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Trees on farms

Ecological and socioeconomic analyses of Tropical agroforestry landscapes using remote sensing

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Abstract

Covering roughly a third of the Earth's surface, agricultural land is central to livelihoods, food security, biodiversity and climate. The need for food and materials, declining soil fertility in agricultural systems, and climate change have all led to wide-scale agricultural expansion into natural habitats. More than 90% of deforestation across the tropics is estimated to be driven by agriculture. Deforestation and degradation damage the ecosystem services that many rural and forest-proximate people rely on. Agriculture, forestry and other land use account for nearly a quarter of anthropogenic greenhouse gas emissions. How we use land is critical to the future trajectories of biodiversity, climate change and poverty alleviation. The global agricultural system needs transformation, and trees on farms have been identified as an important tool in this transformation. Trees on farms can improve biodiversity, sequester carbon, provide ecosystem services and improve livelihoods in agricultural landscapes.

To understand the state of, and changes in, biodiversity in these agricultural landscapes with trees, they must be monitored in a consistent and timely manner. However, efficient wide-scale monitoring methods are lacking, and it is not yet clear how Earth Observation (EO) data can be used for the landscape-level analyses needed to monitor biodiversity. In chapter 2, I test a novel approach to mapping tree species assemblages by mapping ordination axes of floristic composition using EO data. Existing methods for modelling floristic gradients have been confined to more homogeneous landscapes or using hyperspectral imagery and have limited wider utility. The models were tested in three complex agricultural-forest landscapes (in Uganda, Rwanda and Honduras) using a fusion of optical and radar imagery alongside other geospatial datasets. Nonmetric Multidimensional Scaling ordination scores describing floristic composition were modelled using random forest regression (with the remote sensing data as predictors) and mapped across the study sites, testing the approach's applicability in multiple contexts. EO data were able to predict some of the variations in floristic composition: model fits varied from R^2=0.56 - 0.77 and RMSE from 9 - 19% across sites. The resultant maps capture the main landscape features of tree floristic gradients. The results show that

this novel approach using a fusion of optical and radar EO data alongside geospatial data in a machine learning model can map the tree floristic gradients in complex agricultural systems. The floristic gradient map provides more detailed spatial assessments of floristic composition for understanding biodiversity in agricultural landscapes than were previously possible with satellite data and is a step towards monitoring biodiversity in these systems.

EO data can be used to scale up field data to assess aspects of biodiversity at landscape scales, but this is not feasible at national scales. A lack of systematic data on the biodiversity in agricultural land at national scales means monitoring global targets is difficult. There is a need for indicators of agricultural biodiversity applicable at wide-scale and across different landscapes. In chapter 3, I develop and present the proof of concept for an indicator of the biodiversity value of agricultural landscapes by assessing the properties of their trees. The tool uses freely available satellite data products to estimate wooded area, structural diversity and spectral diversity of agricultural lands. It combines them to ascribe a score that can be mapped at national scales. Qualitative photointerpretation validation shows promising results in four case studies in various agricultural contexts. Ideas for developing the indicator to ensure indicator continuity are discussed and include improvements in data that can come from upcoming satellite products, further qualitative and quantitative validation from those with on-site expertise, and testing the applicability of the indicator for change detection and quantification. The indicator should be a valuable tool for planners and decision-makers to monitor agricultural land, report on biodiversity, and plan informed conservation strategies. It has the potential to be a much-needed indicator for the post-2020 agenda for measuring and monitoring agricultural biodiversity.

In order to realise the potential that trees on farms have, it must be adopted widely by farmers. Promoting agroforestry for all its benefits requires an understanding of the determinants of adoption. We know the adoption of agroforestry depends on many factors, including a number of socioeconomic and biophysical conditions. Current research in understanding these determinants is focused on context-specific case studies and is inconsistent between studies. More generalisable information is needed to ensure effective and informed policy and action. Chapter 4 takes a regional approach to exploring these determinants to see how they vary from region to region across Uganda. The results show that, on average, across all regions, travel time to cities was the most important factor, but there is significant regional disparity in which factors are most important as well as inconsistent directions of the relationships. This spatially explicit information can help improve agroforestry adoption through better extension services and interventions tailored to regional circumstances, tackling the most important barriers in each region.

Lay Summary

Agricultural land is central to livelihoods, food security, biodiversity and climate. Wide-scale expansion of agriculture into natural habitats has led to forest loss, damaging biodiversity and releasing stored carbon. More than 90% of deforestation across the tropics is estimated to be driven by agriculture. The global agricultural system needs transforming, and trees on farms have been identified as an important tool in this transformation. Trees on farms can improve biodiversity, sequester carbon, provide materials and food for people, and improve people's livelihoods in agricultural landscapes.

To understand the biodiversity in these agricultural landscapes with trees, they must be monitored. In chapter 2, I test an approach to mapping the gradual changes in tree species groups on agricultural land using satellite data. This method has been used previously, but not on complex landscapes like agriculture. The method was tested in three agricultural-forest landscapes (in Uganda, Rwanda and Honduras). The satellite data were able to predict some of the variations in tree species groups. The maps created by the method captured the main tree species changes in the landscape. This method provides more detailed assessments of trees on farms for understanding biodiversity in agricultural landscapes than was previously possible with satellite data.

Satellite data can be used to scale up field measurements of trees to assess aspects of biodiversity in landscapes, but this is not realistic at national scales. There is a need for indicators of agricultural biodiversity that can be used at broad scales and across different landscapes. In chapter 3, I develop and present an indicator of the biodiversity value of agricultural landscapes by assessing the properties of their trees. The tool uses freely available satellite data to estimate tree cover, structural diversity and diversity of spectral responses measured by the satellite. It combines them to create a score that can be mapped at national scales. Validation shows promising results in four case study countries: Uganda, Rwanda, Honduras and Indonesia. This tool has the potential to be a valuable and much-needed indicator for measuring and monitoring agricultural biodiversity for the post-2020 agenda.

In order to realise the potential that trees on farms have, farmers must adopt it widely. Facilitating sustainable land management through agroforestry is difficult, and so understanding the links between socioeconomic characteristics of farming communities and the adoption of agroforestry practices is critical for promoting agroforestry. Promoting trees on farms for all their benefits requires understanding what determines if a farmer adopts the practice. We know it depends on many factors, including the farmer's characteristics and the area's climate. Current research in understanding these factors focuses on case studies and shows that factors are inconsistent. More generalisable information is needed to ensure policy and action are informed. Chapter 4 takes a regional approach to exploring these factors to see how they vary from region to region across Uganda. The results show that, on average, across all regions, travel time was the most important factor. However, there are significant regional differences in which factors are most important and varying directions of the relationships. This information can help improve the adoption of trees on farms through better services promoting it that are tailored to regional circumstances, tackling the most important barriers in each region.

Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified

Signed:

Date: 22/12/2022

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Chapter 1

Introduction

1.1 Land use issues and agroforestry

Land is central to livelihoods, food security, biodiversity and climate. Human use of land and its impacts on multiple ecosystem services is unprecedented (IPCC, 2019). Roughly a third of land has undergone a land use change since 1960 (Winkler et al., 2021), and as much as 70% of the global land surface has been altered in some way by human use. These alterations to the land surface have pronounced effects on the ecosystem services provided.

Agricultural land covers roughly a third of the Earth's ice-free surface (Ramankutty et al., 2008), feeds a growing global population of over 8 billion (Muttarak and Wilde, 2022) and provides a livelihood to 40% of humans (Ramankutty et al., 2018). Centuries of agricultural innovation and expansion have given rise to highly productive systems, but often at the expense of the environment. It has led to the loss of habitats, land degradation, water source pollution or over-extraction, and increased greenhouse gas emissions. Agriculture, forestry and other land use account for nearly a quarter of anthropogenic greenhouse gas emissions (IPCC, 2019).

The need for food and materials for a growing population, declining soil fertility, and climate change and variability have led to agricultural expansion into natural habitats (Jellason et al., 2021). The primary cause of land use change and biodiversity loss is this conversion of natural land to agriculture (IPBES, 2019). Tropical ecosystems, and forests in particular, are home to some of the highest levels of biodiversity but have experienced some of the greatest rates of land use change, with agricultural expansion as the largest driver of tropical forest loss (Curtis et al., 2018). More than 90% of deforestation across the tropics is estimated to be driven by agriculture (Pendrill et al., 2022; Geist and Lambin, 2002; Busch and Ferretti-Gallon, 2017), and much of this deforestation is to make way for agriculturally productive landscapes (Pendrill et al., 2022). This results in a conflict between the need to protect forest environments and the need to produce food and livelihoods for people. Croplands now cover 12–14% of the global ice-free surface (IPCC, 2019), and the rate of cropland expansion between 2016-2019 was estimated at 9.0 MHa per year, an area roughly the size of Portugal, much of this in tropical regions, with 3.9 MHa per year in Africa alone (Potapov et al., 2022).

How we use land is critical to the future trajectories of biodiversity, climate change and poverty alleviation (Meyfroidt et al., 2022). A trajectory of growth in unsustainable agricultural systems in the tropics will continue the deterioration of biodiversity, damage the ecosystem services from forests that rural livelihoods depend on, and reduce the ability of forests to sequester carbon (IPBES, 2019; IPCC, 2014). Agricultural land systems must be managed differently in order to feed the world's growing population in a sustainable way, addressing the co-crises of climate change and biodiversity loss.

1.2 Agroforestry and trees on farms

The global agricultural system needs transforming and there is no quick fix or single solution, but agroforestry and trees on farms have been identified as an important tool in this transformation. There are many definitions of agroforestry due to the range and complexity of agroforestry systems. At its simplest, agroforestry is a land-use practice that combines perennial trees or shrubs with crops and/or livestock in the same land management unit through active planting and maintenance, preservation of existing trees, or allowing regrowth (Schroth et al., 2004; Atangana et al., 2014). 'Trees on farms' is a broader term, which may include other practices that do not emphasise the interaction between the production systems. Trees on farms also include land uses like woodlots, trees for shade or fruit around a home or trees along riparian buffers (Gassner and Dobie, 2022). The term 'agroforestry' is sometimes used to mean 'trees on farms' more broadly when taking a landscape definition of agroforestry. This thesis is primarily concerned with landscape-level systems and uses the terms 'agroforestry' and 'trees on farms' interchangeably in this sense, using a landscape definition of agroforestry.

