-8

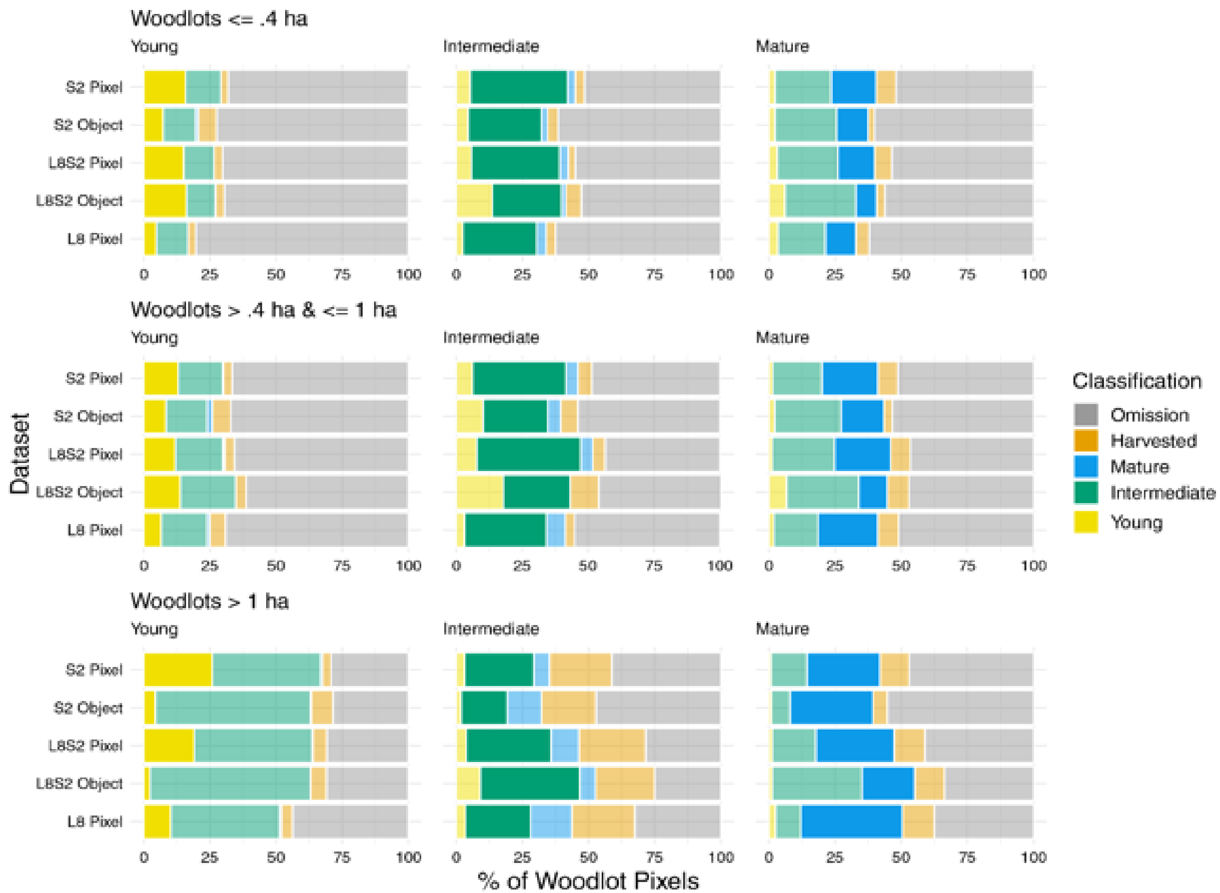

Figure 2. 7: Errors of omission and commission between woodlots of different size classes, given their age. (Top: woodlots < 0.4 Ha, Middle: woodlots 0.4 – 1 Ha, Bottom: woodlots > 1 Ha). The detection patterns are further distinguished by age classes in the vertical columns (Left: young woodlots, Middle: intermediate-age woodlots, Right: mature woodlots) The woodlots with highest omission errors are those that are both young and small (top-left). Abbreviations: S2 = Sentinel-2, L8S2 = Landsat-8/Sentinel-2, L8 = Landsat-8

2.5. Discussion

Our goal was to test whether increased spatial resolution, observation frequency, and an object-oriented classification can improve accuracy and total mapped area of woodlots in southern Tanzania. Across the five maps, woodlots accounted for 20-25% of the overall land cover in our study area, an extent equivalent to that of woodlands and forests. Statistical tests showed that the overall accuracies were not significantly different across the five woodlot maps. However, within-class accuracy metrics showed that woodlots were best detected by an object-based analysis of combined Landsat-8 and Sentinel-2 data. About half of the woodlots were missed by the classifications, particularly if they were both young and small (< 0.4 Ha). Below, we evaluate the three objectives, and discuss implications of our methodology for mapping other fine-scale tree cover.

Increased spatial resolution improved woodlot class accuracy and total area, but not overall accuracy

We expected increased spatial resolution from Landsat-8's 30-m to Sentinel-2's 10-m to improve overall classification results, given the median size of individual woodlots patches (0.4 Ha). In heterogeneous landscapes, imagery with higher spatial resolution should have a lower proportion of mixed pixels compared to imagery of lower spatial resolution, which should theoretically improve classification (Li et al., 2014; Xie et al., 2008). Furthermore, Sentinel-2 imagery is equipped with additional red edge bands, which have been helpful in forest mapping in other studies (Grabska et al., 2019). However, there is no statistically significant difference in overall classification when comparing the lower-resolution Landsat-8 map to the higher resolution Sentinel-2 map. The resolution gain from Landsat-8's 30-m to Sentinel-2's 10-

m was insufficient to improve the overall classification results, most likely because of the very fine-scale nature of the land cover patterns in the region (Carrasco et al., 2019).

Similarly, while the user and producer accuracies for individual classes were slightly different between the Landsat-8 and the Sentinel-2 maps, that difference was not statistically significant for the woodlots class. Surprisingly, the lower-resolution Landsat 8 map had similar accuracy to the Sentinel-2 map. Landsat 8 imagery may have performed just as well for woodlot mapping because some of the woodlots were planted right next to each other (average woodlot separation 66-m see (Kimambo et al., 2020)). Such spatial arrangement may have created contiguous features that were distinct enough for classification with the lower resolution Landsat-8 (Nelson et al., 2009; Ozdogan and Woodcock, 2006).

Finally, the Sentinel-2 woodlot map contained somewhat more woodlot area than the Landsat-8 woodlot map. Area estimates for land cover are sensitive to both the spatial resolution of input imagery and the patch size of the land cover. Coarse-resolution imagery tends to overestimate the area of the large, dominant land cover patches, and underestimate the smaller, rarer land covers (Nelson et al., 2009; Rioux et al., 2019). As a result, there can be a gain in the area of tree cover estimation simply by increasing the spatial resolution, particularly if tree cover is in a small patch that is hard to detect (e.g., in dryland areas (Bastin et al., 2017)). Yet, the area estimate of the fine-scale features are also sensitive to the spatial arrangements of the woodlots. Where the woodlots are clumped together, the increase in area from higher spatial resolution could be less (Wu, 2004). Because of woodlots' small size in our study area, increased spatial resolution of Sentinel-2 may have increased the area estimate of woodlots, but where woodlots are spatially contiguous, the effect of increased spatial resolution would be less.

Woodlots in the study were best detected by the object-based Landsat-8/Sentinel-2 image stack

The combined Landsat-8/Sentinel-2 image stacks had higher accuracy than those produced from either Landsat-8 or Sentinel-2 imagery alone. The object-based Sentinel-2 woodlot map had higher accuracies compared to the pixel-based Sentinel-2 woodlot map. Additionally, the object-based Landsat-8/Sentinel-2 map had the highest woodlot class accuracies. In general, object-based methods tended to improve classification results, especially when the objects of interest can be homogeneous (Li et al., 2014; Ma et al., 2017). Furthermore, our objects had additional attributes that came from generating them at the finer resolution of Sentinel-2, then summarizing the coarser resolution Landsat-8 data into each one, a useful way to use data from two sensors (Zhang, 2010). The objects also allowed for inclusion of spatially varying land cover metrics like texture, object area, and perimeter. For our heterogeneous study area, these metrics may have contributed to improved separability of the woodlot class (Fassnacht et al., 2016).

Woodlots that are young and small are hardest to detect

The characteristics of a target land cover can interact with the resolution of the input image to influence the accuracy of the final map (Ozdogan and Woodcock, 2006; Wu, 2004). In the case of woodlots, age and size are two main attributes that affected how well the woodlots were mapped. Younger woodlots are challenging to map because they resemble grassland, bare land, or annual agricultural land (see S. 2.1 for visual comparison). Small woodlots are challenging to map because the median size of the woodlots is 0.4 Ha, which is equivalent to 4 Landsat-8 pixels. When containing so few pixels, the woodlot patch is susceptible to mixed pixels as information from the surrounding landscape gets mixed into the pixel signal.

Two additional challenges may have limited our analysis of the effect of patch size and age on woodlot detection: 1) varied timing of image acquisition in Google Earth Pro and 2) collapsing of three-year data to one stack in the statistics-based input data. Google Earth Pro imagery comes from different years, and some of the selected study locations had limited quality imagery from our study period. Thus, some of the omission errors observed in our results may have been caused by the lack of the most up-to-date Google Earth Pro imagery.

Our statistics-based input imagery was necessary to overcome cloud cover challenges at the site (Carrasco et al., 2019). Calculating statistics from a three-year window should not affect accuracy of stable classes that did not vary within that time window (e.g., forest, grassland, or a mature woodlots). However, for transition classes such as young woodlots or intermediate-aged woodlots, the computed statistics could have resulted in the misclassification of young and intermediate-aged woodlots as other land covers.

Implications of our study for mapping fine-scale and planted tree cover

Our case study on mapping of African smallholder woodlots reinforces the broader challenges of capturing fine-scale tree cover by demonstrating that the majority of patches of less than half a hectare will be missed. Difficulty in capturing small tree cover patches is a concern given the prevalence of tree cover patches that measure < 1 Ha (Sexton et al., 2016). Sexton et al. (2016)'s study showed that if FAO's definition of 30% tree cover is used to define a forest, most forest patches that meet that criterion are < 0.5 Ha in size. Trees can be found in small patches in a wide range of scenarios, including as remnant habitats that can have ecological importance (Hunter et al., 2017), trees in urban spaces that ameliorate urban heat (Tigges et al., 2013), and in trees in dryland ecosystems (Bastin et al., 2017). Furthermore, with global efforts to plant trees and restore forests, approaches such as ours are needed for mapping emergent, heterogeneous, and fine-scale tree cover, instead of relying on self-reported government statistics, which often overestimate the extent of tree planting (e.g., in China (Ahrends et al., 2017)).

Our findings about the smallholder woodlots mapped in our case study also corroborate a broader trend in plantation extent (Payn et al., 2015). Natural forest extent is decreasing, but plantations are expanding, and in Africa they are expanding in smallholder woodlots (Etongo et al., 2015; Friis-Hansen and Pedersen, 2016; Held et al., 2017; Kimambo et al., 2020; L'Roe and Naughton-Treves, 2016). Yet, global maps of tree cover do not distinguish planted from native tree cover (Brandt et al., 2012; Torbick et al., 2016). As the global community moves forward with policies to combat degradation that are reliant on tree-planting, it is important to be attentive to these ongoing trends, particularly among smallholder landscapes that are challenging to evaluate accurately from global maps.

Our study further showed that accurate quantification of emerging, fine-scale, and planted tree cover is challenging, and can be sensitive to the spatial resolution of the imagery product and analytical approach. Thus, reliance on remote sensing methods for mapping trends in planted tree cover need to be attentive to possible underestimation of woodlots in heterogeneous landscapes. To capture the extant woodlots, Landsat-8 or Sentinel-2 remotely based analysis may need to be supplemented auxiliary datasets. Auxiliary information such as high-resolution imagery interpretation or field-based inventories can augment the assessments from satellite imagery. Reporting the possible confusions and omissions facilitate more robust application of satellite-based maps in smallholder forestry policy.

2.6. Conclusion

Fine-scale tree cover is difficult to map with coarse resolution satellite imagery, and we showed modest gains with Landsat-8 30-m resolution imagery, and Sentinel-2 10-m resolution imagery. We used the rapid emergence of rural smallholder tree planting in some parts of sub-Saharan Africa to test approaches for mapping fine-scale tree cover. We found that analysis of fine-scale tree cover benefits from higher spatial resolution imagery and object-based classification methods. However, even with higher-resolution Sentinel-2 imagery, combined with Landsat-8 imagery, we found that about half of the woodlots were missed, particularly if they were young and small. Our approach has implications for other efforts to quantify tree cover that varies at a fine scale, such as monitoring of global tree planting efforts for restoration.

2.7. Acknowledgements

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Chapter 3: Urbanites participation in rural land sales and woodlot establishment in Tanzania

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3.1.Abstract

30% of sub-Saharan Africa's 1.1 billion citizens live in urban areas. The population is projected to reach 2.5 billion with 60% in urban areas by year 2050. Population growth and urbanization have created high demand for tree products like timber, construction poles, firewood, and charcoal, indirectly driving rural tree cover changes. This chapter explores a heretofore undocumented pathway to rural landscape change associated with urbanization, using a case study of an urban-based association participating in rural woodlot planting in Tanzania. Using a spatially explicit study of the association's land parcels, I traced how the urbanites purchase and manage rural parcels even though they may not have kinship ties in the sites of investment. I also tested whether the parcels belonging to the association members are disproportionately tree-planted using tree cover gain data I generated from LandTrendr. I found that since 2007, individuals in the group (n = 435) have acquired parcels that range in size from 2 HA to 1214 HA, (avg: 45.5 HA; n = 485) in 72 villages across 10 districts. The association members are linked to these rural land parcels via online platforms (e.g., WhatsApp) and nodes of informal intermediary land brokers. These nodes and links enable urbanites to find, purchase, and manage the rural parcels for tree farming. Yet, parcels owned by the association members did not show statistically significant difference in tree cover compared to their surrounding villages (% difference = 0.2%, p-value = 0.4). Site visits suggest that members' parcels may lack tree gain signal partly because some trees are still young, and some parcels

had poor tree growth. Additionally, the urbanites may be simply interested in acquiring the rural parcels as an investment but not farming them. I conclude that land transactions that are enabled by associations and online platforms are creating unusual linkages between African urban investors and rural landscapes.

Keywords

rural-urban linkages; tree planting; land markets; tenure; LandTrendr

3.2.Introduction

East Africa has among the highest present-day urbanization and population growth rates on the planet. The region has urban growth rates of 4-6%per year while the population is growing at 2.3–3.7% per year (The World Bank, 2018; Wolff et al., 2020). Approximately 60% of the population is expected to live in urban areas by 2050 (Guneralp et al., 2017; UN-DESA, 2019).The region's urbanization and population growth is associated with an increase in demand for tree products to meet fuel and construction needs. Thus, the larger, more urban population contributes to both rural forest loss and degradation (Ahrends et al., 2010; DeFries et al., 2010) and rural tree cover gain by stimulating rapid expansion in woodlots (Held et al., 2017; Indufor, 2011; Ngaga, 2011). Though the demands created by urbanization are an important driver of rural tree cover changes (Beltrán, 2019; FDT, 2015; Jenbere et al., 2012), the direct role of East Africa's increasingly urban citizens in rural landscape transformation is less considered. In this chapter, I posit links between urban citizens and rural landscape changes, namely via rural land investment and tree planting.

Rural land use changes in east Africa are generally studied from the point of view of rural households. For example, studies of forest change (Angelsen & Kaimowitz, 1999; Babigumira et al., 2014; Hartter et al., 2011) and rural tree-planting (Beltrán, 2019; FDT, 2015; Hingi, 2018) have focused on the rural household as the unit of analysis and as the presumed agent of change. This assumption that rural households are the main drivers of rural landscape change has persisted even as the region's urbanization increasingly affects the rural landscapes. For example, recent evidence suggests that land ownership patterns in the region are changing. Rural land markets and non-subsistence farmers are emerging (Chimhowu & Woodhouse, 2006; Deininger et al., 2017; Hall et al., 2017; Jayne et al., 2015), which might mean that additional actors are involved in rural land use decisions.

As evidence for increased activity in land markets continues to gather, kinship and other social ties are still assumed to play a critical role in land transactions in sub-Saharan Africa (Hilhorst et al., 2011; Kandel, 2015). The exception to kinship-based land access are land acquisitions by large-scale international actors featured in the 'land grabs' literature, which are facilitated by central governments (e.g., (Atkinson & Owor, 2013; Friis & Reenberg, 2010; Lyons & Westoby, 2014)). Though less visible than large-scale land grabs, purchase of land by local, non-rural actors could have implications for rural landscapes and land ownership (Hilhorst et al., 2011). The land grab literature has pointed to national, non-local investors as major actors, but the key studies are conducted in south Asia (Baird, 2014, but see Olwig et al., 2015 for Tanzanian example). More work is needed to expand extant paradigms for modes of land access in sub-Saharan Africa beyond the 'customary' or 'international land grabs and incorporate the land activities for non-rural but national citizen actors.

Recently, Lusasi et al., (2019) have started to expand the paradigm for land access in the region. They adopted Ribot & Peluso's 'Theory of Access' (Ribot & Peluso, 2009) to more broadly explain the pathways of rural land access in Southern Tanzania by various local actors. They focused on three access mechanisms ('capital', 'social identity' and 'authority'), and used 'social identity' specifically to refer to custom, kinship, or local belonging claims to the land (Lusasi et al., 2019; p. 11-12). The boundaries between those three access mechanisms can be blurry. For example: an urbanite with kinship ties to a rural place can pay relatives to acquire and manage a rural farm (Foeken & Owuor, 2001). However, Lusasi et al., 2019 argue that having capital is the most important access mechanism for urban-based entrepreneurs looking to acquire rural landholdings. How, then, does the urbanite with capital to invest (but not necessarily social identity links) find, purchase, and manage a rural landholding?

This question has started to come up among agricultural policy practitioners in the region. Practitioners interested in sub-Saharan Africa land issues recognize the existence of urban-based entrepreneurial farmers, but grapple with how to reach them (FDT, 2018a; Hall et al., 2017; Lusasi et al., 2019). For example, Forestry Development Trust (FDT), an organization whose goals are to promote forest industry in Tanzania, set an explicit goal of reaching out to urban-based tree planters (FDT, 2018a). The organization's innovation was to recognize that the urbanite farmers rely on online platforms for finding and managing rural tree farms. To that end, then, FDT created *MitiBiashara* (translates as Trees for Business), an online forum where participants view, respond to, and raise topics ranging from land sales to timber species selection. The posts average a thousand view per topic (FDT, 2018b). Such platforms for linking rural lands and urbanite farmers need to be further explored.

After purchasing a rural parcel of land, how does the urban-based landowner secure ownership, manage, and profit from the land? Many turn to planting trees. Planting trees on the land emerges as a low-labor agricultural activity compared to annual crops. After the initial planting and weeding season, the trees require only basic maintenance (e.g., thinning, pruning, fire breaks) (FDT, 2015). Tree-planting also helps the new urban owner secure tenure to the rural parcel by demonstrating that it is in use (Dewees, 1995; Schreiber, 2017). If the parcel is left vacant, the urban-based owner risks a perception that he/she is not 'present'; thus the land could attract squatters or be sold again (Friis-Hansen & Pedersen, 2016; Pedersen, 2017). Finally, because of the high demand for timber, firewood, and poles, the trees are a very high-value crop in the region, which makes the expected return on investment on the land purchase extremely high (Fairbairn, 2014). For these reasons, we could expect lands acquired by urban citizens to be tree-planted.

A landscape full of woodlots could signal presence of urbanite landowners but could also result from rural farmers' responding to urban demand for timber (Indufor, 2011; Kimambo et al., 2020; L'Roe & Naughton-Treves, 2016). Woodlots have been increasing in several sub-Saharan African countries (e.g., Ethiopia, Uganda, Tanzania, and Burkina Faso) but who exactly has planted the observed woodlots is difficult to determine. In Ethiopia, Uganda, and Burkina Faso, it was shown that rural households likely to plant woodlots have more land and more off-farm income than the households without woodlots (Etongo et al., 2015; Jenbere et al., 2012; L'Roe & Naughton-Treves, 2016). In Tanzania, woodlot planters typically planted woodlots in marginal lands (e.g., land that is far from home and with high crop damage risks) and only established woodlots after meeting food needs (Kimambo & Naughton-Treves, 2019). In some ways then, even when we cannot determine whether the woodlot planter is rural-based or urban-based, a woodlot-filled landscape indicates the presence of actors who are not purely subsistence farmers. Still, there is a need to more specifically pinpoint the land users behind the rapid expansion of rural woodlots.

The proliferation of woodlots in East Africa is widely reported (FDT, 2013; Friis-Hansen & Pedersen, 2016; Jenbere et al., 2012; Ngaga, 2011), and with it increased interest in land for growing the woodlots (Friis-Hansen & Pedersen, 2016). However, woodlots are difficult to quantify accurately. Until recently, woodlot estimates came from field-based surveys which consistently underestimated the extent of smallholder woodlots (Jacovelli, 2014; Ngaga, 2011; Said, 2016). Visual interpretation of high-resolution satellite imagery can detect young and small (< 1 Ha) woodlots, but the approach is not feasible for broad-scale studies (Kimambo et al., 2020). Image classification could be used to cover a broader area than visual interpretation, (FDT, 2013; Koskinen et al., 2019), but classifiers miss young and small woodlots (Chapter 2).

For this chapter, I needed a consistent approach for identifying likely woodlots at a broad scale in order to explore links between interests in woodlots and in land acquisitions.

To that end, I turned to LandTrendr – a Landsat-based time-series analysis algorithm (Kennedy et al., 2018). When looking at a dense time-series of satellite images, woodlots have a unique temporal signal. In the study area, a location that goes from a low vegetation land cover to dense trees over a short period (< 6 years) is likely to be a woodlot. If a woodlot is big enough, and frequent imagery observations are available, the temporal changes for every pixel can be charted with LandTrendr. The temporal trends can then be used to flag locations that have likely experienced tree cover gain and are likely to be woodlots (Kennedy et al., 2018). A broad area map of likely woodlots can be paired with information about rural land purchases by non-rural actors to check whether these actors contribute to rural woodlots.

As East African society urbanizes, new connections between urbanites and rural land ownership and management are emerging and some are linked to tree-planting. These changes have implications for our understanding of *who* drives the observed rural land use changes. My goal is to illustrate how urbanization is connected to distant rural land uses, by focusing on the direct involvement of urban dwellers in rural land acquisition and establishment of rural woodlots. Using a case study from an urbanite agricultural association in Tanzania I ask:

1. How do urbanites purchase and manage land in rural areas, including sites where they have no kinship ties?
2. Do parcels owned by urbanite tree planting association members have more trees than neighboring land?

3.3.Methods

Background on Maisha Shamba Association

Maisha Shamba Association (MSA) is composed of 435 urban dwellers primarily living in Dar-es-Salaam, but some members live in other Tanzanian cities and abroad. The association members are interested in garnering income through farming ("Maisha Shamba" is a Kiswahili phrase that translates to "Farm Life"). The main farming activity the association members conduct is tree planting (mostly pine and eucalyptus for timber). The organization started as an informal collective spearheaded by Asifiwe Malila in the early 2000's and grew over the past two decades. Presently, the organization has multiple online forums used for communication, including JamiiForum threads (a popular online open discussion platform in Tanzania), a WhatsApp group, and several Google Group threads. Individuals join the association through three main ways: by knowing the founder (e.g., as a neighbor, from work, from church), by knowing someone who is already in the group, or by following the group discussions on public online forums.

The association started as an informal group that was subsequently registered under the Tanzanian Registrar of Societies in the year 2016 (MSA, 2016). Since the registration, the association has transitioned to elected leadership and holds two meetings per year for all members (MSA, 2016). The role of the association continues to be facilitating land-based investments, connecting urban-based members to rural land managers, and providing means for the members to share management costs between neighboring rural parcels. The interests of the association members are not solely limited to buying land for trees, but sometimes include buying land for other crops and residential development. In other words, the tree-planting activities are part of a broader land-driven investment interest.

MSA is similar in form to other "trees for business" associations that have emerged in the region, and in function to the region's online forums and platforms facilitating land transactions. Other associations in the region that look to trees as means to garner income include Uganda Timber Growers Association (UTGA, 2019) and the Farm Forestry Smallholder Producers Association of Kenya (FF-SPAK, 2017). In function, MSA is also a platform that facilitates urban dwellers to access distant rural lands. These accesses often occur in informal and invisible transactions, but the way they are initiated is becoming increasingly visible via online platforms like MitiBiashara in Tanzania (FDT, 2018b) or JamiiForums (JamiiForums, 2019).

Study area

My study area includes 72 villages in southern and eastern Tanzania where Maisha Shamba Association (hereafter MSA) members have acquired parcels (Figure 3. 1). The southern Tanzania parcels were generally in areas with both historical and contemporary tree planting (Jacovelli, 2014; Kimambo et al., 2020; Ngaga, 2011). The southern Tanzania parcels are in a region that has climatic suitability for trees, and is a top producer of sawn timber in Tanzania (Indufor, 2011). The eastern Tanzania area is closer to the largest city in Tanzania, Dar-es-Salaam (population 4.4 million (National Bureau of Statistics, 2013)) (Figure 3. 1). This area thus experiences agricultural and non-agricultural land market pressure (Briggs, 1991). The rural land uses in the area respond to the demand from the nearby city, including demand for farmland and residential development (Mwamfupe, 1994).