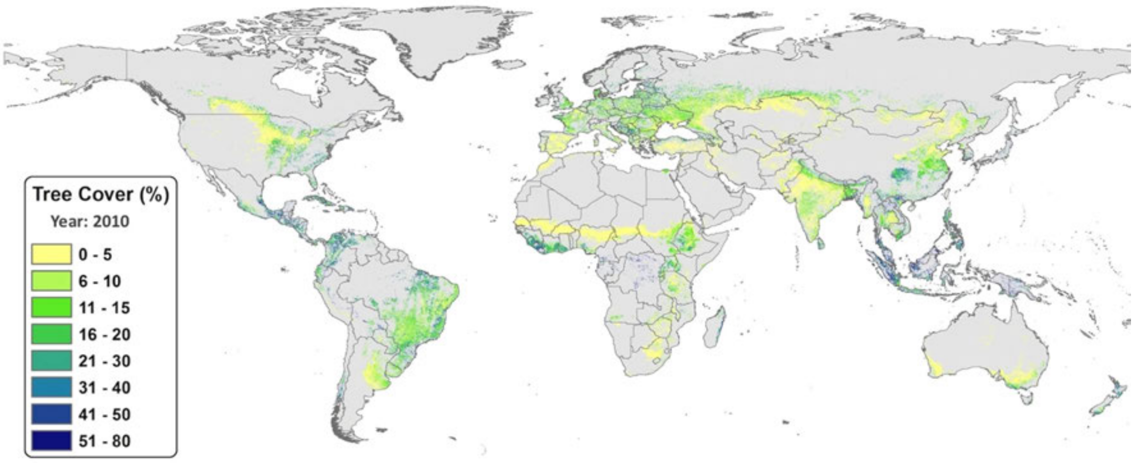
Agroforestry and trees on farms lead to complex landscapes and vegetation units which can be classified in several ways based on the vegetation structure, ecosystem function, the socioeconomic activities conducted within them, or the ecological conditions (Atangana et al., 2014). A common and straightforward categorisation is based on which components are present alongside trees (Nair, 1985). This defines three groups: agrisilviculture, the combination of trees with crops; silvopastoral systems, which consist of trees and livestock; and agrosilvopasture, the combination of trees with both crops and livestock. Other ways of using trees on farms, without crops or livestock may be included as a fourth group. The components in a given system may be combined spatially, in any range of densities, or temporally, with components being used on the land at different times.

Agroforestry has been called a 'new name for an old practice' (Atangana et al., 2014) as people have long been cultivating crops and rearing livestock among trees. Throughout the 20th Century, however, as the importance of tropical forests was becoming more widely known, attention on forest conservation and agroforestry as a more sustainable land use grew from research, government and non-state actors (Nair, 1993; Atangana et al., 2014). Attention on agriculture and deforestation from organisations like the World Bank and the Food and Agriculture Organization of the United Nations (FAO) led to research and financing addressing agricultural and forest challenges. A landmark report by the International Development Research Centre (IDRC) in 1977 recommended the establishment of a dedicated council to research and promote agroforestry in the developing world (Bene et al., 1977), which led to the creation of the International Council for Research in Agroforestry (ICRAF; later the International Centre for Research in Agroforestry, subsequently World Agroforestry, and now CIFOR-ICRAF). This institutional structure cemented agroforestry as a field of research. In recent decades, as environmental issues have become more acute, the attention on agroforestry has been growing from scientific and development actors. Agroforestry's ability to provide more sustainable outcomes on agricultural land means it is promoted as a climate-smart agricultural practice, delivering on climate mitigation and adaptation, conservation, and development agendas, restoring ecosystems in both agricultural and forest landscapes.

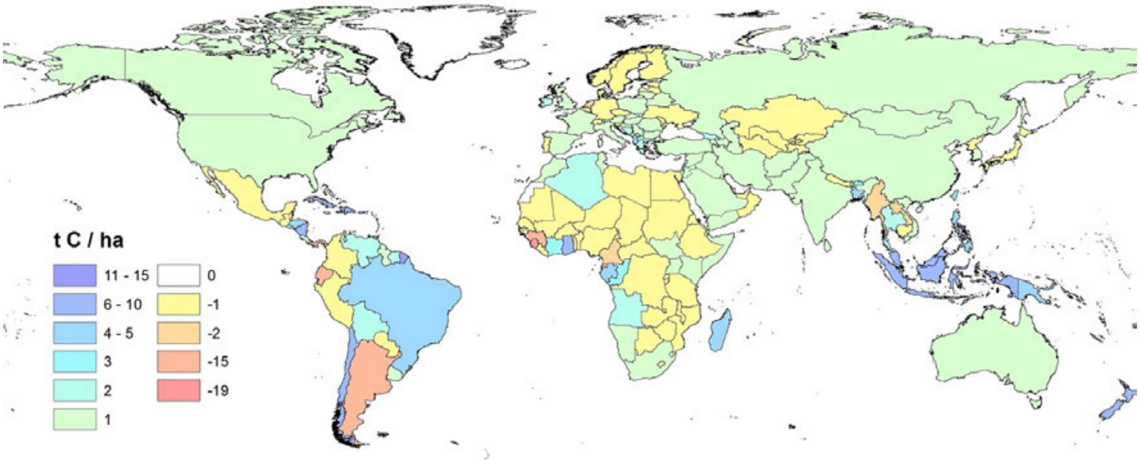
It is estimated that in 2010, over 40% of agricultural land globally had at least 10% tree cover, though there are significant regional differences that broadly follow climatic gradients (Zomer et al., 2016). The highest levels of tree cover on agricultural land were found in humid climates and the lowest in dryer climates. These trees also contributed most of the total biomass on agricultural land, estimated to be 34.2 PgC. While these figures suggest a growing global extent of agricultural land with trees since 2000, the increase is small at around 2% in the decade to 2010 for tree cover and 4.6% for biomass carbon (figure 1.1; Zomer et al., 2016). These are the only global estimates available and may underrepresent the extent of tree cover on farms. The dataset used has difficulty in estimating tree cover in areas of low woody covers like agricultural land and only accounts for trees that are taller than 5 metres (Adzhar et al., 2021).

1.3 Trees on farms for biodiversity and climate

Agricultural expansion is seen as the primary driver behind biodiversity loss in the tropics (IPBES, 2019), but agricultural landscapes can support considerable biodiversity if managed in more sustainable ways. Trees on farms also have considerable potential for carbon sequestration, being a key part of climate-smart agriculture (Zomer et al., 2022). We face a trade-off between using land for agricultural production or environmental protection and climate mitigation (Mertz and Mertens, 2017). This trade-off has led to research around both agricultural intensification to reduce expansion and lower-intensity agroecological approaches (Kremen, 2015; Ramankutty and Rhemtulla, 2012). Depending on the context, both approaches have a role to play, and agroforestry can be seen as contributing to both (Mertz and Mertens, 2017). Trees on farms are often seen as a way of improving the sustainability of agricultural land uses, fostering more diverse landscapes (Estrada-Carmona et al., 2022). Agroforestry can also be designed with sustainable intensification aims, to intensify subsistence agriculture and prevent agricultural expansion (Minang et al., 2014). When managed for benefits to biodiversity and people, trees on farms are a way of promoting conservation while maintaining land for production (Kremen and Merenlender, 2018).



(a) Global tree cover on agricultural land in the year 2010



(b) Change in biomass carbon on agricultural land from 2000-2010

Figure 1.1: Global distribution of tree cover and biomass carbon changes on agricultural land from Zomer et al. (2016)

Trees on farms directly contribute to the biodiversity of agricultural landscapes (Barrios et al., 2018). Different systems have different benefits, but nearly all agroforestry systems improve agrobiodiversity, the variety of plants, animals and microorganisms in agricultural landscapes (Gassner and Dobie, 2022). Agroforestry systems may not always enhance the biodiversity of indigenous species or connectivity when mostly exotic species are planted — incorporating native species into agricultural systems further increases biodiversity.

Schroth et al. (2004) put forward three key mechanisms by which agroforestry can support biodiversity in agricultural landscapes. The 'Agroforestry-Deforestation Hypothesis' suggests that trees on farms reduce the pressure on forests by providing a subset of key forest ecosystem services. The 'Agroforestry-Habitat Hypothesis' outlines the role of agroforestry in providing habitats for species that can tolerate some disturbance. The final mechanism is the 'Agroforestry-Matrix Hypothesis' which states that agroforestry creates a set of corridors through agricultural lands that connect areas of natural vegetation, allowing flora and fauna to move through an otherwise more hostile habitat. Two further key ways that agroforestry can support biodiversity in agricultural landscapes are the preservation of species germplasm and providing other environmental ecosystem services like the controls on soil erosion and water availability, supporting wider ecosystem health (Jose, 2009).

Agroforestry systems can improve three key facets of soil health: soil organic carbon, soil nutrient availability, and soil biota (Dollinger and Jose, 2018). In agricultural land, tree-based systems are shown to have higher SOC stocks than agriculture without trees (Chatterjee et al., 2018). The addition of trees into an agricultural landscape increases the volume of litter on the surface and below ground, adding organic matter to the soil. The agrobiodiversity associated with agroforestry increases the diversity of functional plant groups, which in turn increases nutrient supply and cycling in the soil. Trees influence soil biota by improving the conditions in the soil for a healthy soil ecosystem, providing cover, water, and nutrients to soil organisms (Barrios et al., 2013). The diversity of litter, including recalcitrant litter such as woody material, is important in promoting the diversity of soil biota (Wardle, 2006). The soil benefits vary depending on the type of system; improvements in soil carbon are much greater for silvopastoral systems than woodlots, for example. Benefits also often shift over time; for example, soil carbon sequestration may decline after tree harvesting (Feliciano et al., 2018). Trees also play an important role in controlling soil erosion on agricultural land, reducing soil losses by stabilising land on slopes, controlling runoff or preventing wind erosion through windbreaks (Nair et al., 1995).

As a land-based climate change mitigation measure, agroforestry has one of the highest potential carbon mitigation densities per land area for agricultural land use (Roe et al., 2021). Alongside improving soil carbon, trees on farms store a large amount of carbon in their above- and below-ground biomass, removing it from the atmosphere. Globally, for each percentage increase in tree cover on agricultural land, 1.83 PgC is sequestered in tree biomass carbon (Zomer et al., 2022). This changes by bioclimatic zone, with the greatest increases in tropical and humid climates.

Agroforestry systems can mitigate some of the water quality issues associated with some agricultural practices, especially those with inputs like fertiliser and pesticides, and improve ecosystem health (Jose, 2009). Much of the fertiliser applied to cropland is not used up by the crops and is often washed off fields or washed out of the soils through leaching. This runoff, which may be rich in fertiliser, pesticide and sediment, can find its way into water systems, contaminating them. Trees, especially those planted as riparian buffers, can mitigate some of this damage to water quality (Pavlidis and Tsihrintzis, 2018). Trees can reduce the speed of surface runoff, facilitating greater infiltration or deposition of sediments, and preventing them from reaching water courses. Trees may also take up excess nutrients themselves, with roots that often extend below the rooting depth of common crops and growing seasons that are longer than most crops. This reduces the number of agricultural inputs that reach groundwater sources, moderating water quality issues and improving input efficiency by keeping the nutrients in the system through litter fall and root turnover of the trees.

1.4 Trees on farms and livelihoods

Eighty percent of the global poor are rural, and most depend on agriculture for a living (de la O Campos et al., 2018). So the way in which this land is used is inextricably linked to poverty alleviation through land productivity, resilience and reliability of agriculture. Agroforestry, as an agroecological approach, is an important way of tackling these livelihood issues (Altieri, 2002). In the rural tropics, much of the population relies heavily on their surrounding environment, from the provision of food and fuel to regulating the state of the lands on which rural livelihoods depend. The state of the surrounding environment affects communities through energy, food security, dietary diversity, income and subsequent effects of wealth on education and opportunities (Brocklesby and Hinshelwood, 2001). Trees are a particularly critical resource for rural communities in the tropics (Angelsen et al., 2014; Jagger et al., 2022). Both inside and outside forests, trees provide innumerable ecosystem services. Many of the environmental benefits have knock-on effects on human wellbeing and livelihoods. For example, mitigation of flooding and landslides contributes to the reliability of farm products and food security (Jose, 2009), productive agricultural systems need pollinators which are befitted by agrobiodiversity (Jeanneret et al., 2021), and mitigating damage to water quality has health benefits.