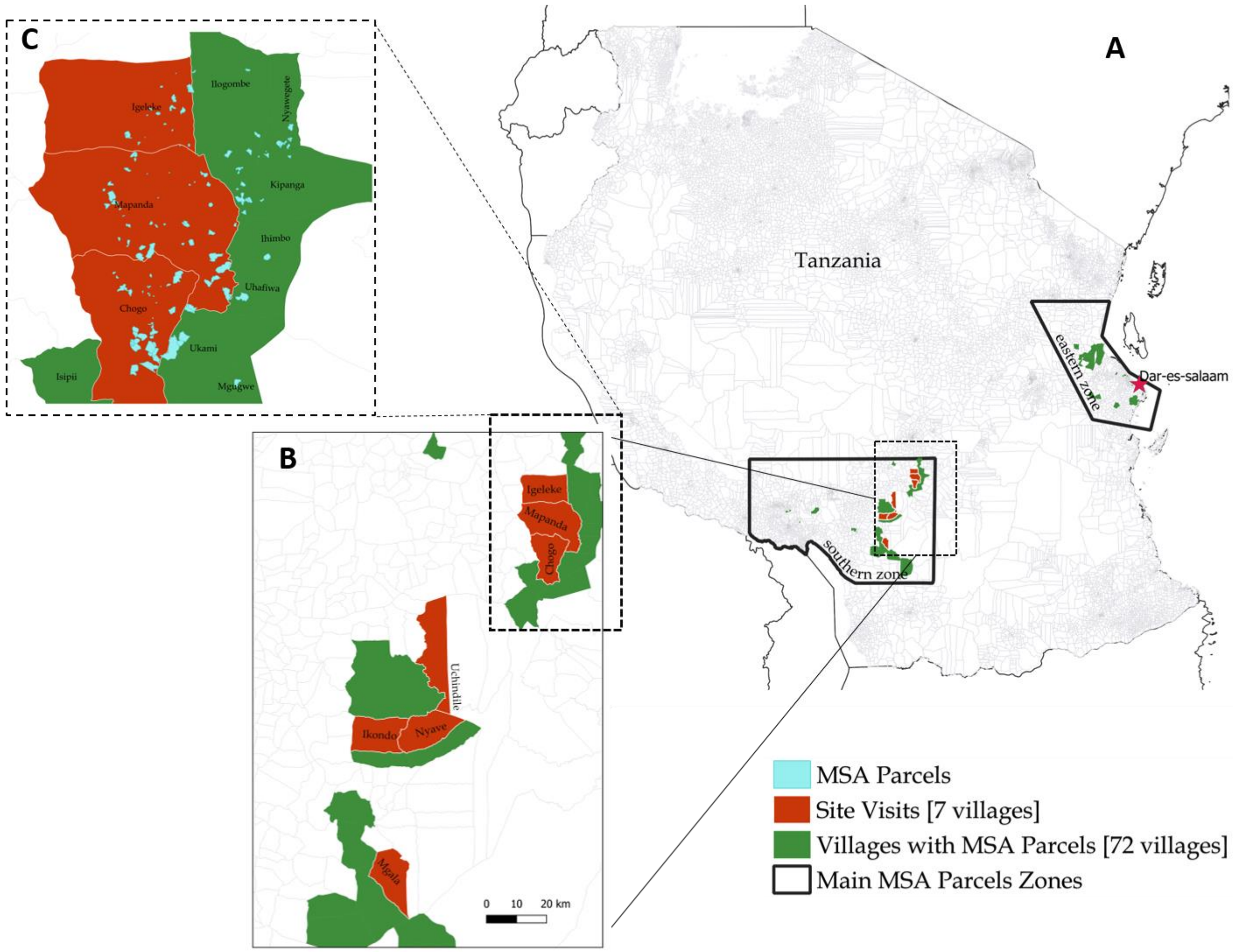

Figure 3. 1: Context and study area map. A) Two zones (eastern and southern) where MSA urbanites, who mostly live in Dar-es-Salaam, have acquired land parcels in rural areas. B) Seven villages visited during site visits. C) Close-up of GPS outlines of parcels purchased by MSA members.

Data Collection

To learn about the process of land acquisition and quantitatively determine if locations with urbanite-based landholdings had more tree-planting compared to the surrounding landscape, I created three datasets: 1) Acquisition, management history, and the location for MSA's parcels; 2) a LandTrendr tree cover gain raster; and 3) validation points for presence/absence of woodlots. The field data collection followed due procedure for ethical research with the UW Madison's Institutional Review Board (IRB) (approval number 2019-436) and Tanzanian Commission of Technology (COSTECH) (permit number 2018-414-NA-2017-257).

1. *Georeferenced locations of MSA farms*

To examine how urbanites obtain and maintain their rural parcels I collected specific information about each geolocated parcel, conducted participant observations, and carried out site visits. First, I started with all available GPS outlines that MSA had collected of members' parcels (n = 485). I then collected acquisition and management information for each parcel from the association leader and the rural-based farm managers. For each available GPS outline, I inquired how the urbanite found out about the land, what processes they used to acquire it, and how the current parcel is used and managed. Second, I conducted online participant observations on two online platforms used by the urbanites (a Google Group and JamiiForum) and in-person observations at an association meeting. On the online platforms and during the in-person observations, I learned from the urbanites' perspective how urbanites join the association, and how they acquire and manage the rural parcels. Finally, I also conducted site visits to 38 MSA members' parcels across seven villages. From the list of the 72 villages that urbanites had invested in, I selected seven of the 72 villages for site visits during the field session in June – August 2019. The villages were selected to cover those that were nearer to town centers with older MSA parcels vs those that were further and with more recently acquired MSA parcels. The visits were in Mufindi District (Chogo, Mapanda, Igeleke) and in Njombe District (Ikondo, Nyave, Mgala), and in Kilombero District (Uchindile) (Figure 3. 1 B). Along with farm visits, I conducted 11 key informant interviews total with rural-based managers of urbanite parcels (n = 8) and rural laborers (n = 3). Together, the parcel census and the participant observations inform the descriptions of the rural land acquisition and management process.

2. *LandTrendr tree cover gain raster*

In Google Earth Engine, I generated a raster layer for tree cover gain based on the LandTrendr algorithm (Kennedy et al., 2018) for tree gain after year 2008. I selected year 2008 as the earliest record of an urbanite parcel purchase through MSA is from year 2007. I used Normalized Difference Vegetation Index (NDVI) as the tree cover indicator and set a tree cover gain threshold between 0.3 and 0.4 units over three years. I customized these parameters for each footprint with visual assessment for whether the tree cover gain corresponded to woodlots visible in Google Earth imagery. I exported LandTrendr output for all the villages that have MSA parcels. I checked for overall accuracy of the raster layer using the validation points below.

3. *Woodlot presence/absence validation points*

Before using the LandTrendr dataset to assess the tree cover proportions for the urbanite-owned parcels, I needed to validate it to determine if the identified tree cover gain was indeed woodlots. I performed the validation in a sub-section of the LandTrendr output, using validation points used in Chapter 2. I also checked the estimates of landscape proportion that is tree-planted for a subset of villages and parcels that were within Chapter 2's extent. Within that subset, I could compare the woodlot map generated with classification results from Chapter 2 to the tree cover gain map generated from LandTrendr.

Objective 1 Analysis: How do urbanites purchase and manage land in rural areas, including sites where they have no kinship ties?

To make land transactions between rural lands and urbanites more legible, I organized the qualitative data from interviews around 'nodes' and 'links' that explain relational aspects of the transaction. I looked for key individuals that were necessary for the transaction to take place (i.e., the nodes), and enabling conditions that uniquely facilitated the transactions (i.e., the links). This categorization allowed me to construct a schematic that illustrates two processes: 1) how a parcel of land passes hands from the rural owner to the urban buyer; and 2) how the rural land parcel is managed or farmed after purchase.

Objective 2 Analysis: Do parcels owned by urbanite tree planting association members have more trees than neighboring land?

To quantitatively determine whether parcels owned by urbanites in MSA were disproportionately covered in trees compared to the surrounding village, I performed the following steps: I calculated the proportion of parcel area that showed tree cover gain from LandTrendr. I obtained village boundaries from Tanzania's 2012 census data (National Bureau of Statistics, 2013). Then, I aggregated all the MSA-owned parcels to village level. If there was more than one MSA parcel in a village, I grouped them into one entry. I removed the areas owned by MSA and calculated the proportion of the remaining village area that showed tree cover gain. Finally, I compared tree cover proportion in the MSA parcels to the tree cover proportion in the surrounding village area. I also separated the MSA parcels that the association leader and rural managers had reported as containing trees from those that did not and compared the proportion of tree cover between the subsets.

3.4.Results

Individual members in MSA (n = 435) have purchased 485 properties totaling 14957 Ha in 72 villages. Properties are owned individually, with 139 members owning multiple parcels (average number of parcels per person = 1.3; average acreage per person = 46.5 Ha, see S 3.1 for ownership distribution across villages). For the individuals in the association that have acquired multiple parcels, their parcels are located in geographically distinct villages, suggesting lack of prior kinship identity across all the areas (See S. 3.1). MSA members have acquired parcels since year 2007. Parcel acquisition peaked at different times across villages, but overall, years 2010, 2011, and 2017 show the most overall parcel acquisitions (See S 3.2). Two-thirds of parcels purchased by the urbanites in MSA are in the southern zone, and the rest are in the eastern zone. The parcels in the southern vs the eastern zones have different characteristics (Table 3. 1). From interviews, rural managers reported that a good parcel, in general, should be near a natural water source and with road access. For MSA members, a parcel located near other MSA parcels is an added advantage as it simplifies management. The key informants reported that the majority of parcels in the southern zone are for tree planting, while the majority of the parcels in the eastern zone were reported to be for other agricultural activities (e.g., aquaculture, beekeeping, cashew farming, banana farming, and rice farming) or for residential uses.

Table 3. 1: Differences in parcel characteristics and their surrounding context between the parcels located in the southern zone and those located in the eastern zone.

	Southern Zone parcels (n = 325)	Eastern Zone parcels (n = 160)	Difference	Statistical Significance (p-value)
Mean parcel area (Ha)	24.8	13.0	11.8	< 0.001
Mean parcel elevation(m)	1517.6	84.5	1433.1	<0.001
Mean population density of village surrounding parcel (n = 72) (people/HA)	0.66	2.4		0.2

I now report 1) how informal brokers and associations facilitate land transactions; 2) how the MSA urbanites manage their rural parcels; and 3) the proportion of tree planting in urban-owned parcels compared to surrounding villages.

How urbanites use informal land brokers and associations to acquire and manage rural land

It is becoming increasingly common to see advertisements for rural land parcels in cities and online suggesting that sales to distant land owners are a growing phenomenon (see Figure 3. 2 to Figure 3. 4). These advertisements can be found on public online forums, in public posters in cities, or in closed online forums (e.g., closed WhatsApp groups or Google Groups). The advertisements are typically either for a specific, presently available parcel (Figure 3. 4), or a more general advertisement of the possibility of rural land ownership for the distant, and often urban owner (Figure 3. 2). Sometimes the advertisements are not for a specific parcels on hand, but about the advertiser’s ability to obtain other parcels of desirable specifications, sometimes even obtain a title deed (Figure 3. 2), and then manage the land on behalf of the new owner (Figure 3. 4 and S. 3.3). In the advertisements, rural lands are positioned as a low-risk investment to anyone who can seize the chance. The new purchaser, often an urbanite, doesn't need to have pre-existing kinship or identity ties to this prospective investment. These examples are particularly noteworthy as they are specific to parcels of land to be used for trees (Figure 3. 2, Figure 3. 3 and Figure 3. 4)

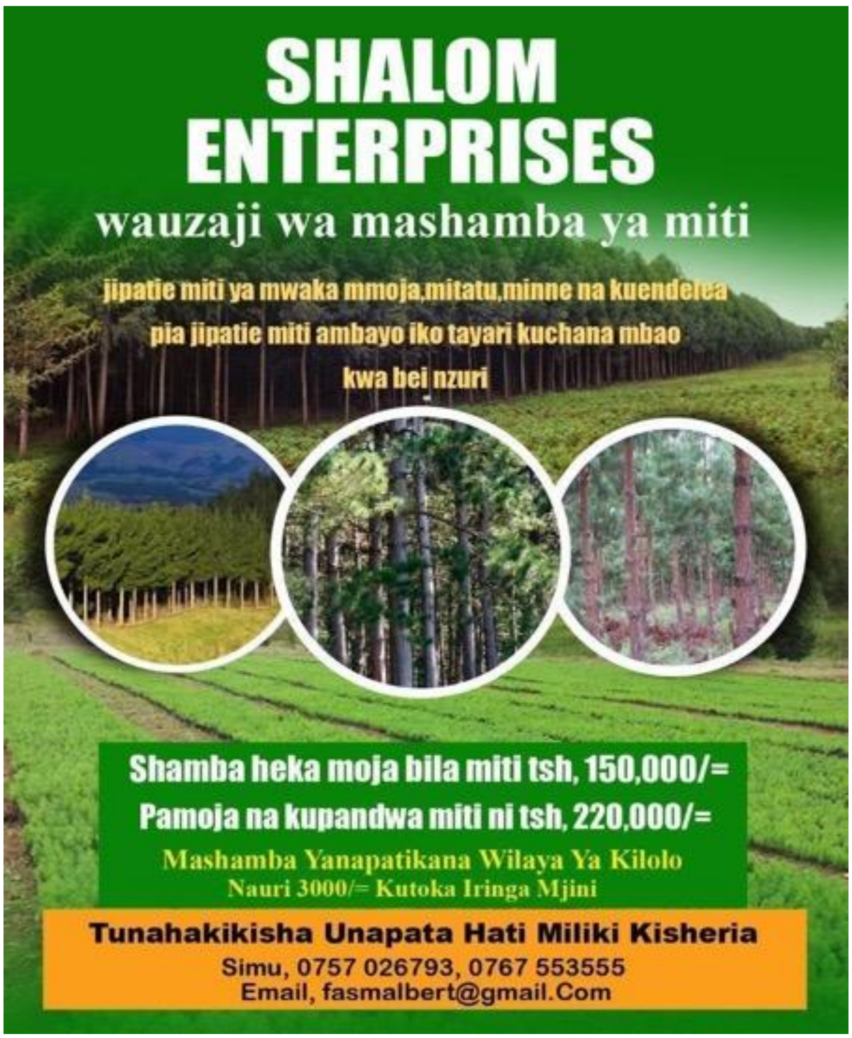

Figure 3. 2: An advertisement directed at urban dwellers promoting rural land sales and tree planting. The advertisement was posted in January 2018 (via Google Group and WhatsApp). The

ad translates to: "**Shalom Enterprises**/Sellers of tree farms/buy for yourself trees aged one, three, or four years and above/ also buy trees ready for timber-harvesting/at a fair price. A farm of one acre without trees is TSH 150,000 (~ USD 65)/ Along with planting trees is 220,000 (~ 95 USD)/ Farms are available in Kilolo district/ Bus fare from Iringa Town is TSH 3000 (1.30 USD)/ We make sure you get a legal title deed. Phone 0757026793, 767553555/ Email fasmalbert@gmail.com.

Figure 3. 3: An advertisement for timber growing as an economic opportunity as seen on a car bumper in downtown Kampala, Uganda. Both advertisements on the car bumper target urban dwellers and highlight availability and profitability of rural parcels for tree farming. Photo credit: L.Naughton.

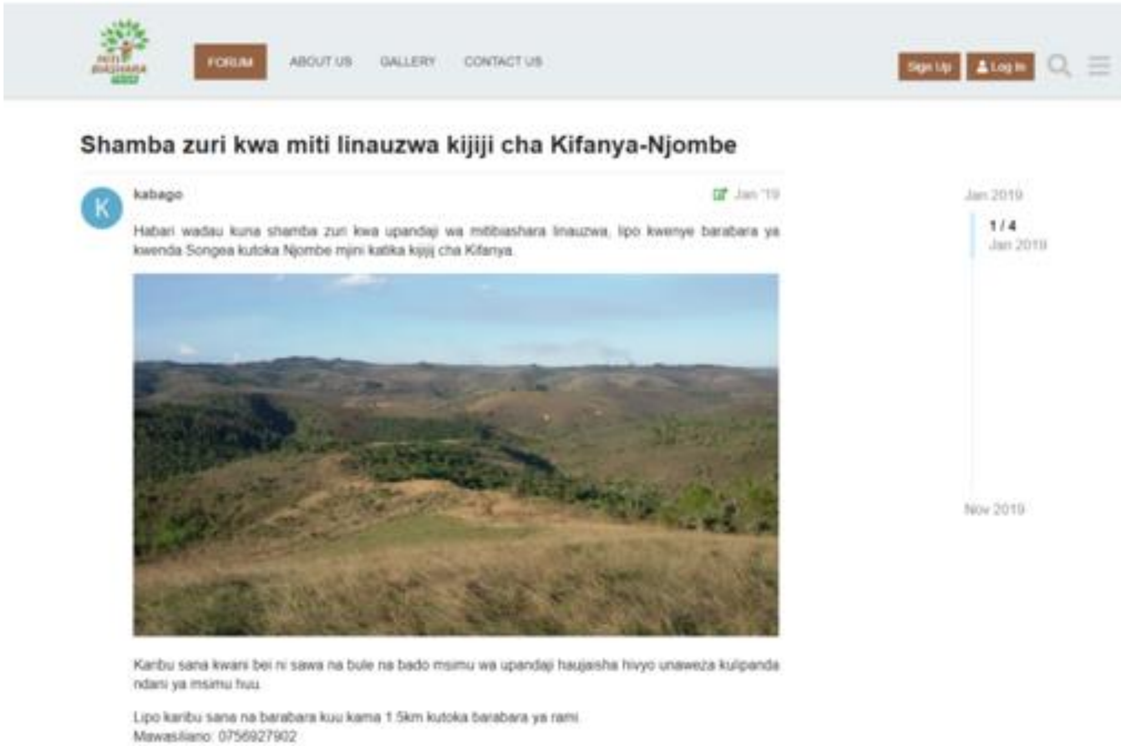

Figure 3. 4: An advertisement for a rural parcel for sale, posted on an online forum, Miti Biashara, by a land broker. Translation for the advertisement: **A good farm for trees is on sale in Kifanya-Njombe Village.** / Hello entrepreneurs there is a good farm for commercial tree planting for sale, it is located along the road to Songea from Njombe Town in Kifanya village/ Picture/ Welcome everyone, since the price is practically free and it is still planting season so you can plant your trees this season / the farm is close to the main road about 1.5 km from a tarmac road / Call 07569227902

Such advertisements present a puzzle, as they are a snapshot of a possible exchange between urban and rural citizens that is not fully visible. The advertisements suggest that the advertisers are individuals with an ability to access rural parcels *and* the ability to reach urban dwellers. Maisha Shamba Association (MSA) allowed me to trace the rest of the transaction process by which urbanites acquire rural land. The schematic (Figure 3. 5) synthesizes how a parcel may go from a rural owner to an urban one.

In the schematic, the individuals who are behind the advertisements above are the central figure, who straddle the rural-urban divide. In MSA, A. Malila, who is the founder, performs that role of the advertiser/broker and links the association members to the rural network. This central figure is further linked to other rural-based middlemen, who can also eventually become a central figure. In other words, the central broker and the middlemen are 'nodes' in the land transaction network, and the online platforms are the 'links.' Thus, information about a land parcel flows from those with primarily rural networks, to those with primarily urban networks via a series of these middlemen brokers. To make a jump from rural to urban areas, there must be the central figure, a node for connecting across rural and urban areas.

From interviews, I learned that both the central and rural-based brokers can become known entities in villages where they have accrued transactions and are sometimes approached with information about parcels for sale. To initiate this process in a new area, however, the brokers would actively scout for new villages by travelling to the area and inquiring about parcels for sale.

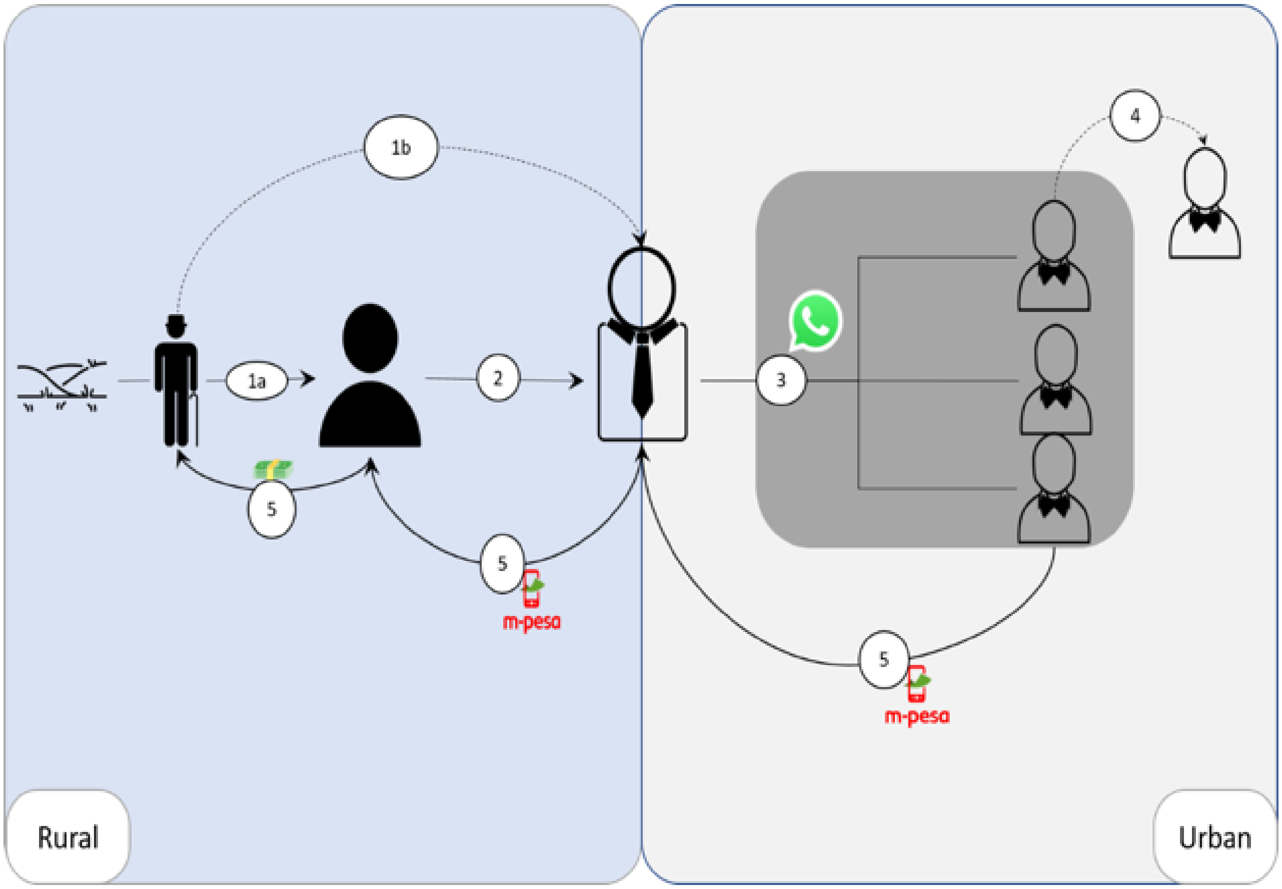

Figure 3. 5: Summary of how an urban dweller with no kinship ties to a specific rural location may gain access to a rural land parcel.

(1a) From the left, the rural landowner is solicited by a rural-based broker to sell the land, or the owner reaches out to the broker expressing interest in selling. (1b) Alternatively, the rural landowner could have reached out to the central broker themselves.

(2) The rural-based broker passes the information to the central broker, the one straddling the rural-urban divide.

(3) The central broker advertises the parcel to urbanites via WhatsApp, Google Group, JamiiForum, MitiBiashara, other public places, or via word of mouth.

(4) If the group is not public, someone outside of the online groups can be told of the availability of the parcel by someone from within the group

(5) The interested urbanite buyer uses cellphone-based money transfer to send money to the central broker, who sends it to the rural intermediary or directly to the rural landowner to purchase the parcel.

Note that these steps may happen without the urbanite ever going to the rural area or meeting the rural seller. Furthermore, the process could start from the urbanite, with the urbanite expressing interest in a parcel, which engages the intermediary brokers to look for it.

The network facilitating parcel acquisition facilitates parcel management and tree-planting

Part of the incentive for the informal brokers to find land for urbanites is the opportunity to benefit from the subsequent farm management process. This is true for the central figures in MSA, who rally the urbanites on the online platforms for subsequent management work. For example, threads in this Google Group are not just about available land for sale, but also about available tree seedlings, funds needed for putting in fire breaks, and payments for work completed in the owners' parcels. Additionally, the rural informal brokers become rural farm supervisors to facilitate the conversion of the purchased parcel to a tree farm. (See S 3.3 for land sales intermediaries' involvement in parcel management). The rural broker-turned-supervisor finds a group of locals (often young men) who prepare the tree nurseries, dig planting holes, create a fire break, and plant the trees (Figure 3. 6). The central broker can continue to be involved in the management process by receiving money for farm management, and coordinating labor activities between neighboring parcels, and sending updates to urban owners from field visits.

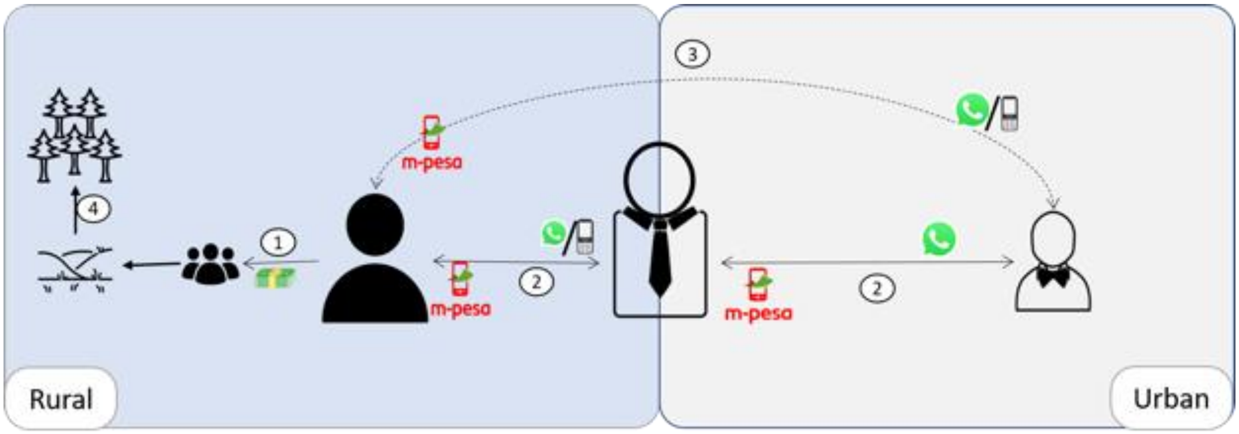

Figure 3. 6: Part of the network that facilitated acquisition of the rural parcel is used to manage the parcel. Following the numbered arrows:

(1) A new node in the rural-urban network is the addition of rural-based laborers who are hired by the rural broker-turned-supervisor to do the farm work on the parcel

(2) The urban dweller pays for the work by sending money to the central broker, who sends it to the rural supervisor. In turn, the rural supervisor and the central broker provide the central broker with pictures and updates for the progress of the work via WhatsApp/phone calls. The central broker relays this information to the urbanite

(3) The urbanite may also exchange money and information directly with the rural supervisor, skipping the central broker.

(4) These activities ultimately convert the purchased rural parcel to a tree farm

Urbanite-owned landholdings do not have more tree cover compared to surrounding villages

I checked the accuracy of the LandTrendr raster layer before using it to compare tree cover between urbanite landholdings and the surrounding villages. The LandTrendr raster had 64% overall accuracy, and generally under-captured locations that had experienced tree-planting. At a village level, LandTrendr estimated 0 – 13% of the village area as experiencing tree cover gain, while at an urbanite parcel level, the estimate was 0 – 89%. Comparing a smaller sample that fully overlapped with Chapter 2’s classification area, LandTrendr seems to be underestimating the potential woodlot extent (Table 3.2).