There are more direct benefits too, including a number of provisioning services for livelihoods by trees on farms like fuelwood, fodder for livestock, food like fruits, nuts or honey, and materials for construction (Kuyah et al., 2016). The provision of these products closer to home reduces a household's need to purchase them or source the products from forests.

Household incomes can be supplemented by trees, providing an estimated 17% of total household income for households that grow trees (Miller et al., 2017). Tree products are used for both subsistence and cash: they can be sold to provide an alternative income stream for households. Multipurpose trees on farms provide a more stable and flexible production system, giving farmers greater choices and the ability to better manage shocks to crop performance or the market (Idol et al., 2011). Trees help diversify income streams from these provisioning services of timber and non-timber forest products, as well as from direct remuneration in payments for ecosystem services schemes (PES). Where households are involved in PES schemes that adequately compensate farmers, the direct payments received supplement farm incomes (Benjamin and Sauer, 2018). The regulating and supporting services to the soil, water, and the control of pests improve conditions for crop growth and result in yield increases. Agroforestry significantly increased crop yields in 77% of on-farm trials in agrisilvicultural and agrosilvopastoral systems (Kuyah et al., 2019). These yield increases can improve food security and boost household incomes for farmers.

Agroforestry can contribute to human health through nutrition and medicinal plant provision. The use of herbal medicinal products is hugely important, with as much as 80% of the world's population relying on traditional medicines, mainly plants, for some primary healthcare (Ekor, 2014). While much is harvested from wild trees, agroforestry is an opportunity to cultivate medicinal plants (Rosenstock et al., 2019a).

Poor nutritional quality, diversity and quantity of food are serious problems for global health. Agroforestry has been linked to improved health by improving nutrition for farmers. Increased yields and more reliable income can not only improve household finances, allowing farmers to purchase more food but also boosts the quantity of food available to subsistence farmers. Where agroforestry systems include food trees, dietary diversity can be improved by introducing different fruits or nuts to farmers' diets (McMullin et al., 2019). Tree cover has been associated with better child nutritional diversity across Africa (Ickowitz et al., 2014). Improvements to soil quality are also seen to improve the nutrient quality of grains grown in agroforestry systems (Wood et al., 2018). Increasing the diversity or supplementing of livestock fodder can improve the diet and health of livestock and boost milk production in cows (Place et al., 2009).

1.5 Risks, barriers and negative interactions

Agroforestry is generally a labour-intensive (Kiptot, 2014; Ollinaho and Kröger, 2021) and knowledge-intensive system (Röling and van de Fliert, 1994) that requires a set of skills to improve success. This intensity is generally focused in the earliest stages of adopting the practice (Ollinaho and Kröger, 2021); once the knowledge and skills are acquired, and the trees reach maturity, the labour and knowledge inputs are reduced. The marketability for tree products can also create a barrier and present risk to farmers in agroforestry. The income potential from trees on farms is dependent on if there is a market for products and where this market is (Ollinaho and Kröger, 2021). There is a wide variety of tree products that may lack markets, or markets may be too distant to benefit from them.

While positive interactions with crops can improve productivity, there is also the potential for negative interactions between tree and crop species. Negative interactions also can co-occur alongside positive interactions. Poor planning in agroforestry systems can result in competition for water, light and nutrients between species (Atangana et al., 2014), leading to poor productivity in crops. Competition depends on the combinations of species, the climate and soil types, and can occur above-ground, below-ground, or both. Some combinations of trees and crops can result in detriment to crop production in allelopathic interactions (Devi, 2017). Allelopathy is the term for a damaging effect a plant has on the germination or growth of other nearby plants due to substances they produce. Trees are more likely to have allelopathic effects than other types of plants (Gassner and Dobie, 2022), including many common agroforestry species (Rizvi et al., 1999). Poor understanding of tree-crop combinations and potential allelopathic effects can result in reduced productivity from crops.

1.6 Promoting trees on farms

Agroforestry is promoted widely, especially across the tropics due to these numerous benefits outlined briefly above. It plays a part in meeting development targets (Sustainable Development Goals; SDGs; Waldron et al. 2017; Noordwijk 2019; Andersson 2018), biodiversity targets (Aichi target 7, Post-2020 global biodiversity framework target 10, Dobie et al. 2020; CBD 2021) and carbon targets (Nationally Determined Contributions to the Paris Agreement; Duguma et al. 2017; Roe et al. 2021). Over $10 billion has been spent in aid to agroforestry projects in low- and middle-income countries since the 1992 UN Earth Summit in Rio (Castle et al., 2021). Some of the biggest aid donors commit to climate-smart agriculture or sustainable intensification that provides important ecosystem services alongside improved agricultural production in their policy documents (The World Bank Group, 2016; IFAD, 2018; FAO, 2013; Pretty et al., 2018). Promoting agroforestry is part of most sub-Saharan African countries' nationally determined contributions to the Paris Agreement (Rosenstock et al., 2019b). It is also included in many nations' environmental, forest or agricultural policies.

Promoting agroforestry through extension or intervention is a task of innovation diffusion and adoption. There are four elements in the diffusion of an innovation (Rogers, 2003): the innovation itself, i.e what form of agroforestry; how it is communicated to a population, this could be through extension agents, mass media campaigns, and opinion leaders or influential community members; the time it takes to spread; and the social system of the population adopting the innovation. Agricultural innovations and technology are often spread through extension services that aim to transfer knowledge from research to farmers, advising and educating farmers to assist in their decision-making (Anderson and Feder, 2007). Agroforestry is particularly important to include in advisory services as it is a knowledge-intensive practice and requires skills to raise trees from seedlings and maintain trees through pruning (Kiptot, 2014). Advocating for tree planting on farms in developing countries occurs through pluralistic intervention and extension. Government and non-state actors like non-governmental organisations (NGOs) provide farmers with agricultural extension and rural advisory services, resources like germplasm or incentives for tree planting. Miller et al. (2020) identifies six main classes of agroforestry intervention: farmer capacity development which includes advisory services, training, and technical information; access to tree germplasm which provides the required resources and connects farmers to nurseries; direct payment incentives include payment for ecosystem services schemes (PES) or commodity certification schemes that ensure commodities are grown under certain conditions; community-level campaigning to spread information on beneficial practices and encourage uptake; facilitating market access connects farmers to the value chains for tree products; and policy and institutional change provides an enabling environment that encourages the adoption of agroforestry.

1.7 Monitoring trees on farms and satellite Earth observation

Understanding how widespread trees on farms are can help us quantify the above-mentioned benefits and support informed decision-making in agricultural and forest policy, to improve the sustainability of land use and livelihoods. Trees on farms will also be an important contributor alongside natural ecosystems and protected areas to reaching national and international goals on climate, biodiversity and sustainable development.

A set of biodiversity targets is being developed by the UN Convention on Biological Diversity (CBD) to replace the Aichi targets, the previous goals which ended in 2020 (CBD, 2021). These Aichi targets broadly failed, and no target was fully met by 2020 (IPBES, 2019; CBD, 2020). Experts reflected that the targets were unrealistic and progress was too difficult to measure (Green et al., 2019). The draft framework for the next set of goals, to be achieved by 2030, includes a target to "ensure all areas under agriculture, aquaculture and forestry are managed sustainably" (CBD, 2021). It is critical that these goals can be monitored at scale, and satellite Earth Observation (EO) data will be essential to this. Trees on farms will also be important for meeting national contributions to the Paris climate agreement and need to be monitored for reporting these contributions (UNEP, 2019).

Monitoring trees on farms can help us monitor progress on specific goals, but can also help us make more informed decisions to achieve other goals. The sustainable development goals (SDGs), for example, include several goals that are relevant to trees on farms, including goals on poverty alleviation, food security and human health (Andersson, 2018). Monitoring trees on farms does not monitor progress on these goals, but can inform policy and action taken to achieve these goals.

Monitoring agricultural systems with trees for their contribution to livelihoods, biodiversity and meeting goals and targets is therefore important, and satellite remote sensing is a key data source for the broad-scale monitoring that is required. There is an established field of research successfully applying satellite EO data and tools to studying trees within protected or intact habitats for biodiversity (Kerr and Ostrovsky, 2003; Turner et al., 2003; Wang et al., 2010; Anderson, 2018; Wang and Gamon, 2019; Reddy et al., 2021), and the socioeconomic links to environmental conditions to estimate wellbeing (Hargreaves and Watmough, 2021), bit little in monitoring trees in transformed landscapes.

Research on trees on farms is predominantly field-based, and there is limited work using satellite EO data. Airborne instruments rather than satellite data are often used in applications of EO in agroforestry research (Graves et al., 2018; Pádua et al., 2017), and where satellite data are used, it is often hyperspectral or very high resolution. However, existing EO-based datasets have been used to make global estimates for the extent of trees on farms. Several studies by Zomer et al., use global EO tree cover and land cover datasets to estimate the extent and carbon sequestration potential of trees in agricultural land (Zomer et al., 2009, 2014, 2016, 2022). Some similar, regional scale, mapping of agroforestry extent and biomass estimates has taken place using optical multispectral satellite data (Laosuwan and Uttaruk, 2016; Rizvi et al., 2016; Vikrant et al., 2018; Prasondita et al., 2019; Macedo et al., 2018; Shrestha et al., 2020), but research using satellite EO data has not often gone beyond extent mapping (Sharma et al., 2022). Remote sensing-based tree density measures have been included in crop yield models (Leroux et al., 2020), and to assess the impact of shelterbelts (Yang et al., 2021). Radar data is rarely used in studying agroforestry systems despite research across various landscapes in the tropics showing relationships between radar backscatter and aboveground biomass (Mitchard et al., 2009; Ryan et al., 2012; Mitchard et al., 2013; Mermoz et al., 2014; Ningthoujam et al., 2018; Braun et al., 2018). Rare examples of research in agroforestry systems using radar data include using radar data alongside optical data to map shelterbelts (Ha et al., 2019), and for assessing biomass change in agroforestry systems (Mitchard et al., 2013)

1.8 Thesis outline

1.8.1 Overall aim

The aim of this thesis is to carry out spatial analyses in tropical agricultural landscapes, focusing on methods for monitoring the trees in these landscapes and the determinants involved in their planting or maintenance by farmers. It begins by looking at the landscape scale (chapter 2), scaling up ground data to monitor tree species in the landscape and then panning out to ask similar questions at regional or national scales, requiring a new set of methods in chapter 3. Finally, chapter 4 explores the relationships between socioeconomic factors within farming communities and the tree cover on their farms.

This aim is covered in three chapters which tackle the overarching themes from different angles but can stand alone. It is followed by a general discussion tying these chapters together and drawing out the implications of the work and further questions it elicits.