Table 3. 2: Comparison of the proportion of the village area and the MSA parcels that is tree-planted between the LandTrendr output and imagery classification output from Ch. 2

Village Name	Woodlot proportion in village from Landsat classification (%)	Tree gain proportion in village from LandTrendr (%)	Proportion Woodlot in Urbanites' farms from Landsat Classification (%)	Tree gain proportion in Urbanite's farms from LandTrendr (%)
Ihanu	14.5	0.8	21.0	16.6
Mpanga	8.3	0.9	3.3	0.8
Mapanda	19.3	3.0	31.2	0.7
Kibengu	12.9	5.4	41.0	10.0
Rungemba	1.4	4.0	5.1	3.4
Kiyowela	8.0	3.6	0.1	0.0
Uchindile	6.3	5.5	1.0	1.1

I proceeded with the LandTrendr output to analyze all the MSA parcels. I summarized the urbanite-owned parcels at a village level to compare the proportion of the area that is tree-planted in the parcels compared to the surrounding village (Figure 3. 7). In some areas, the urbanite parcels have proportionally more trees than the surrounding village (e.g., in Kihesa Mgagao, Wangama, and Mapanda). In other villages, the urbanite parcels have fewer trees, particularly where the urbanites’ total land area is large (e.g., Chogo, Nyave).

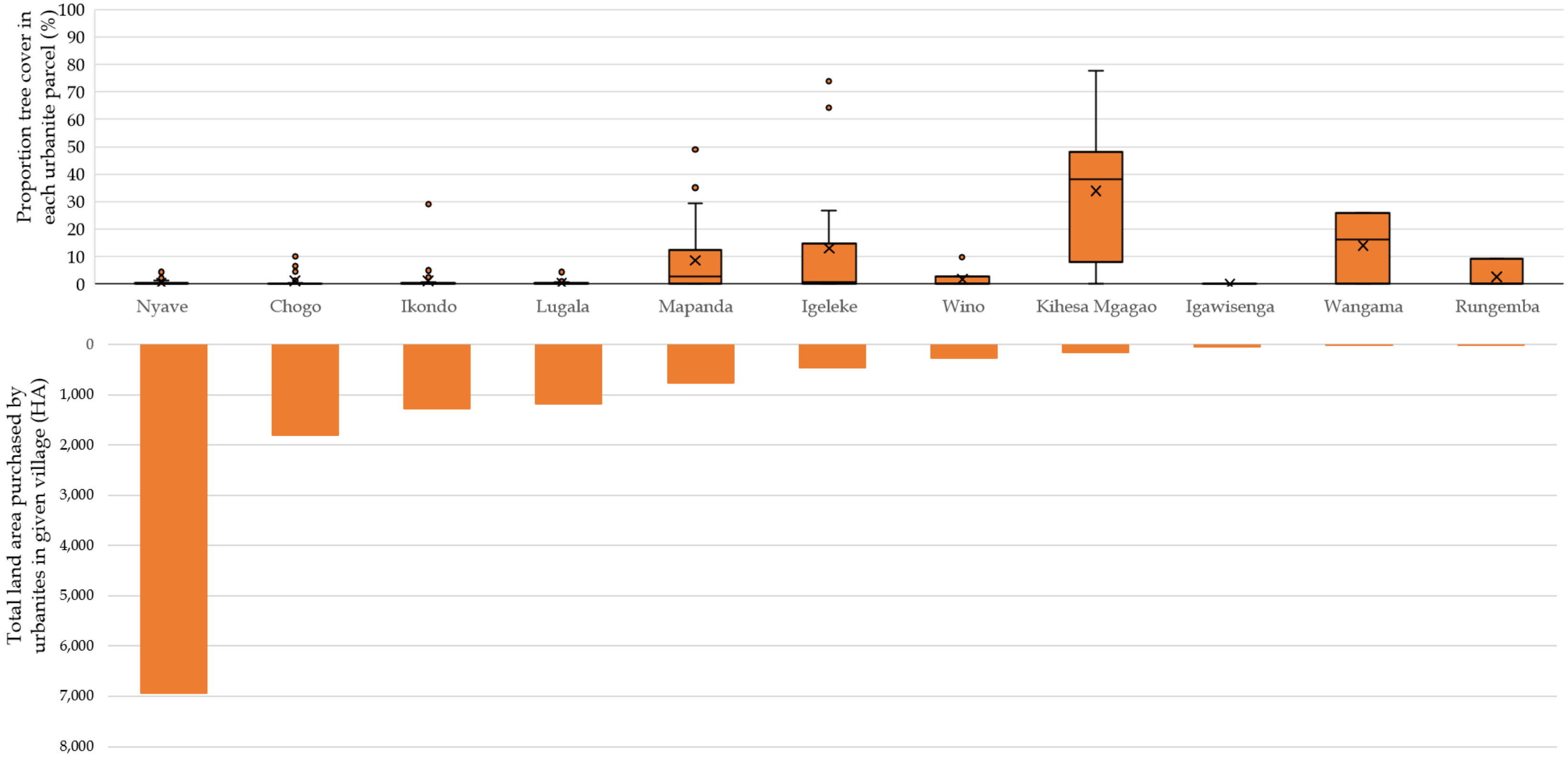

Figure 3. 7: Amount of land purchased in a village (bottom chart) compared to the proportion of urbanite parcels in that village that are registered as planted with trees in LandTrendr (top box and whisker chart). Larger land purchases, like Nyave, show smaller proportion of tree planting, while smaller parcel purchases, like in Kihesa Mgagao, show more tree planting.

A paired comparison of the overall proportion of land area that is planted with trees at a village level shows that the urbanite-owned parcels are not significantly different from their surrounding landscape (Tree-planted area in urbanite parcels = 2.3%; Tree-planted area in surrounding village = 2.1%, p-value = 0.4). The difference in the proportion of land area that is tree-planted remains not statistically significant even when I looked at parcels that are only in the Southern Zone, or parcels that are reported as fully tree-planted (Table 3. 3).

Table 3. 3: Paired two sample for means t-tests for the proportion of planted tree area in the urbanite owned parcels and in the surrounding villages. The parcels are aggregated to village level.

	Tree-planted area in all urbanite parcels (Surrounding Village) (%)	Tree-planted area in urbanite parcels in the Southern Zone (Surrounding Village) (%)	Tree-planted area in Fully Tree-planted Parcels (Surrounding Village) (%)
Mean	2.2 (2.1)	3.4 (2.8)	3.5 (3.3)
Variance	30.0 (7.9)	44.3 (9.3)	51.5 (11.4)
Observations	72	45.0	33
Pearson Correlation	0.2	0.3	0.2
Hypothesized Mean Difference	0.0	0.0	0.0
df	71.0	44.0	32.0
t Stat	0.2	0.7	0.2
P(T<=t) one-tail	0.4	0.2	0.4
t Critical one-tail	1.7	1.7	1.7
P(T<=t) two-tail	0.8	0.5	0.9
t Critical two-tail	2.0	2.0	2.0

3.5.Discussion

Associations and online platforms facilitate rural-urban land transactions

The main contribution of this chapter is tracing how urban citizens in MSA were able to gain land in rural places, often where they have no kinship ties. Although I didn't seek to evaluate socioeconomic outcomes, associations like MSA can have substantial impact. For example, in Nyave and Ikondo villages, the association has purchased 6938 Ha and 1271 Ha of land, respectively. The members, for better or worse, are also driving the formalization of land claims in these two villages as they register the areas they have purchased. These land transactions were enabled and strengthened by 21st century communication platforms, such as advertising and communicating online and instantly transferring money with mobile phones.

Having embraced the use of these platforms, this group of urbanites and others are forging various linkages that may not always be visible to policy makers or scholars. In this case, the enabling platforms and money-sharing networks are allowing urbanites to use the capital for rural land acquisition. For example, during one site visit I observed one rural farm manager as he paused to take several pictures of ongoing farm preparation for tree-planting (Figure 3. 8). He immediately shared the pictures to a WhatsApp group as evidence of progress. He then quickly followed the pictures with a WhatsApp text to remind the other farm owners to keep up with sending money, via mobile money, in order to prevent work in their parcels from stalling.

Figure 3. 8: A picture sent to urbanite MSA member of farm preparation for tree-planting. Note the older tree farms in the background and the cut tree in the foreground, which is a result of this parcel experiencing a fire in a previous season, thus necessitating the re-planting.

MSA is not an anomaly, but a group whose activities are indicative of African urbanites' involvement in agriculture (Hall et al., 2017; Jayne et al., 2016). Since this group is organized, it makes for an easier case study of linkages. Another analogous urbanite tree farming group exists in Uganda, where a European Union grant for sawlog production (EU, 2015) was available to urban farmers who were able to co-finance the tree planting (Jacovelli, 2009). Further evidence for the importance of urban-based farmers comes from studies that show an increase in medium-scale farms, and some of their owners are urban dwellers (Jayne et al., 2016). These factors, combined with increased land transactions (Hilhorst et al., 2011) and increasing land prices (Wineman & Jayne, 2017), make the land acquisitions and management activities of MSA worth examining.

A main limitation of this study is that it did not systematically study the motivations and experiences of the rural-based individuals selling their land, nor those of the urban-based individuals buying land via MSA. Instead, I focused on the entrepreneurial individuals connecting those two groups, including MSA leaders, the brokers, and the land managers. That said, these individuals that straddle the rural-urban divide, like the association leader, the online advertisers, and the rural managers play an outsized role in pushing the rural-urban land transactions.

The MSA case study showed that the intermediaries benefit not from the land sale itself, but from participating in the subsequent management of the parcel. The brokers can sell tree seedlings, charge for recruiting and supervising rural labor, and get a stipend for a parcel visit. For this reason, the land brokers have an interest to facilitate land sales because it may create further work and income for them. An unpublished survey conducted by FDT of tree nursery growers in Iringa Town also showed that these individuals also serve as land brokers (S. Milledge, personal communication, July 24, 2019) and extension service consultants to tree farmers (Hingi, 2018). Facilitating the sale of land then, is part of a broader livelihood strategy for the broker, with the land sale itself being a small component.

In terms of land access mechanisms, I argue that the brokers observed in this study may depart from what Lusasi et al., (2019) proposed. In their adaptation of Peluso & Ribot's framework, Lusasi et al., (2019) suggested that eventually, capital as an access mechanism must be mediated by social identity. In other words, the urbanites that buy land in rural areas would have to find someone with social ties in the rural areas, who will help them with the land acquisition. The MSA case study shows how at least some urban residents can acquire land without having kindship ties or certain social identities. Social identity may be important in one-on-one cases, or in helping brokers initialize transactions in a new village. Eventually, the brokers may have built informal reputations that function as their social identity capital.

Invisible trees, invisible tree planters

The MSA is certainly shaping land transactions and ownership in a novel way and one that can be prominent in some areas. The new links include rewriting rural land ownership. But is it changing land use? It is evident from advertisements and forum discussions that the parcels on offer in southern Tanzania are intended for tree-planting. A surprising finding for this study was the limited tree cover gain even in parcels that were supposed to be fully tree-planted. This surprise finding could be for two related reasons – the limits of the LandTrendr and remote sensing methods in general to detect woodlots, and the ability of MSA urban farmers to manage their tree parcels well.

Quantifying woodlots in satellite imagery is challenging, particularly if the woodlots are young and small (Chapter 2). This challenge is exacerbated by the management of MSA-owned tree parcels. In site visits and in select visual interpretation of the parcels, the parcels are not well-managed to yield uniform tree cover that would be detectable via remote sensing. Some parcels are only planted in small segments, or too sparse, or too young. For example, the parcel whose outline and picture are shown below is a 46 Ha parcel that was planted with pine in November 2016. However, available Google Earth imagery (Figure 3. 9 A) Sentinel-2 imagery (Figure 3. 9 B), or the LandTrendr algorithm (Figure 3. 9 C) are unable to show the tree planting. During a site visit on 20/July/2019, the 3-year old trees, though present in the parcel were present but hard to discern from the surrounding shrubs (Figure 3. 9 D).

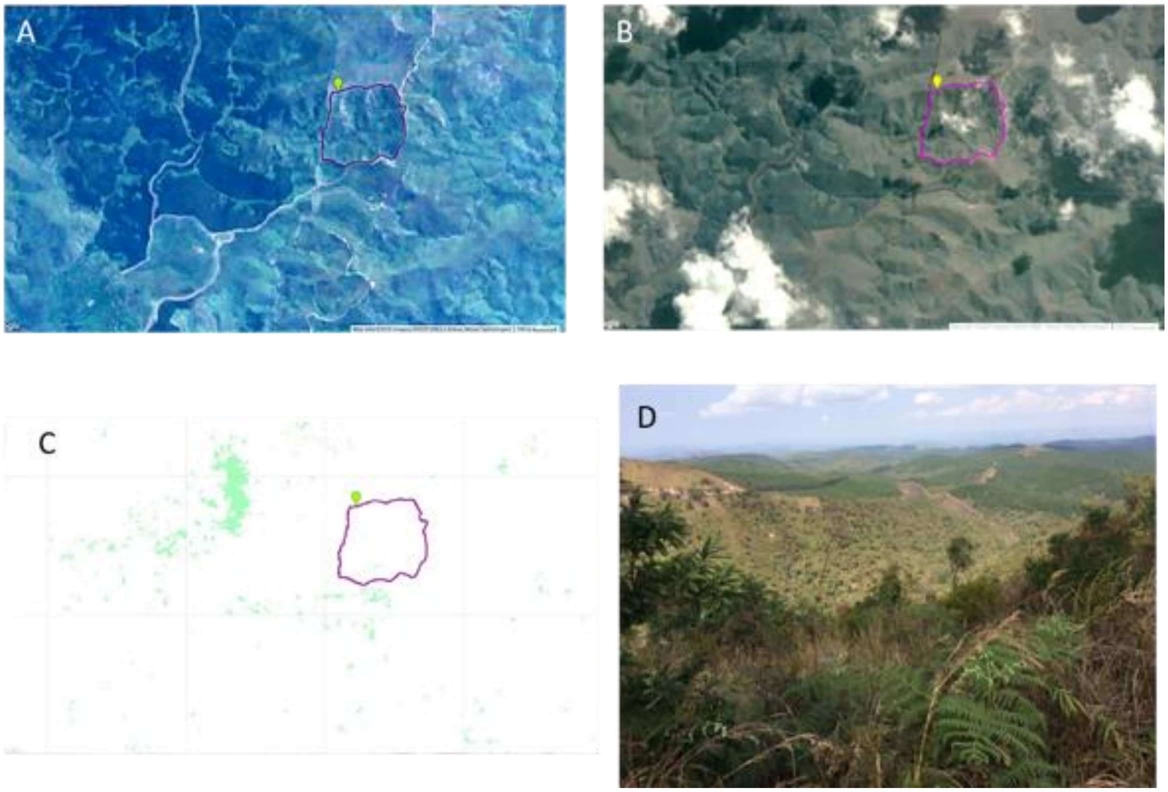

Figure 3. 9: Dual challenges of limited detectability of the planted trees in MSA parcels and poor management of the owners. The pictured parcel is fully tree-planted with pine, but the trees are hard to discern in imagery because they are mixed in with shrubs.

Even though this analysis of MSA's parcels did not show its members contributing to a more treed landscape as yet, other studies have documented urban-based tree planters playing a significant role in woodlot expansion in Southern Tanzania (FDT, 2018a; Friis-Hansen & Pedersen, 2016; Lusasi et al., 2019). Forestry Development Trust (FDT) conducted a representative field survey of woodlot-owning households in tree-planting districts of Tanzania (FDT, 2015). They found that at an average of 2 HA (range: 0.3 Ha to 5.6Ha) per household, at an estimated grower population of 60,000 rural households, the rural households can account for less than half of the observed woodlots in the surveyed districts (FDT, 2015, 2013). However, quantifying the total contribution of other possible tree planters is challenging, even when the outcome of tree planting can be observed (e.g., in satellite images or via site visits). Unfortunately, it is hard to make a complete census of which woodlots belong to which actors solely from observing the tree gain outcome.

3.6.Conclusion

Understanding MSA activities contributes to a broader challenge of studying drivers of changing land use in sub-Saharan Africa. This study focused on how urban actors access and change rural lands. Whereas one extreme of the rural land access paradigm limits land ownership to kinship ties, the other extreme views all the rural land acquisitions as violent dispossessions. The latter has gained prominence in the 'land grabs' studies, acknowledging the power imbalance between multinational companies and poor rural farmers who are getting dispossessed of their land. This study elucidates an additional rural land access and management pathway for local citizens that have no personal links to those rural areas. The citizens access rural land using capital and mediated rural-urban networks. Value judgements about the equity of these land acquisitions aside, they are emerging and need to be considered for their role in transforming rural landscapes.

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Conclusion: Summary for Policy Makers

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WOODLOTS

In Brief

Overview

Trees are in high demand in Tanzania where firewood and charcoal remain the primary source of fuel. Population growth and rapid urbanization have further increased the demand for timber for construction, as have electrification programs reliant on trees for electric poles. Tanzania alone is predicted to have a timber deficit of 2.7 million cubic meters by year 2025[1]. Government plantations and company-owned plantations used to meet these tree needs, but adjustments in resource management policies have diminished their role. Paired with dwindling supply from natural forests, woodlots of pine and eucalyptus have emerged to fill the gap in supply. As such, monoculture exotic woodlots are likely to account for much of the region's tree cover gain.

Who is planting woodlots?

Rural smallholders have long-established tree woodlots for firewood and cash. Woodlots are now becoming an attractive activity for non-rural citizens. Urban-based entrepreneurs have begun to partake in rural woodlot establishment by acquiring land in rural areas and planting it with trees. The full contribution of urban-based woodlot planters has not yet been quantified. However, urbanites are strongly altering rural land ownership and use patterns in the villages in which they have purchased land (Table 1). Policies on woodlots need to distinguish these two sets of actors.

Why do woodlots matter?

Rural smallholders and non-rural citizens gain valuable income from woodlots. Woodlots are also the way Tanzania and her neighbors are projected to meet most of their timber needs. In the year 2018, planted trees covered up to 1.2% (233,765Ha) of the Southern Highlands. Small woodlots (< 1Ha) accounted for half of this planted tree cover, an extent that is equivalent to the combined known extent of government and company-owned plantations. These smallholder woodlots have been planted much more recently: 54% were planted between 2012 and 2015[2]. The woodlots are afforesting and reforesting landscapes, but with monocultures of pine and eucalyptus.

Box 1: Highlights

- Woodlots in Tanzania have expanded recently in pine and eucalyptus monocultures
- Rural households and urban-based citizens are both involved in planting rural woodlots
- The woodlots have expanded independent of Tanzania's ambitious 5.2M Ha restoration pledge
- If the restoration pledge will be met by exotic tree-planting, smallholders should benefit first

Table 1: Acreage of land owned by one group of urbanites. The table shows the top ten villages (out of 72) where the urbanite association has purchased the most land. Some of the land purchased for tree-planting is yet to be cultivated. However, the urbanites have altered land ownership patterns in these villages.

Village Name	Total Urbanite-Owned Area (Acres)	Number of Association Members
Nyave	17144	111
Chogo	4470	47
Ikondo	3142	45
Ukami	2302	22
Uchindile	1910	34
Mapanda	1883	42
Kipanga	1198	26
Igeleke	1130	18
Wino	667	10
Mgala	638	10

Woodlots and restoration

Tanzania, like other East African countries, has set an ambitious 5.2M Ha restoration goal to mitigate climate change, reduce forest loss, and combat land degradation. At the same time, her smallholders are playing a key role in provisioning tree products from their woodlots. Whereas smallholder monocultures of pine and eucalyptus are not ecologically equivalent to native forests, they have two roles in restoration. 1)In select cases, woodlots could be a step towards fostering native regeneration[4]. 2) If Tanzania formulates a restoration plan to include extensive monoculture tree planting, then these extant tree planting activities – by rural and non-rural actors – need to be considered.

To include rural woodlot planters, funds can be directed towards supporting longer rotations or to subsidize fast-growing and ecologically beneficial seedlings. Reaching thousands of rural smallholders may pose logistical challenges, but village-level tree planting cooperatives can facilitate coordination.

Including urban-based actors must be done carefully. On one hand, subsidies to establish and maintain rural woodlots could result in bigger, better-managed woodlots, as it did in Uganda [3]. However, such actors may accelerate rural land rush and pose rural/urban equity concerns. Supporting urban-based actors will need to be paired with strong safeguards and land use planning at the village-level.

In addition to directly funding tree planters, some restoration funds can be directed to researching whether woodlots contribute to ecological outcomes indirectly by taking pressure off native forests.

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Supplemental Information

S 1. 1: Detailed protocol for woodlot digitization and age class assignment, with pictorial examples.

Goal: To delineate all the woodlot **PARCELS** within randomly sampled locations (circles)

Why:

1. To get a sense of the age and area composition of tree planting in the region
2. To obtain a sample of woodlots that can be used for ground-truth of classified imagery

What you need:

1. Google Earth Pro (https://www.google.com/earth/desktop/)
2. KMZ file indicating random locations to be digitized

BEWARE!

Google Earth Pro is a heavy and clunky application, prone to frequent crashes and loss of work. Please, please, please: **SAVE** your work at least **EVERY 15 minutes** and in multiple places.

Here is how to save your work:

1. Right-click your My Places folder and email it to yourself
2. Right-click your working folder and click "Save-As" and save it to a folder that is backed up in the cloud. Change the file name extension to add a time-stamp (that way you don't overwrite previous files)

Step-by-step instructions:

1. Work one quarter of the circle at a time, to make sure you are not missing anything
2. Draw linear sections in the quarter of the circle, to guide your eyes and to work in a smaller sub-section
    a. Draw the parcel boundary

- In the attributes box, write out the characteristics of the parcel, following this formula:
  (Adhere to this formula for labelling attributes so to minimize data cleanup later on. Note that there is a comma and then a space (,) which will be used as delimiters to split the text later on so it needs to be exact.)

  NAME, SECTIONNUMBER, AGENUMBER, IMAGEDATE

  NAME --> the tree type, (eg: Pine, eucalyptus) if known. If unknown, distinguish the trees by labelling "darkwoodlot" and "lightwoodlot" is helpful. No spaces in the name.
  SECTIONNUMBER --> This is the number of the circle section the woodlot falls in: eg "36S_9"
  AGENUMBER --> This is an age-class density measure, on a scale of 1-5. 1 is very sparse, very young woodlots. 5 is very old, mature woodlots. See examples in the pictures below
  IMAGEDATE --> This is the date the image was acquired. You can access this date using the time machine feature. Write the date consistently using this format: DD/MM/YYYY

  Flagging strange parcels: Put an asterisk (*) at the end of the name to indicate a parcel that needs reviewing.

- Save the parcel
- Find the next parcel and repeat

Definitions:

What exactly is a woodlot Parcel?

An area with UNIFORM planted trees.

- If two tree farms are adjacent to each other, one younger, one older, they are two different parcels.
- If two tree farms are separated by a fallow area, a farm, or a shruby region, they are two different parcels
- If two tree farms are separated by a fire break or a path, they are two different parcels

Here are two examples of parcels: On the left, are parcels separated by other land uses, and on the right parcels separated by fire breaks.

Why does a parcel have to be uniform?

We would like to infer the different types of tree planters (eg: smallholders, medium-holders, institutional) based on their landscape signatures (parcel size, total area covered in planted trees, concentration etc). We make an assumption that if the planted trees are uniform, they represent one unique actor. Granted, one person may plant several adjacent plots in phases (We do know this to be true, in fact). However, it is less likely for multiple different actors to all plant at the same time, with same spacing and same lines to give trees so uniform it looks like one parcel. So yes: we are probably over-estimating unique actors, but by mapping uniform parcels we will overestimate consistently.

Secondly, this dataset will be used as a training and as a validation dataset for remote sensing analysis. Since computers get confused if you give them heterogeneous inputs, we need the parcels to be neatly uniform.

What if there are no high-resolution images in a section of the image?

Draw a polygon in the area.
Place it in the "OTHER" folder.
Label the polygon as you would a woodlot, but in the NAME section write NODATA.

What if there are no woodlots (any tree parcels) in the area?

Then label the dominant/interesting land covers. In the shared folder, there is a KMZ. file that shows the land cover classes common in the region, and their examples.

Draw a polygon on the land cover.
Place it in the OTHER folder.
Label the polygon as you would a woodlot, but in the NAME section, write the name of the landcover (eg: Woodland, Urban/Bare Earth, Dense Forest, Water, Annual Agriculture, Shrubland, Bamboo, Tea).

What do I do with Orchids, coconut trees, banana trees, and other mysterious planted-like, tree-like parcels?
Label the polygon as you would a woodlot, but in the NAME section, write the name of the landcover (eg: Banana, Mangoes, Coconuts, orchid… if you can tell. Otherwise call it UNKNOWN with an asterisk at the end for future review).

How do I know that the trees are a woodlot, and not a forest?
Woodlots look darker in google Earth.
Woodlots have regular boundaries (sharp corners).
Woodlots often have a texture that suggests the trees were planted in lines.
Woodlots "appear" in the landscape, where there were no trees before (see picture below).