1.8.2 Chapter 2: Mapping tree community composition gradients in forest-agriculture mosaic landscapes with satellite remote sensing: potential and limitations

Trees on farms allow agriculture to support biodiverse landscapes and complement protected areas to reach national biodiversity targets. However, efficient wide-scale monitoring methods are lacking, and it is not yet clear how EO data can be used for the landscape-level analyses needed to monitor biodiversity. This study tests a novel approach to mapping tree species assemblages by mapping ordination axes of community composition using EO data. The main aim of this chapter is to test the efficacy of an EO-ordination modelling method in complex agriculture-forest mosaic landscapes, and to answer the following research questions:

1. Is it possible to map tree community composition in agriculture-forest mosaic landscapes?
2. Which EO data are most useful in predicting tree floristic composition and is this consistent between sites?
3. Is EO-ordination modelling a useful monitoring tool in these landscapes?

1.8.3 Chapter 3: A farm biodiversity score for consistent monitoring of biodiversity based on the measurement of trees on farms

Monitoring landscapes such as those in chapter 2 provides detail on agroforest biodiversity, but to report at national levels, wider scale analyses and indicators are needed. There is a lack of systematic data on the biodiversity in agricultural land, which means monitoring global targets is difficult. The aim of this chapter is to develop a proof-of-concept indicator for national monitoring of the biodiversity of agricultural land based on trees on farms. The indicator uses freely available satellite data to score agricultural land based on its wooded area, structural diversity and spectral diversity.

1.8.4 Chapter 4: Socioeconomic determinants of trees on farms: regional variation and regularities in Uganda

The adoption of agroforestry depends on many factors, including several socioeconomic and biophysical conditions. Current research in understanding these factors is focused on context-specific case studies, but to ensure effective and informed policy and action, more generalisable information is needed. This chapter uses Earth Observation products combined with census and household survey data to explore the determinants of tree cover on farms across Uganda. The chapter aims to determine the national patterns of the factors that affect agroforestry adoption and answer:

1. How much do socioeconomic factors explain tree cover on farms in Uganda, and which factors are most important?
2. Do the relationships between tree cover on farms and socioeconomic factors vary spatially?
3. How much influence does climate have on tree cover on farms?

1.8.5 General discussion and conclusion

The final chapter discusses the importance of the findings from the three chapters. It addresses the research aims and draws wider conclusions about how useful the methods and results may be to practitioners and policymakers, how remote sensing and geospatial analysis can contribute to agroforestry systems science, and building on the research.

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Chapter 2

Mapping tree community composition gradients in forest-agriculture mosaic landscapes with satellite remote sensing: potential and limitations

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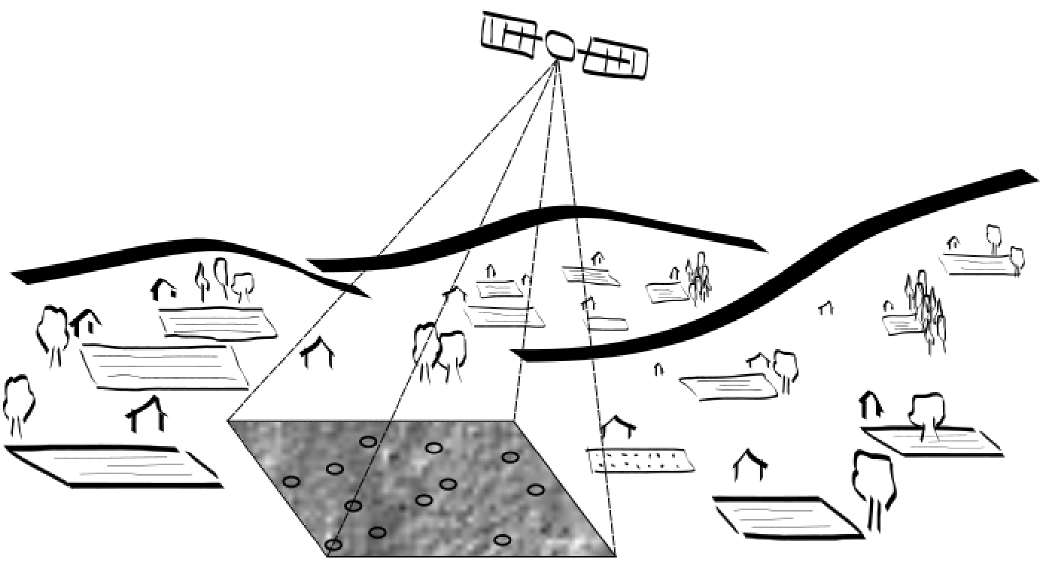

SBH conceived the research with inputs from CMR and RDH. Data collection was led by PK in Uganda, EBN in Rwanda, and EG in Honduras.

Abstract

Agroforests and agricultural-forest mosaics support important biodiversity and complement protected areas as a means of reaching national biodiversity targets. To understand biodiversity and its changes in these complex agricultural landscapes, it is important they are monitored in a consistent and timely manner. However, efficient landscape-scale monitoring methods are lacking, and it is not yet clear if Earth Observation (EO) data can be used. Tree species composition is an important aspect of such monitoring because different trees provide very different biodiversity benefits, but monitoring floristic composition with EO data is in its infancy. This study tests a novel approach to monitoring tree species gradients by mapping ordination axes of floristic composition using 10-30 m resolution, free-to-use, EO data. We test the approach in three complex agricultural-forest landscapes in Uganda, Rwanda and Honduras and use a fusion of optical and radar imagery alongside other geospatial datasets. Nonmetric Multidimensional Scaling ordination scores describing floristic composition were regressed against the geospatial data using random forest regression models and then mapped across the study sites, testing the applicability of the approach in multiple contexts. EO data were able to predict most of the variation in tree floristic composition: model fits varied from R^2=0.56 - 0.77 and RMSE from 9 - 19% across sites. The resultant maps capture the main landscape features of tree floristic gradients. The results show that a fusion of optical and radar data helps map these tree floristic gradients in complex agricultural systems. The most important remote sensing data in the model was not consistent between sites, reflecting the differences in gradients explained by the ordinations. The floristic composition maps can be used for detailed assessments of biodiversity in agricultural landscapes, and these methods provide a step towards monitoring biodiversity in these systems.

2.1 Introduction

Agricultural-forest mosaic landscapes can support appreciable biodiversity when managed appropriately, with agriculture complementing forests or protected areas as a means of reaching national biodiversity targets (Perfecto and Vandermeer, 2008; Pretty et al., 2018). One important way of enhancing biodiversity in agricultural mosaic landscapes involves adding or maintaining trees on farms (Schroth et al., 2004; McNeely and Schroth, 2006; Steffan-Dewenter et al., 2007; Jose, 2009). However, without wide-scale monitoring, understanding the contribution of trees on farms to biodiversity is difficult (Herzog et al., 2013). There is established research applying remote sensing data and tools to monitor biodiversity within untransformed habitats, but methods applying Earth observation (EO) data to biodiversity monitoring in transformed landscapes are yet to be fully developed.

Trees on farms support biodiversity in three key ways: providing habitat for species that tolerate a degree of disturbance; reducing the pressure on resources in nearby forest habitats; and acting as buffer zones around more permeable habitat patches, improving the biodiversity in these non-farmed patches (Schroth et al., 2004). Other ecosystem services provided by trees on farms reduce biodiversity loss, supporting soil biodiversity, erosion control and water regulation (Jose, 2009). There are many outcomes for which trees on farms are managed, and this management depends on numerous socioeconomic and biophysical constraints. Some tree management supports greater biodiversity than others through cultivating certain species, keeping trees in certain arrangements and how the trees are used.

To understand the state of, and changes in farmland biodiversity, it is important that trees can be monitored in a consistent and timely manner. Field surveys can be difficult to scale up and repeat consistently (O'Connor et al., 2015; Gillerot et al., 2021), and can be expensive, labour-intensive and time-consuming (Danielsen et al., 2005), particularly as trees on farms have a highly organised spatial pattern which makes field sampling difficult (Harrison et al., 2019). EO data can be a useful addition to field-based assessments of biodiversity, enabling field measurements to be scaled across landscapes. Reviews on remote sensing for biodiversity show that much of the literature is focused on natural or intact ecosystems (Kerr and Ostrovsky, 2003; Turner et al., 2003; Wang et al., 2010; Anderson, 2018; Wang and Gamon, 2019; Reddy et al., 2021). There remains a lack of studies employing EO to estimate biodiversity in tropical agricultural systems (Ranganathan et al., 2010).

Previous approaches to estimating biodiversity using EO data are largely based on indirect methods that rely on measuring environmental parameters as a proxy for biodiversity (Turner et al., 2003; Gillespie, 2005; Cayuela et al., 2006; Nagendra et al., 2010; Pouteau et al., 2018). Indirect approaches include land cover classifications which categorise the land surface based on similar spectral responses and assign vegetation into discrete habitat classes such as closed-canopy forests, grasslands or croplands. This approach typically contains only limited information about species composition, even though community composition has been proposed as an Essential Biodiversity Variable (EBV; Pereira et al. 2013). The discrete land cover categories assume consistent composition within classes, ignore overlap, and omit gradients of species composition within and between classes. In reality, community composition is a continuous variable across space, with species occurrences in multiple classes (Feilhauer et al., 2021). These floristic gradients can appear as discrete if the gradient is steep, but are often more gradual, especially in landscapes of low land use intensity.

Ordination methods provide an alternative to discrete classifications. Ordination extracts floristic gradients in multidimensional species composition space. Several studies have mapped floristic gradients by modelling ordination values with EO data, often complemented with other biophysical datasets like topography, soil or climate (Feilhauer and Schmidtlein, 2009; Ohmann et al., 2011; Feilhauer et al., 2021; Rocchini et al., 2017). Ordination axis values are used as dependent variables in models with EO data as predictor variables (hereafter, "EO-ordination" models). The models predict the ordination scores of each pixel and thus its floristic composition. These maps can be important for analysing beta diversity (Rocchini et al., 2018). These methods have mostly been applied using airborne, high-resolution, or hyperspectral data (Feilhauer et al., 2014, 2011; Gu et al., 2015; Harris et al., 2015; Neumann et al., 2015; Schmidtlein and Sassin, 2004; Schmidtlein et al., 2007; Schmidtlein, 2005; Schmidtlein et al., 2012). Studies using open-access satellite data have been restricted to optical data, applied mostly to forests (Feilhauer and Schmidtlein, 2009; Hernández-Stefanoni et al., 2012; Ohmann and Gregory, 2002; Thessler et al., 2005).

In transformed landscapes, the species-environment relationship is likely to be altered and so contributions of ancillary biophysical datasets may be lower than elsewhere. Other EO data may have greater importance here. EO-ordination models have not been tested using open-access optical and radar data, nor on landscapes as heterogeneous and intensely managed as tropical agricultural-forest landscapes.

This study applies EO-ordination modelling to three agricultural mosaic landscapes using multi-spectral optical, radar, and ancillary datasets in machine learning models. This is a critical test to advance the utility of these methods. Using open-access data makes these methods more accessible as an operational monitoring tool. Outputs at the landscape level provide insights into the continuous variability in tree species composition. Using these methods in complex mosaic landscapes enables monitoring of biodiversity in these agroecosystems that are overlooked in conservation, facilitating approaches to harnessing the potential of trees on farms for biodiversity.

Specifically, we aim to answer the following:

1. Is it possible to map tree community composition in agriculture-forest mosaic landscapes?
2. Which EO data are most useful in predicting tree floristic composition and is this consistent between sites?
3. Is EO-ordination modelling a useful monitoring tool in these landscapes?