Year	Image	Age class
2008		1
2013		2-3
2017		3-4

S 1. 2: Replication R code for bootstrapping mean woodlot area extent

```
if (!require("boot")) {
  install.packages("boot")
  stopifnot(require("boot"))
}

# SET WORKING DIRECTORY FIRST

setwd("") # Provide a path to your working directory here

# Define your single-column dataset whose mean you want to obtain via a
bootstrap #

data <- # Provide path to your data here

# create a function that samples your data and obtains a mean value of the
sample
Bmean <- function(data, i) {
             d <- data[i] # allows boot to select sample
         return(mean(d))
    }

# bootstrapping: sample the data 2000 times, calculating the mean each time
results <- boot(data, statistic=Bmean, R=2000)

# view results
results
plot(results)

# get 95% confidence interval using your boostrap, which has 2000 samples
now

confint<- boot.ci(results, type=c("norm", "basic", "perc", "bca"))

(confint)

bootmatrix <-results$t
(bootmatrix)
```

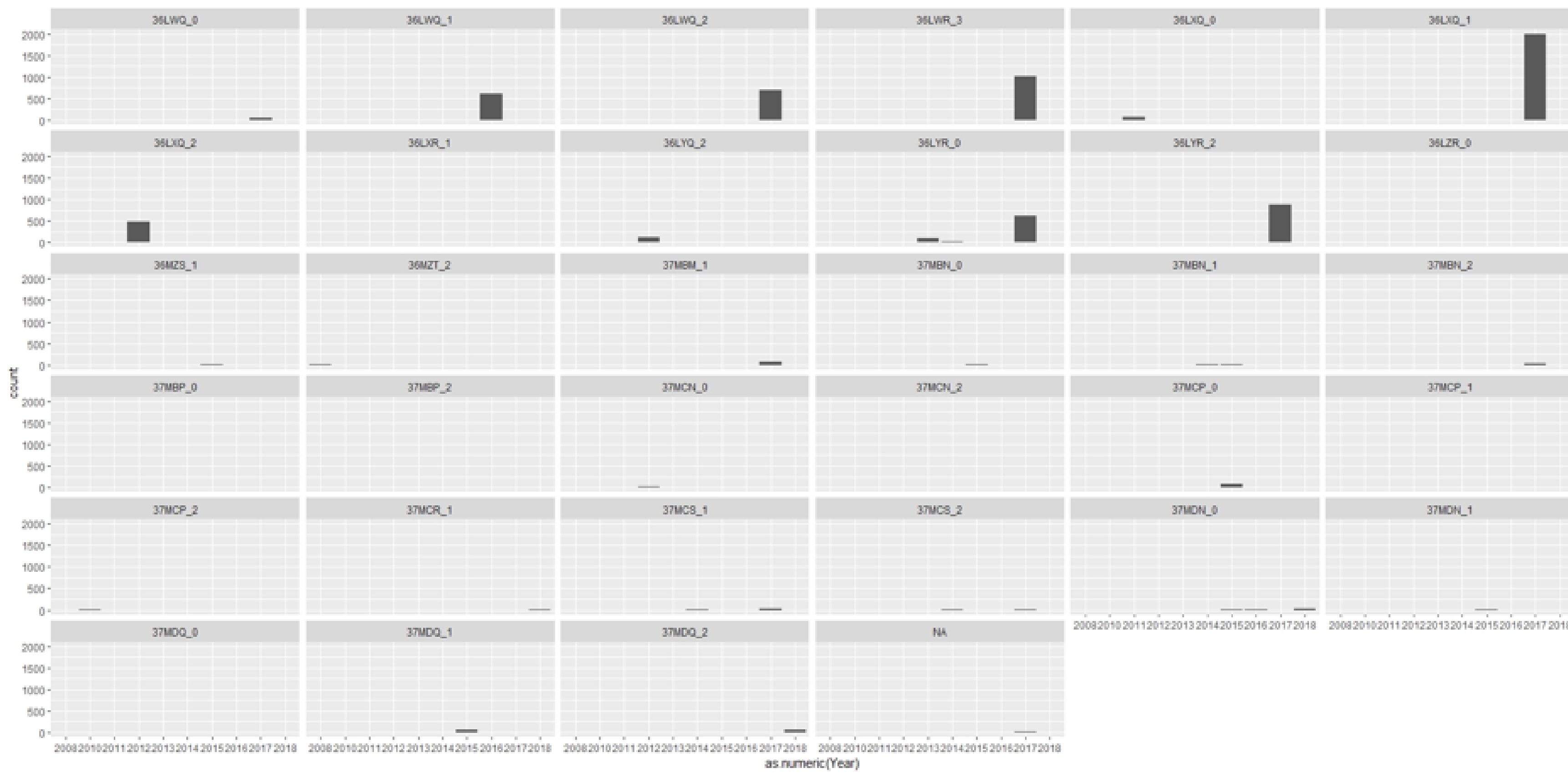
S 1. 3: A time-lapse of transition of density of woodlots, a measure used to infer woodlot age. The three pictures show the same location over three years: 2011, 2013 and 2017. Note that locations with sparse, young woodlots in 2011, are denser by 2013. Also note that locations with sparse woodlots in 2013 and those with no woodlots in 2013 that are dense by 2017 are indistinguishable. This means that after ~ 4 years of growth, the ability to discern recent planting from old planting via visual image interpretation diminishes, as the woodlots all appear dense.


7/30/2011
7/30/2011
Image © 2018 DigitalGlobe
Google Earth
2011
Imagery Date: 7/30/2011 8°20'34.60" S 35°20'08.88" E elev 0 ft eye alt 5773 ft

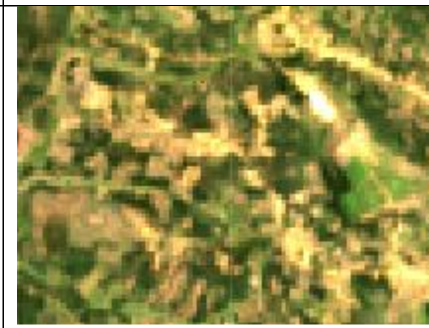
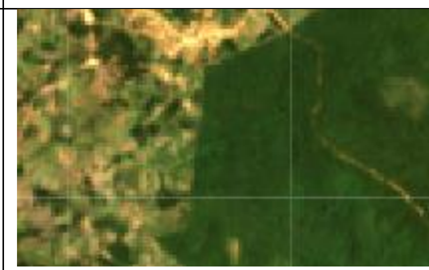

7/12/2013
7/12/2013
Image © 2018 CNES / Airbus
Google Earth
2011
Imagery Date: 7/12/2013 8°20'34.60" S 35°20'08.88" E elev 0 ft eye alt 5773 ft


7/13/2017
7/13/2017
Image © 2018 CNES / Airbus
Google Earth
2011
Imagery Date: 7/13/2017 8°20'50.41" S 35°19'33.98" E elev 0 ft eye alt 5773 ft

S 1. 4: Distribution of woodlots by sampling location, and by the observation year of the Google Earth Pro imagery. Sampling locations tended to be covered by imagery that comes from the same calendar year, and most sampling locations had observations from year 2016 and 2017.

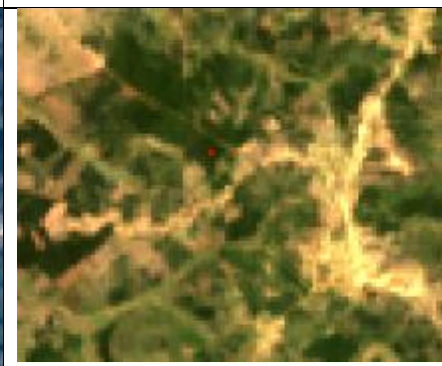


S 2. 1: Spatial characteristics of the 12 land cover classes classified in our analysis. Highest resolution Google Earth imagery provided best detail for visual interpretation, but the details had to be cross-checked in the lower resolution imagery due to spotty availability of Google Earth imagery.

Class	Class Definition	Google Earth (1-m resolution)	Sentinel-2 (10-m resolution)	Landsat-8 (30-m resolution)
cropland	Small parcel, evidence of tilling, close to other tilled parcels.			
forest	Dense, evergreen forest, greenness stable all year			

grassland	No tilling evidence, strong seasonal variation			
tea	Uniquely very vibrant green in plantations or in smallholder plots			
urban	Built-up area; also included bare land e.g., roads, unpaved village settlements			

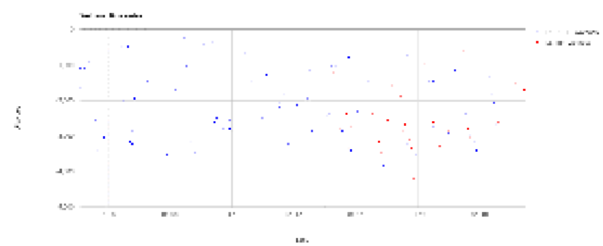
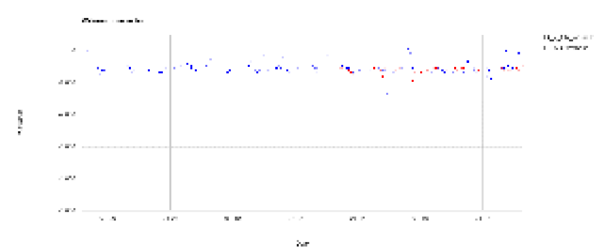
wetland	Naturally vegetated, along rivers, steady greenness throughout the year			
woodland	Sparser tree density than forest, more seasonal variability			
water	Water bodies like rivers, lakes			

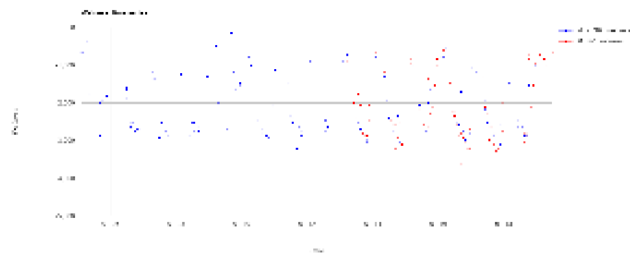
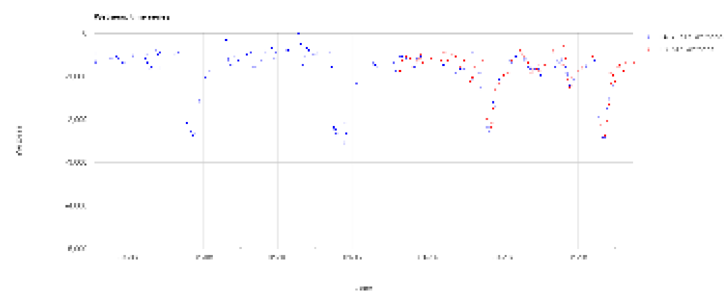
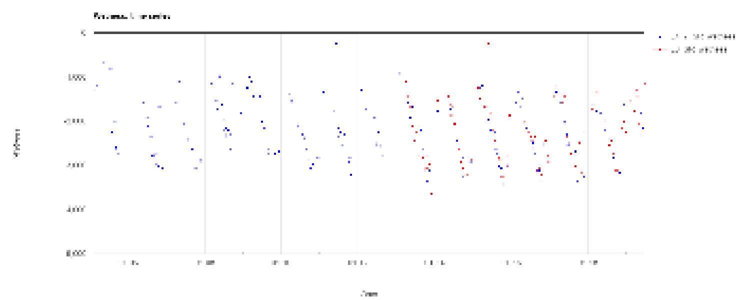
woodlot young,	Planted (parcel has sharp corners), linear trees, crowns of each tree separable			
woodlot intermediate	Planted (parcel has sharp corners), darker than native forests, linear trees still somewhat visible, crowns touch but still individually visible			
woodlot mature	Planted (parcel has sharp corners), darker than native forests, linear trees may be faintly visible, but canopy has filled out			

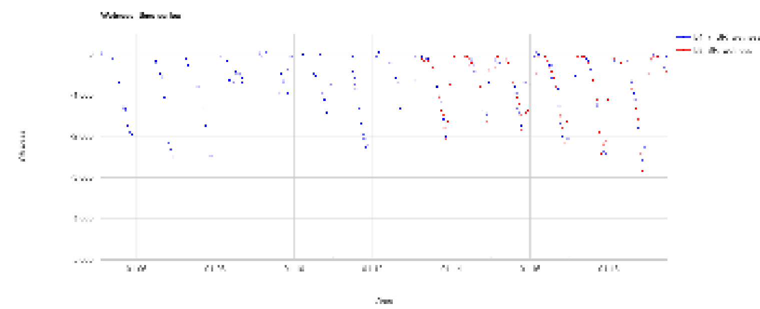
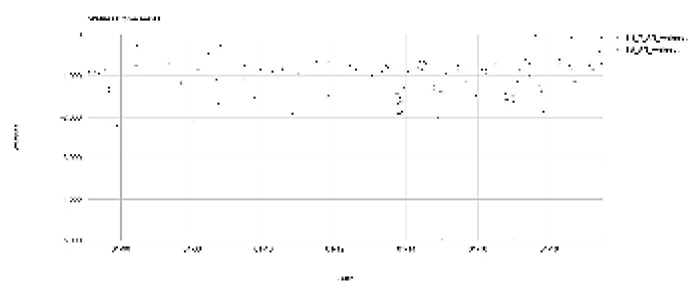
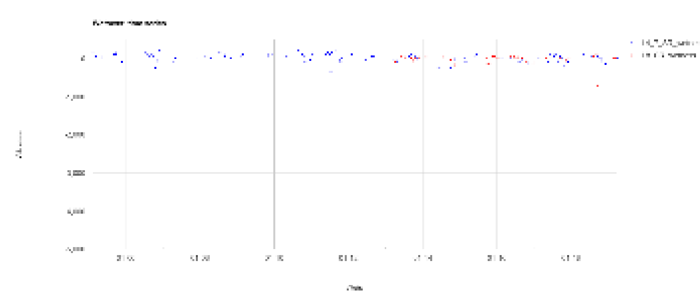
woodlot harvested	Evidence of clearing – shiny saw-dust piles in parcel			

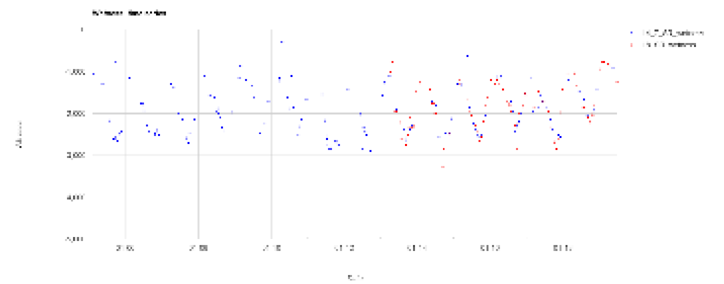
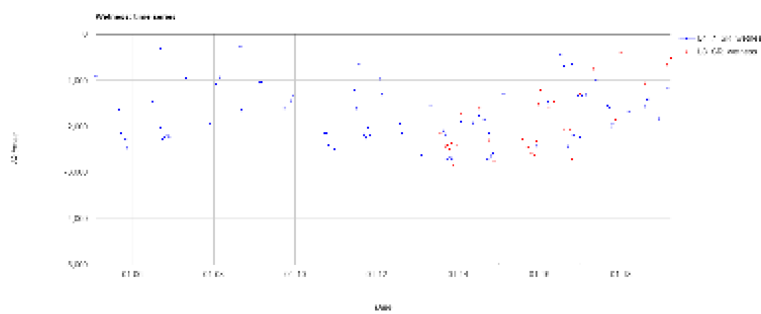
S 2. 2: Temporal spectra of the 12 land cover classes mapped in our analysis.

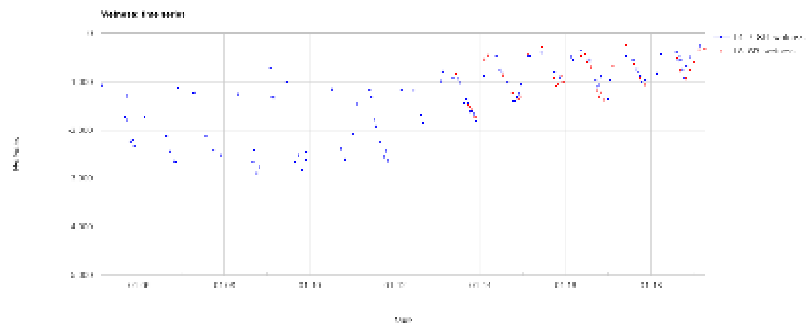
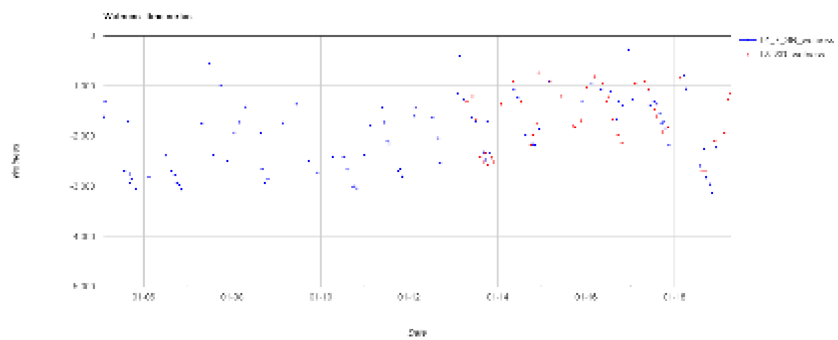
Temporal spectra was helpful in distinguishing age of woodlots, and distinguishing woodlots from other land cover classes. Whereas most land cover classes have annual phenology, when woodlots are planted they have an ‘increase’ signal superimposed on the annual phenological variation.

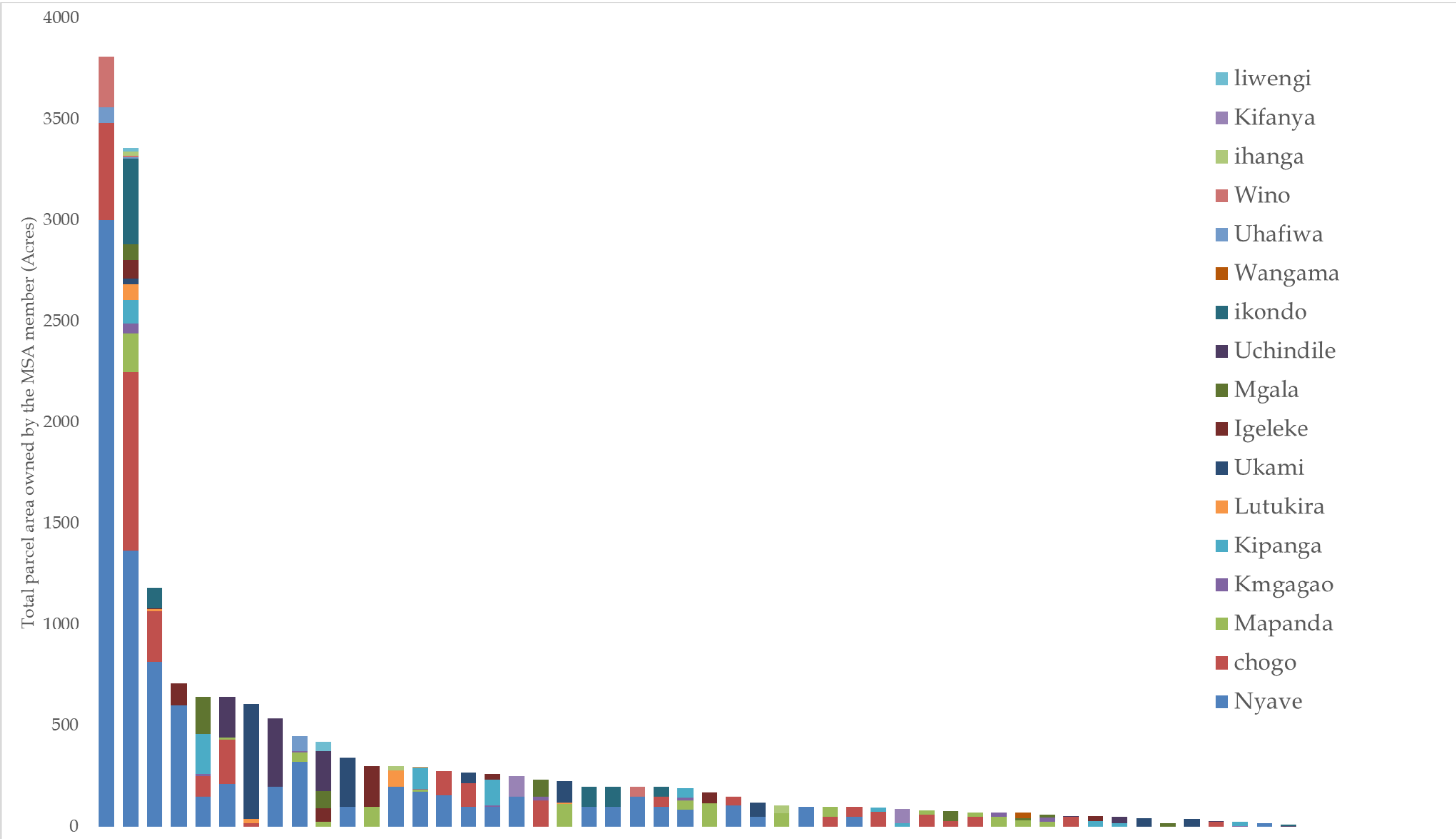
Class	Class Definition	Temporal spectra
cropland	Small parcel, evidence of tilling, close to other tilled parcels. Seasonally varying spectra	
forest	Dense, evergreen forest, greenness stable all year, across entire timeseries	

grassland	No tilling evidence, strong seasonal variation in temporal spectra, but more predictable than agriculture. Helpful to look at both spatial and temporal spectra for accurate interpretation	
tea	Uniquely very vibrant green in plantations or in smallholder plots, steady spectra that can have sudden dips from tea trimming	
urban	Built-up area; also included bare land e.g., roads, unpaved village settlements. Seasonal variation in spectra confusingly similar to grassland or farmland, so spectra interpretation need to be accompanied with spatial characteristics interpretation	

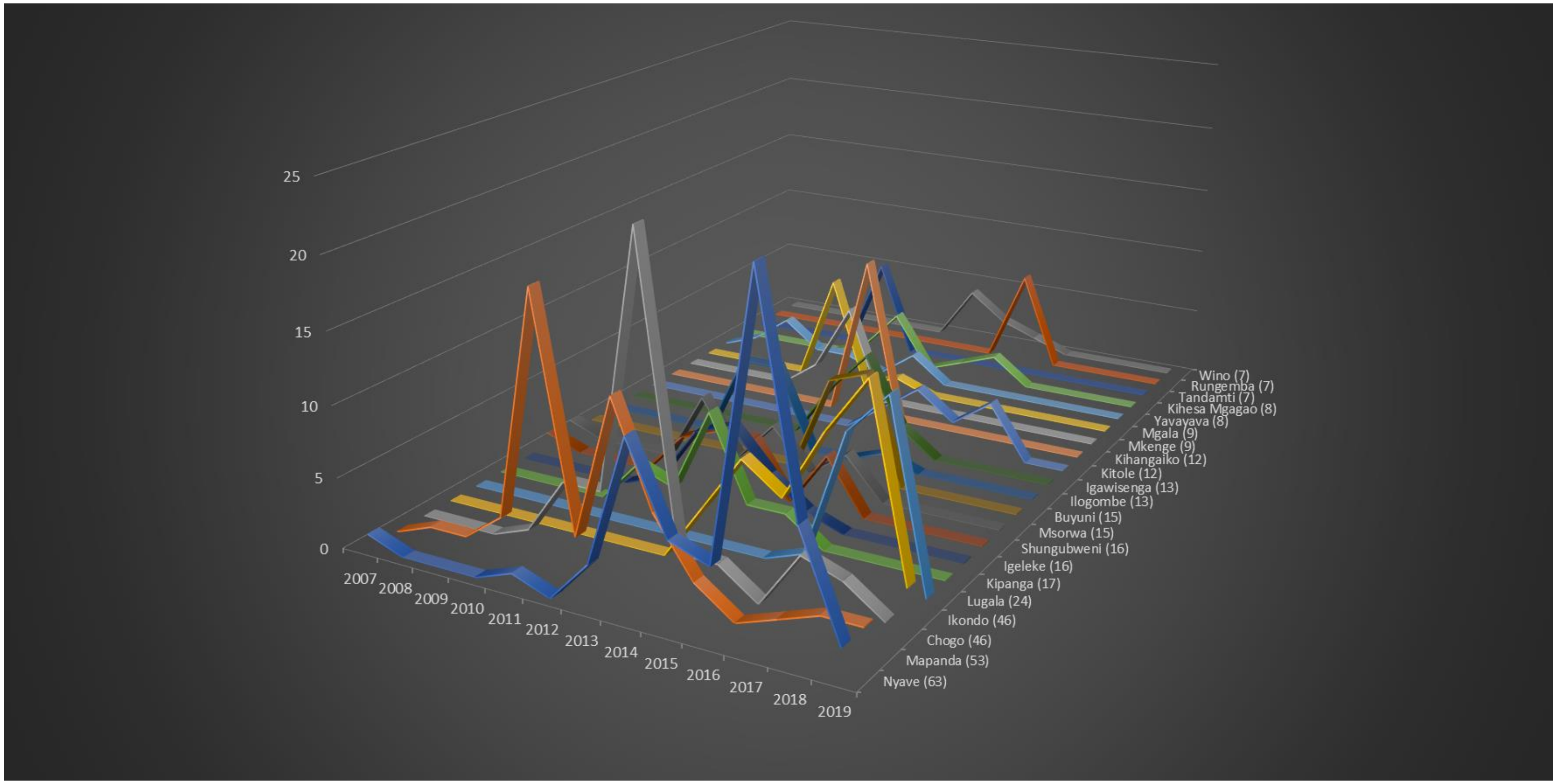
wetland	Naturally vegetated, along rivers, steady greenness throughout the year	
woodland	Sparser tree density than forest, more seasonal variability than dense forest	
water	Water bodies like rivers, lakes. Has least spectral variability	

woodlot young,	Planted (parcel has sharp corners), darker than native forests, linear trees, crowns of each tree separable. Inflection point in temporal spectra after year 2014	
woodlot intermediate	Planted (parcel has sharp corners), darker than native forests, linear trees still somewhat visible, crowns touch but still individually visible. Inflection point in temporal spectra between year 2012 and 2014.	

woodlot mature	Planted (parcel has sharp corners), darker than native forests, linear trees may be faintly visible, but canopy has filled out. Inflection point in temporal spectra prior to 2012.	
woodlot harvested	Evidence of clearing – shiny saw-dust piles in parcel. Sudden drop in temporal spectra. No recovery.	



S 3. 1: A chart indicating parcel ownership across multiple villages for the MSA owners that have more than one parcel. Each bar represents the land portfolio for an individual member. Land ownership across multiple dispersed villages reveals MSA members are likely using more than kinship ties to access land.



S 3. 2: Temporal trends in land acquisitions across villages for the 21 villages with the greatest number of parcels. Parcel purchases are concentrated by villages, but also over time within a village. Each village experiences a peak purchase year when the association members purchase the most land in the area. Overall, years 2010, 2011, and 2017 stand out in terms of the most parcel purchased.

S 3. 3: Table showing involvement of rural intermediaries in both the parcel acquisition and subsequent management for a subset of the MSA parcels (n = 130). In the identified villages, the numbered managers were involved in the acquisition process for the parcel. Most of the time, the same managers are involved in the subsequent management of the parcels. Other MSA parcels do not have specific rural managers.

Rural Manager / Intermediary	Village	Not managing the parcel	Managing the parcel
1	Ilogombe		8
	Kipanga		14
	Nyawegete		1
2	Chogo		1
	Igeleke		1
	Ilogombe		1
	Mapanda	1	10
3	Marogoro		1
	Msorwa	4	
	Shungubweni	1	
	Yavayava	2	1
4	Ikuwo	4	4
	Mgala	3	3
	Nyave	1	1
5	Idete		1
	Mgala	4	4
	Nyave	1	2
6	Kidugalo	1	
	Kihangaiko	6	
7	Isange	1	
	Isyonje	1	
	Itulike Amani	1	1
	Maheve		1
8	Njiwa		5
	Lilombwi		2
	Liwengi		1
	Mikongo		2
9	Kihesa Mgagao		5
	Gama		4
	Wino		4
10	Chogo	1	2
	Msorwa	2	
	Shungubweni	1	
11	Wangama		3
12	Mapanda	2	
	Lilombwi		2
13	Mapanda		1
	Ukami		1
	Lilombwi	1	
	Lutukira	1	
14	Mgala	1	
	Beno Kiwelo		1
	Uhafiwa		1
15	Chogo		1
Total		40	90