2.2 Methods and Materials

2.2.1 Study sites

The three study sites were Elgon, eastern Uganda; Gishwati, western Rwanda; and Catacamas, southeast Honduras. In Elgon, the agricultural land is almost entirely smallholdings with forests of Mt. Elgon national park to the East. This landscape has high land use intensity, and almost all tree species in the agricultural land are cultivated for various uses (Mukadasi et al., 2007; Gram et al., 2018). In Gishwati, small areas of remnant forest are surrounded by pasture areas, tea estates and commercial forestry (Clay, 2019). The landscape around Catacamas is largely cattle ranching with some grain production between mountainous protected forests. Small pockets of forest remain among the ranches, predominantly along rivers (Sepúlveda et al., 2019). The three sites, with different characteristics, allow for a stringent check of the floristic gradient mapping method, testing if the method is robust in various agricultural contexts. Few studies have applied EO-ordination modelling to landscapes with such heterogeneous land cover as those in this research.

2.2.2 Tree inventory data

Tree inventory data were sampled across a 25 $\times$ 25 km sampling area in each study site. A stratified random sampling method was used, with plots distributed across the main land covers and at a range of distances from forest-agriculture boundaries. In agricultural land, circular plots of 1 ha were sampled, whereas forest plots were 0.5 ha due to the demands of surveying the quantity of trees. The sampling strategy resulted in 54 plots in Elgon, 115 in Gishwati and 84 in Catacamas.

For each sampled tree stem in the plot, the tree species and diameter at breast height (dbh) were recorded. All trees with a dbh $\geq$ 5 cm were sampled in agricultural plots, and trees with a dbh $\geq$ 10 cm were sampled in forest plots.

2.2.3 Earth observation data

Multi-wavelength radar and optical EO data were fused to exploit their complementary information (table 2.1). Sentinel-2 (S2) imagery was acquired during the late wet to early dry season to ensure active vegetation and minimal cloud cover.

Synthetic Aperture Radar (SAR) backscatter data from Sentinel-1 (C-band, $\lambda \sim 6$ cm) and longer wavelength L-band ($\lambda \sim 24$ cm) data from ALOS PALSAR were also used, with all available polarisations included (HH, HV and the HH:HV ratio for ALOS, VV and VH for sentinel-1). The radar backscatter intensity and polarisation from vegetated land are dependent on the structure and dielectric properties of the vegetation and the roughness and moisture content of the soil. The size, shape, density and orientation of vegetation components compared to the radar wavelength affect how the energy is scattered and received by satellite (Mc Nairn and Brisco, 2004; Joshi et al., 2016).

The yearly range of C-band backscatter (95th to 5th percentile) was calculated as a proxy for phenology. The standard deviation of 9x9 widows for the near-infrared and visible red S2 optical bands was also calculated because texture bands have been noted to capture vegetation heterogeneity (Farwell et al., 2021) and improve classification accuracy by reducing heterogeneity where land cover is the same and preserving feature boundaries (Wood et al., 2012; Vaglio Laurin et al., 2016).

Ancillary geospatial datasets were used to incorporate some important drivers of floristic composition. These included climate (seasonality and annual means for both temperature and precipitation from WorldClim v2, Fick and Hijmans 2017), aspect (from SRTM elevation, Jarvis et al. 2008), and soil (soil surface variables from ISRIC SoilGrids, Batjes et al. 2020).

To obtain meaningful variable importance values, colinearity tests were performed and principal component analysis was used for dimension reduction separately on the visible optical data (bands 2-4), soil data, and climate data. The first principal component of the visible optical data explained over 90% of the variance in each site. Soil and climate data were reduced to three principal components, accounting for over 85% of the variance in all sites. All data were resampled to a 20 m spatial resolution.

2.2.4 Floristic composition mapping

A plot-by-species matrix of abundance was used in a nonmetric multidimensional scaling (NMDS) ordination (Kruskal, 1964). NMDS is robust in complex ecological datasets (McCune and Grace, 2002) and is not subject to the distortion problems of some other methods (Schmidtlein and Sassin, 2004). It is an unconstrained ordination technique, which keeps scores independent of constraining predictor variables (Gu et al., 2015). NMDS describes the floristic gradients within the data based on a distance dissimilarity metric. In this analysis, the Bray-Curtis distance was used as it robustly deals with pairs of plots with similar species compositions (Legendre and Legendre, 2012). In this

Table 2.1: Remote sensing data used in the EO-ordination modelling

Data source	Date	Band	Notes
Sentinel 2	2019	PCA (B2,B3,B4) B8	Optical reflectance from vegetation depends on leaf structure, pigmentation and moisture
		B4 texture B8 texture	Texture bands can capture vegetation heterogeneity
Sentinel 1	2019	VV VH VH annual range	Radar backscatter from vegetation is dependent on structure and dielectric properties of vegetation and roughness and moisture content of soils
PALSAR	2018	HH HV HH/HV	
SRTM	2000	Northness	Aspect, climate and soil influence vegetation dynamics in natural ecosystems
Worldclim	1970-2000	Climate PCA1 Climate PCA2 Climate PCA3	Climate PC are seasonality, annual temperature and precipitation means and isothermality
ISIRIC		Soil PCA1 Soil PCA2 Soil PCA3	Soil PC are organic carbon, clay proportion, pH, cation exchange capacity and bulk density

analysis, the ordination space was constrained to 2 axes with the stress in each ordination under 0.2, indicating a fair solution (Kruskal, 1964; Dexter et al., 2018). The NMDS axes scores were then used as a variable for the gradient of tree species composition in the plots. The ordination was implemented in R using the vegan package (Oksanen et al., 2022).

2.2.5 Regression

The EO and geospatial data pixel values of the plots (Optical, SAR, and auxiliary data) were used in two Random Forest (RF) regression models (Breiman, 2001), one for each

NMDS axis. The predictors were the EO and geospatial data, and the responses were the NMDS axis scores. Sites without trees cannot be included in the ordination of tree composition and so were removed. The model outputs are displayed as a colour image with the first axis in red, and the second in green. The resulting map shows the predicted ordination scores of each pixel (figure 2.1). Random forest models provide variable importance values (impurity), indicating the importance of each predictor. To assess model performance, 25% of the plot data was held back as a validation dataset. The R^2 and RMSE were calculated using the validation dataset and repeated for 4-fold cross-validation. The validation data were a stratified random subset of the plots so used the same ratio of agriculture to forest plots as the training dataset.

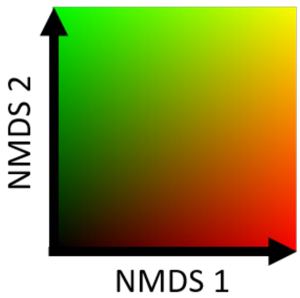

Figure 2.1: The colour space legend for mapped ordination axes. Ordination axes scores are mapped using Earth observation and geospatial data. Each pixel is coloured according to its predicted ordination score in this colour space (axis 1 in red; axis 2 in green).

We quantified uncertainty by calculating how well the predicted pixel values were represented in the field data as a measure of the information lost from the training data (Feilhauer et al., 2021). The Euclidean distance between each pixel's predicted value in the ordination space and the nearest ground plot point in the ordination space is calculated. This visualisation of uncertainty shows how supported the predictions are by the coverage of plots.

2.3 Results

2.3.1 Uganda

In Uganda, the NMDS scores distinguish tree communities in agriculture from forests along axis 1 (figure 2.2). The second axis shows a compositional gradient within both forest and agricultural plots. In forest plots, species with higher NMDS2 scores tend to be native Afromontane forest species associated with primary forest (*Tabernaemontana johnstonii, Xylamos monospora*). Species with middling and lower values are associated with disturbed forests, containing pioneer species (*Maesa lanceolata*, *Alangium chinense*) or species left after land clearing (*Ficus sur*, *F. sycamorus*). The gradient in agricultural plots appears to be biogeographic. Drier woodland species have greater NMDS2 values (*Grewia spp.*, *Combretum spp.*), while humid species have lower NMDS2 values (*Grevillea robusta*). More species with lower NMDS2 values were fruit or tree crops (*Persea americana*, *Atocarpus heterophyllus*, *Coffea arabica*, *Mangifera indica*), while species with higher NMDS2 values were likely to have other uses like construction or fuelwood.

The most abundant species across the Uganda dataset was *Eucalyptus grandis*, found in farmland as small woodlots and in forest plots on the forest edge where the National Park boundary is planted with a *E. grandis* buffer. The buffer is mapped in the model separate from the rest of the forest (labelled 'y' in figure 2.3).

Spatial predictions from the model shows that the forest is defined by low NMDS1 values shown in shades of green. The brightness of green indicates the pixel's modelled position along the second axis, with brighter greens having higher values. There are patterns of green within the forest with darker greens at the forest edges and a patch in the southeast (labelled 'z' in figure 2.3). The agricultural land shows a gradient displayed from deep orange to yellow, showing predictions moving up the second ordination axis, from predominantly fruit trees nearer the forest to the savannah species. The uncertainty map (figure 2.4) shows areas near the forest boundary are predicted to have ordination values further from the training data collected.

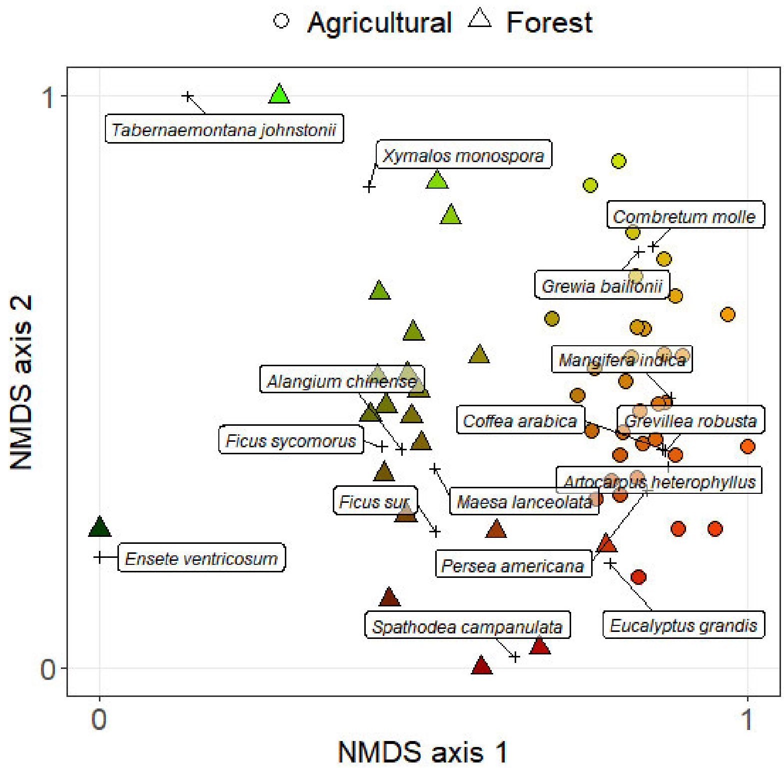

Figure 2.2: Ordination plot for Elgon showing the distribution of all plots and a subset of species, with field plot points coloured as they appear on the map

2.3.2 Rwanda

The ordination shows a general agricultural-forest divide along the second axis but shows overlap in species occurrences (figure 2.5). The predominant species in forest plots are exotic plantation species (*Pinus patula, Eucalyptus spp., Acacia melanoxylon*). There is overlap with agricultural plots where there are woodlots of these plantation species. Plantation plots are modelled with medium-to-low values on the first axis and medium-to-high values on the second. The common woodlot species were exotic *Alnus acuminata* and *Cupressus lusitanica*. Trees on farms were generally more native species with various uses like fruit (*Persea americana*), live fencing, fodder (*Erythrina abyssinica*), fuelwood and timber (*Markhamia lutea*), modelled with medium-to-low values on both axes. The plots with high values on both axes had native species more associated with

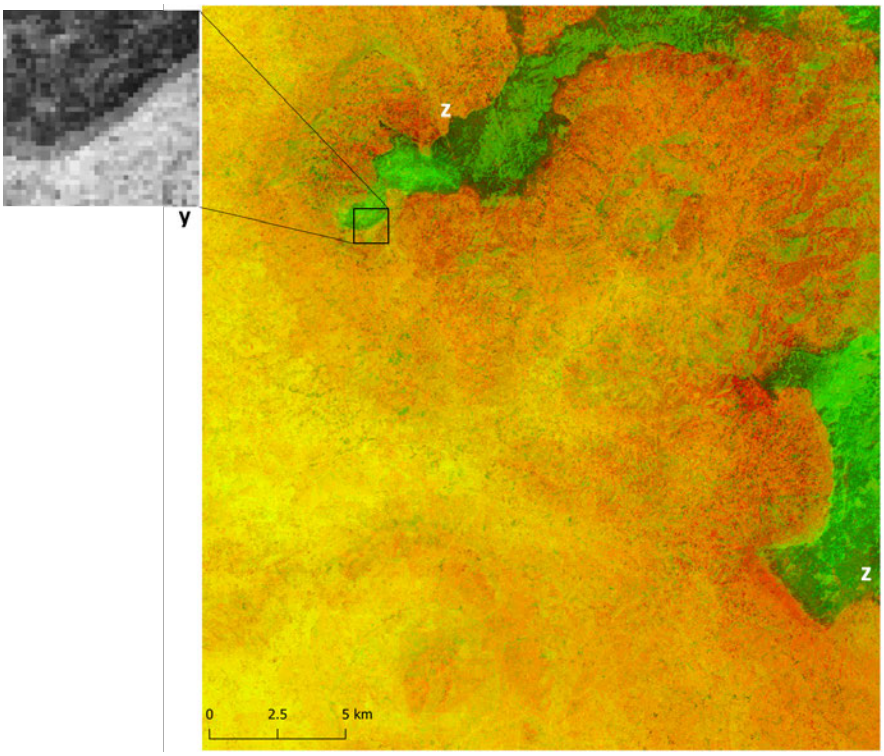

Figure 2.3: Tree floristic composition for the Elgon, Uganda landscape with mapped ordination axes values predicted by the random forest model. Each pixel is coloured according to its ordination scores. The eucalyptus buffer on the forest edge is shown by the inset labelled 'y'. The inset map is the prediction of the first ordination axis values. Forest patches of lower second ordination axis are labelled 'z'.

disturbed lands. Pioneer species (*Macaranga kilimandscharica*) and species left after clearing (*Polyscias fulva*) were more common here.

The forest is mapped in shades of green, being predominantly exotic plantation species. The agricultural land is mapped in reds and oranges. The agricultural mosaic surrounding the forests and pasture is mapped as a patchwork of dark green, red, and orange. These are ordination values of different compositions of agroforestry tree species, with greener values likely to be plantation woodlots. The spatial model cannot predict NMDS values on land without trees. There are large areas of pasture without trees in the landscape. The model attempts to predict ordination values here with high axis 1 values as the few pasture plots with trees have high axis 1 values. The uncertainty map (figure 2.7) shows

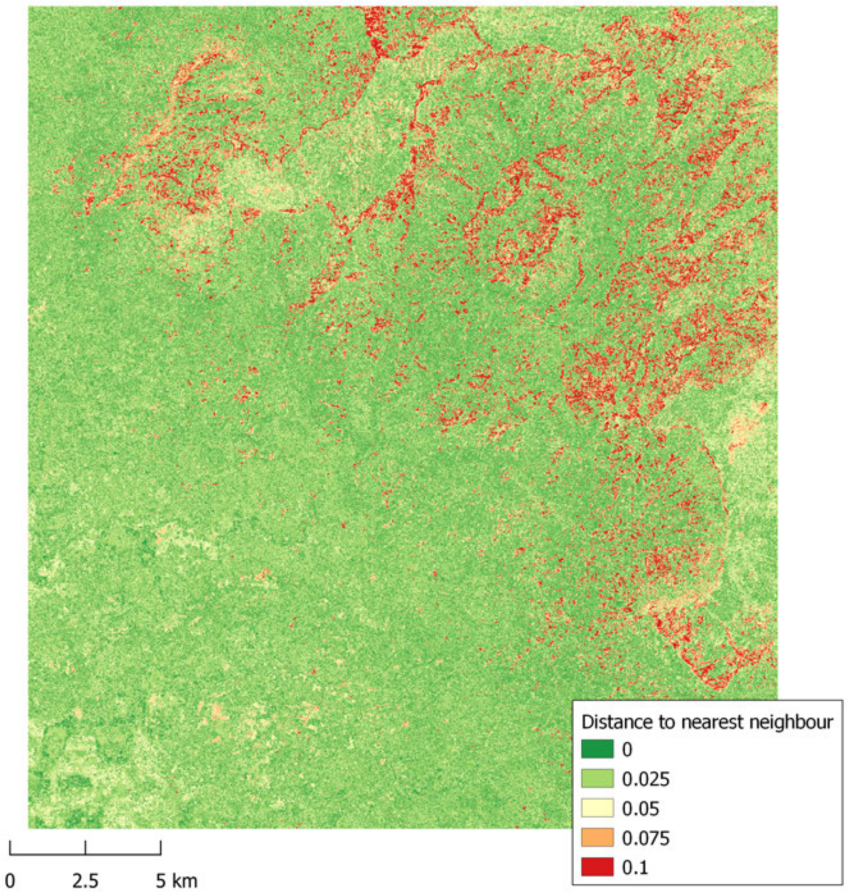

Figure 2.4: Uncertainty of the tree floristic composition map for Elgon, Uganda, measured by the predicted pixels euclidean distance to the nearest neighbour from the plot data

areas within the pastureland in the centre of the landscape are being predicted to have ordination values further from those of the plot data.

2.3.3 Honduras

There is a gradient of forest to agricultural plots with overlapping species in the ordination for Honduras (figure 2.8). The species with low first-axis and high second-axis values are species of Central American Oak-Pine forests (*Pinus spp.*, *Quercus spp.*, *Curatella americana*). Higher first-axis forest plots have native species associated with lowland forests

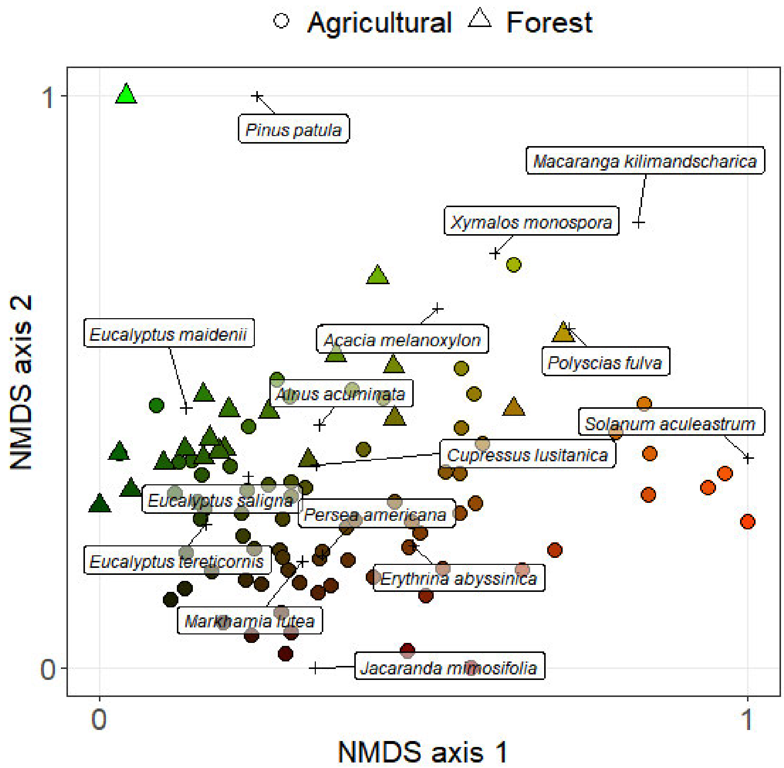

Figure 2.5: Ordination plot for Gishwati showing the distribution of all plots and a subset of species, with field plot points coloured as they appear on the map

or forest edges (*Goethalsia meiantha*) through to premontane forest species (*Clarisia biflora*). The majority of agricultural plots have low second-axis values with native species typically found in pasture (*Guazuma ulmifolia*) and species cultivated for use on farms like fencing, shade or fodder (*Gliricidia sepium, Tabebuia rosea*).

When ordination axes are modelled spatially, the map shows the gradient from yellow to green to dark green and orange, broadly following the gradient of forested hillsides into the agricultural valley floor (figure 2.9). Many of the trees in the agricultural land form linear features across the landscape. Linear features of riverine forests are modelled in deep orange (higher first-axis values than second; labelled 'q' in figure 2.9). While pioneer species are found across the landscape, the tree species that can be found in these riverine areas are species expected in secondary succession (*Vachellia collinsii*,

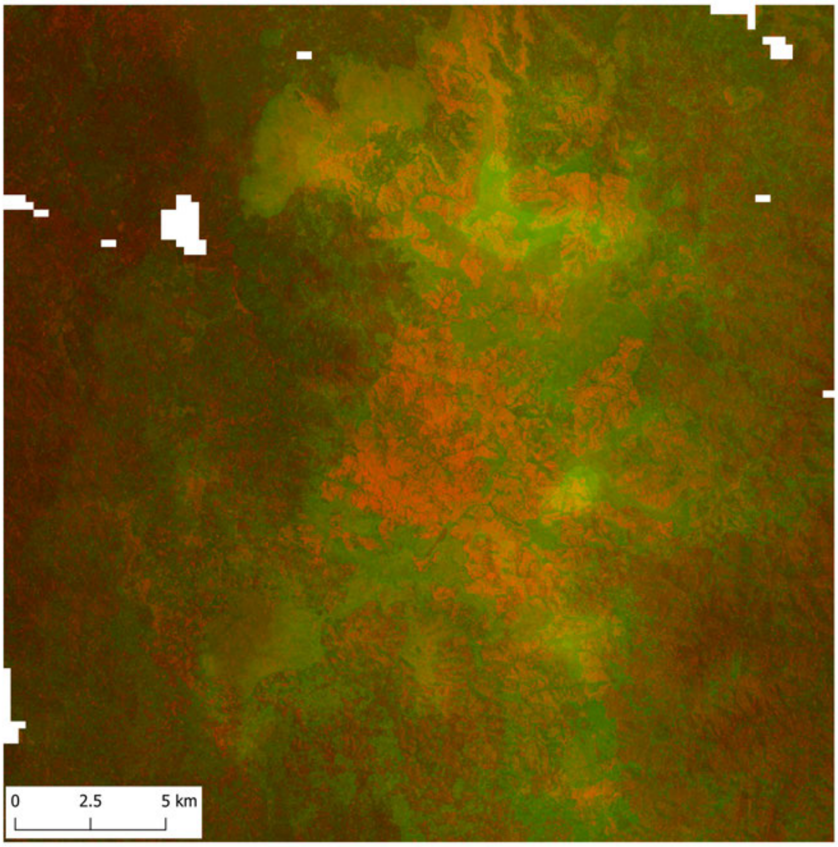

Figure 2.6: Tree floristic composition for the Gishwati, Rwanda landscape with mapped ordination axes values predicted by the random forest model. Each pixel is coloured according to its ordination scores.

Maclura tinctoria, *Ceiba pentandra*). Where trees form live fences, they are modelled in deeper green (Higher second-axis values than first; labelled 'r' in figure 2.9) and have species cultivated for live fencing (*Bursera simaruba*, *Cordia alliodora* and other uses like fruit (*Psidium guajava*, *Chrysophyllum cainito*). This shows the gradient of composition between these different linear features. The uncertainty map (figure 2.10) shows that most of the pixels are predicted to have values close to the field data, indicating the mapped area was well sampled by the field data.

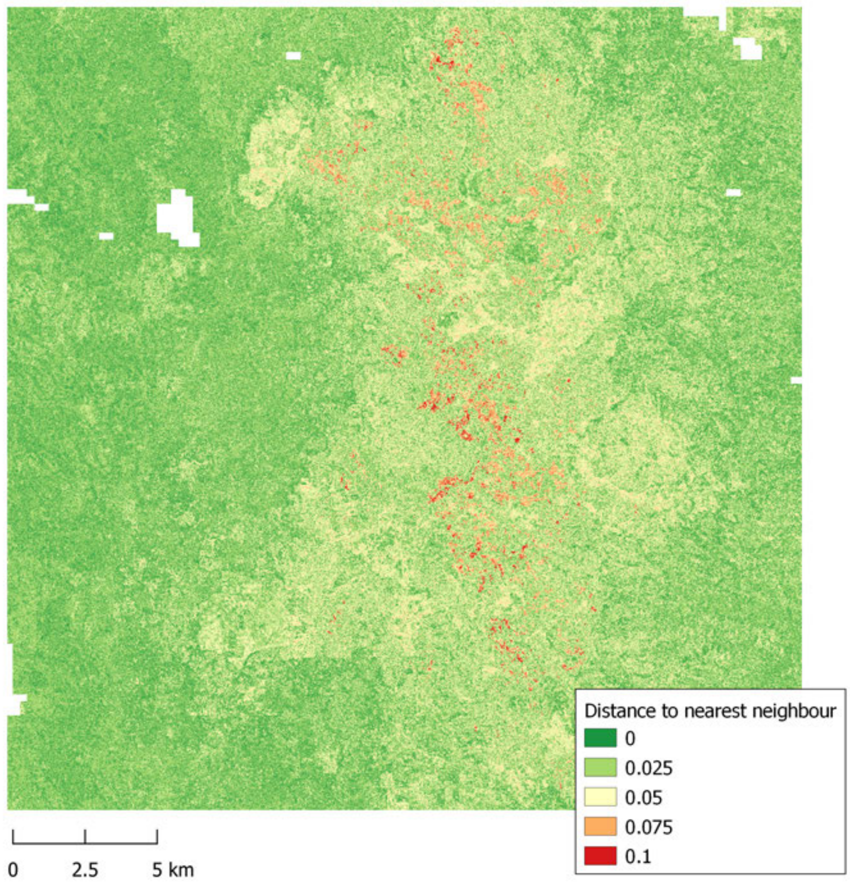

Figure 2.7: Uncertainty of the tree floristic composition map for Gishwati, Rwanda, measured by the predicted pixels euclidean distance to the nearest neighbour from the plot data

2.3.4 Validation

Model validation shows encouraging results (table 2.2). The models for Uganda performed best with mean RMSE at 11% of the axis length, and both axes performed well. The models at other sites were more variable. The models for Rwanda had the highest and lowest RMSEs across all models. The mean RMSE values for all models were between 10% and 15%, ranging from 9% to 19% for individual axes.

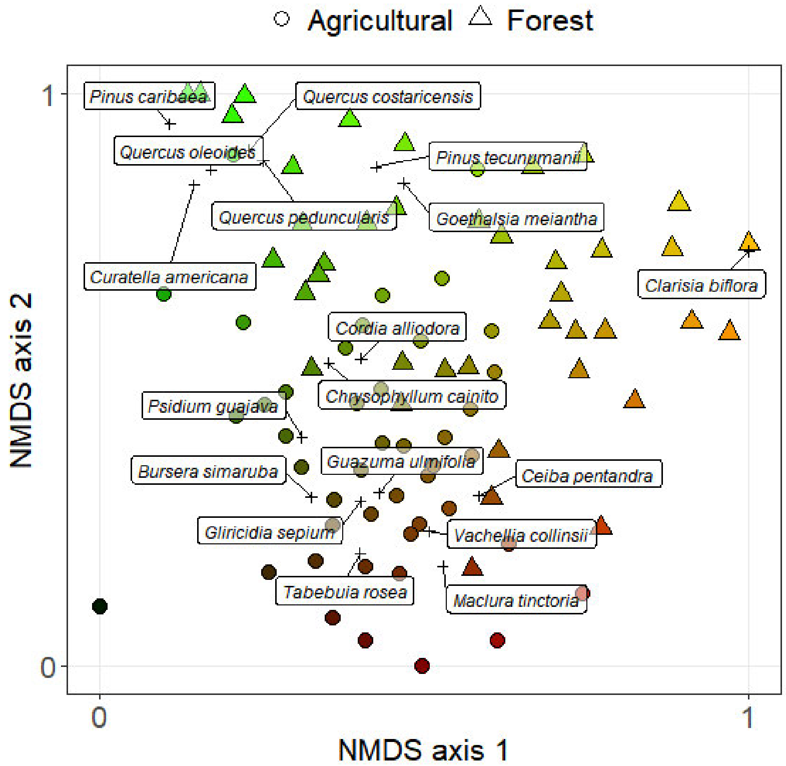

Figure 2.8: Ordination plot for Catacamas showing the distribution of all plots and a subset of species, with field plot points coloured as they appear on the map

2.3.5 Model band importance

The relative importance of the EO bands shows that a wide range of data sources contributed to model performance (figure 2.11). The most important bands were not consistent across sites. Overall, the most important variables for modelling the gradients were climate and optical reflectance variables, followed by radar backscatter and texture bands, with soil and aspect being the least important on average.

In Uganda, the most important bands for predicting the first axis (natural forest - cultivated) were optical, textural, and L-band radar polarisation ratio, whereas climate variables were the most important for the second axis (forest / agroforest type). The spread of important bands for Rwanda was wider, meaning the model harnessed a broader range

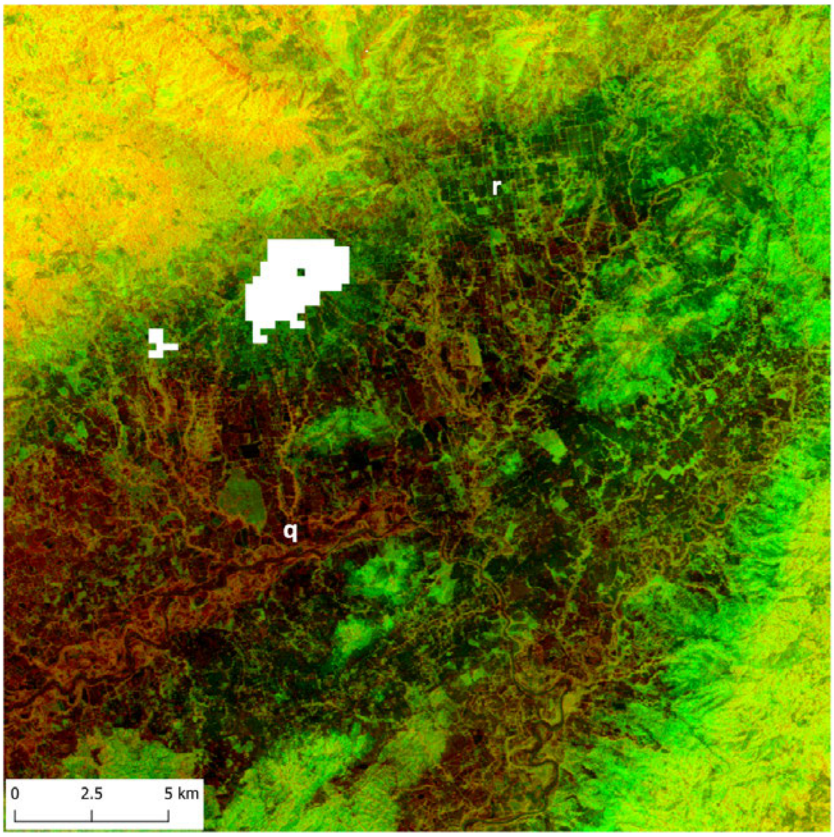

Figure 2.9: Tree floristic composition for the Catacamas landscape with mapped ordination axes values predicted by the random forest model. Each pixel is coloured according to its ordination scores. The riverine forest features are labelled as 'q'. Areas of live fencing are labelled 'r'.

of inputs to make its prediction. The gradient along the first axis (planted - pioneer) is related to near-infrared and cross-polarised radar bands. Along the second axis (forest - agriculture), optical, radar and biophysical predictors were important. In Honduras, climatic predictors were important in both axis, with the first axis supported by texture and the second axis supported by other optical bands.

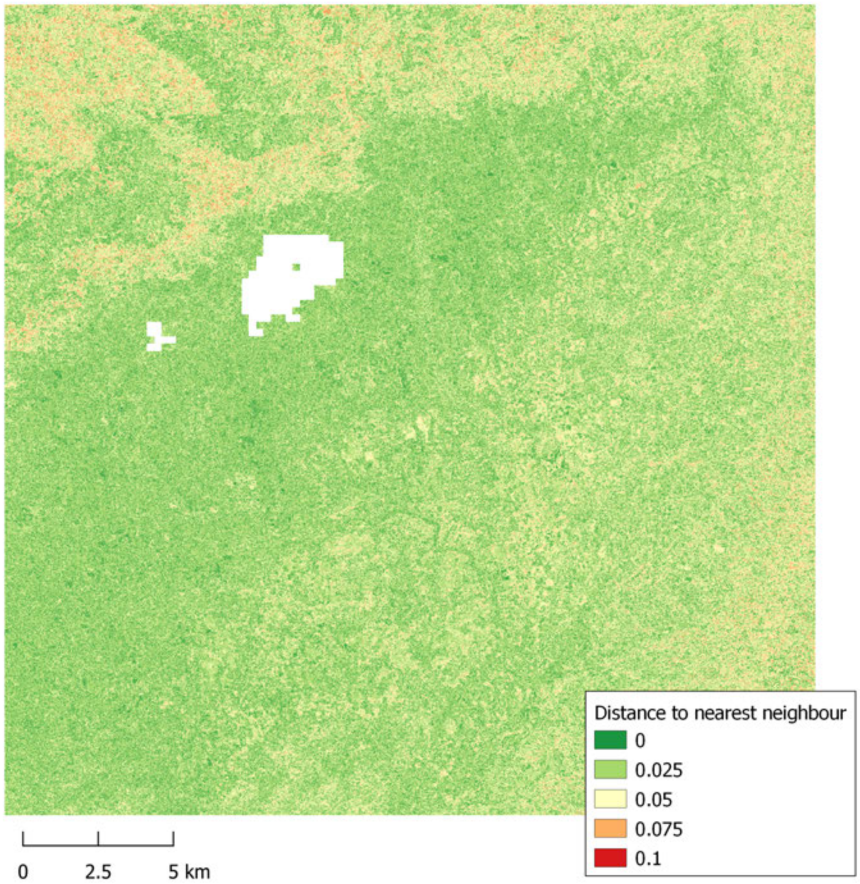

Figure 2.10: Uncertainty of the tree floristic composition map for Catacamas, Honduras, measured by the predicted pixels euclidean distance to the nearest neighbour from the plot data.

2.4 Discussion

Our results show it is possible to model tree floristic composition with remote sensing. This is a novel finding in the context of agricultural-forest landscapes and supports the findings of previous work in other landscapes. This research extends the method to trees in agricultural land, showing the method can be an important tool for biodiversity monitoring, which will be important as agricultural lands are increasingly recognised for their potential for maintaining biodiversity (Vandermeer and Perfecto, 2007). Conservation

Table 2.2: The hold out accuracy of EO-ordination modelling at three agricultural-forest landscapes. The accuracy of the predictions from the model was assessed with 25% of the data held back from the training (repeated 4 times with stratified random data partitions). Mean R^2 and RMSE values are given for predictions of each NMDS axis, with RMSE shown as a % of the range of axis scores

	Axis 1		Axis 2	
	r^2	RMSE	r^2	RMSE
Elgon, Uganda	0.77	10%	0.61	12%
Gishwati, Rwanda	0.56	19%	0.57	9%
Catacamas, Honduras	0.74	12%	0.56	17%

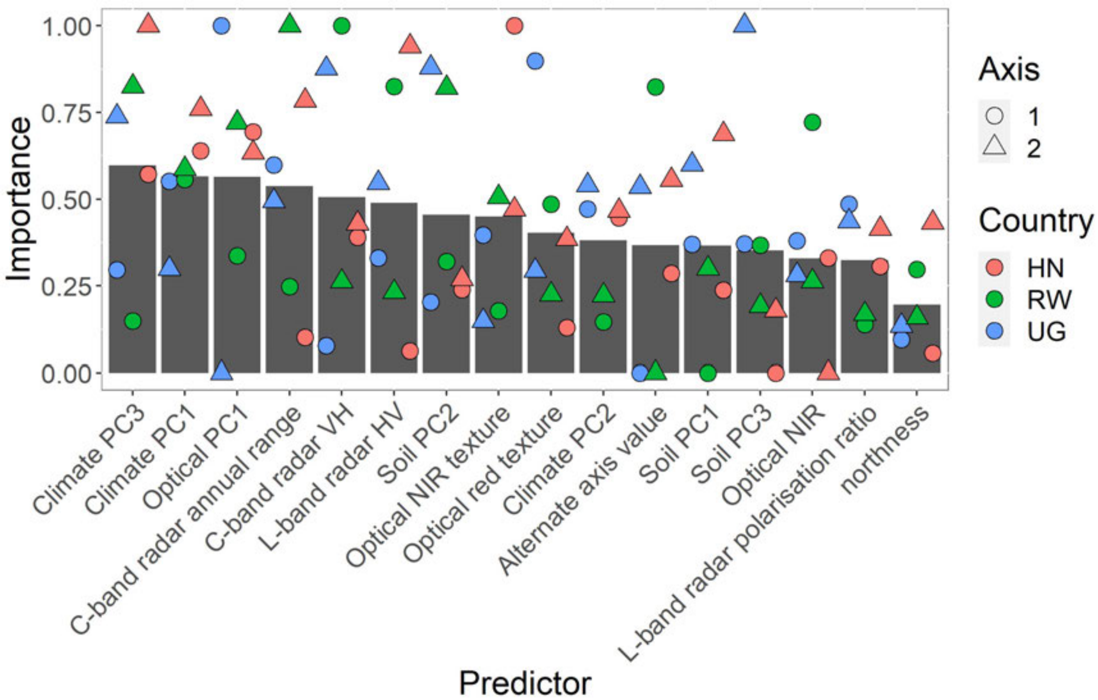

Figure 2.11: Normalised band importance values for EO-ordination models. Importance values taken from random forest models of ordination scores using optical, radars and other geospatial datasets for three agricultural-forest landscapes. Individual model importance values are given, one for each ordination axis at each site, and sorted by overall mean importance value.

of biodiversity within natural ecosystems needs to be complemented with biodiversity conservation within transformed landscapes, such as the farmland that covers 30-40% of global land area (IPCC, 2019). Trees are where much of the biodiversity management in agricultural landscapes can take place (Barrios et al., 2018). While tree cover maps provide an indication of the number of trees in these lands, this method provides important detail in indicating the types of trees growing, which is critical for understanding and monitoring biodiversity (Pereira et al., 2013; Rocchini et al., 2018).

2.4.1 Mapping tree floristic composition in agricultural-forest mosaic landscapes

The geospatial data clearly contains considerable information about tree floristic composition in these landscapes. This information is reflected in the complex relationships between the EO variables and the ordination scores. Overall the results show that EO-ordination can map tree community composition in agriculture-forest mosaic landscapes. While the validation of the models differs between sites (table 2.2), all models performed well against a validation dataset proving the utility of the method for this application.

The ordinations axes found interesting spatial gradients of composition in these mosaic landscapes. The sites contain a mixture of land covers and habitats within these land covers. The ordinations pick up these discrete transitions in land cover and more continuous transitions between and within them. Methods for mapping habitats typically employ discrete classifications, which is appropriate where there is little species overlap, relying on spectral responses being 'pure' representations of the habitat or land cover (Feilhauer et al., 2021). Here we find that most of these landcovers have nuanced gradients of tree species found from forest to agriculture (figures 2.3, 2.6, 2.9). Furthermore, field data in these complex landscapes are rarely 'pure' assemblages of a discrete class, because of the small-scale heterogeneity and active management of trees in the landscape. EO-ordination models can show this spatial variability as a continuous gradient, reflecting the real fuzziness of habitat transitions. The results from these heterogenous landscapes support Feilhauer et al. (2011), who compared different ordination methods in a range of environmental conditions and management across heathland, grassland

and early successional forest, mapping the axes with hyperspectral data, showing that gradient mapping could be applied to heterogeneous landscapes.

The distribution of species across ordination space allows us to infer spatial patterns of land use or tree use. In these heavily managed landscapes, understanding patterns of tree composition is useful beyond biodiversity, helping us understand how people use the landscape and what they choose to grow. In agricultural land in Uganda, we see a gradient from more fruit trees to fuel and fodder species; in Rwanda a mosaic of homegarden and farms trees with woodlots; and in Honduras, fence boundary trees are separated from riverine features. Species associated with these gradients show how people use the landscape. Understanding how people use the landscape has implications for biodiversity and development. Modelling the current patterns of tree composition on farms provides a better understanding of tree use by farmers, which can inform the advice and guidance given to increase the uptake and diversity of trees on farms to help farmers and biodiversity.

Several other studies have applied EO-ordination to forest habitats to map tree floristic composition (Ohmann and Gregory, 2002; Feilhauer and Schmidtlein, 2009; Hernández-Stefanoni et al., 2012; Adams et al., 2019), but few have included forests with such active use by humans. The results show that, like other studies, the forest gradients could be mapped. The results in Uganda show that the gradients in forest type can be gradients due to disturbance or human use rather than natural transitions of forest types, the latter being seen in the results from Honduras. Existing methods of mapping forest disturbance using remote sensing data often do not use ground data but image-to-image change detection, classing pixels as disturbed or undisturbed (Hirschmugl et al., 2017). These results show more nuanced species- or community-specific information can be extracted from a single date. This shows how human use is shaping these forests. From a biodiversity perspective, this provides more detail into what disturbance means for composition and its effect on habitat.

The validation statistics are comparable to similar studies. All axes could be regressed with an RMSE $<$20% with R^2 $>$0.5 (table 2.2). Other studies report similar validation at $\sim$10-15% (Schmidtlein et al., 2007; Feilhauer and Schmidtlein, 2009; Harris et al., 2015; Adams et al., 2019). This study in three sites with different agricultural contexts extends the utility of this method to new landscapes in need of monitoring. In these study sites, the model in Rwanda performed more poorly than the others. This may be due to the large range of land covers in which the dominant tree species occurs. If few large tree species are ubiquitous across the landscape as in Rwanda, where almost three-quarters of plots had a *Eucalyptus spp.* present, it can reduce the model performance. While Eucalypts are present throughout, the compositional differences are driven by non-dominant species. This is a harder task for the model, where larger, more dominant tree species drive variability in EO predictor variables, so models may struggle to separate these plots. Feilhauer et al. (2011) suggest local regression approaches to overcome situations where similar compositions may have spatially variable appearances. This approach could also be tested where the location in the landscape may influence the composition as a proxy for management. In Rwanda, Eucalypts planted in farmland or small woodlots are managed differently than in large plantations and will have different community composition.

The EO-ordination models were able to map tree community composition in both agricultural land and forests in these mosaic landscapes. Gradients between and within land covers were identified in the ordination plots and were subsequently mapped across the landscape with good validation statistics.

The uncertainty maps also indicate what areas within the landscape the model is making predictions that are not represented by the field data. There are some wide areas of higher uncertainty in Rwanda, in this case highlighting where within the landscape is without trees (pasture, tea plantations etc.) and therefore without input data. In Uganda, these areas of uncertainty are predominantly on very steep slopes where the remote sensing data is more distorted, but also include small areas of agricultural land that may indicate .

2.4.2 The most useful EO data are site-specific

This research used a combination of optical, radar and biophysical geospatial datasets. The results show a range of bands are important for model predictions and separating composition. Climate, optical and radar predictors were the most important variables on average. The variable importance suggests that some of the gradients of composition are driven more by climate, and others are modelled by their spectral properties. They differ between sites probably because the ordinations explain different and site-specific compositional gradients, which will be realised as different electromagnetic properties of the land surface. Data fusion from optical and radar data provides information on canopy biochemical properties (leaf chemistry) and woody structure (Joshi et al., 2016). This likely helps pick apart effects of land use, management, ecological stresses and phenology compared to when using a narrower part of the electromagnetic spectrum. Plant physical traits have different signatures across bands (Ollinger, 2011), and the auxiliary data helps define ecological bounds (climate and soils) of potential compositions across the landscape.

Optical data were one of the most important predictors on average across all the models. Gradients in composition may be predicted by optical data as different tree communities will reflect optical bands in different ways depending on the species' biochemical and biophysical properties. Tree communities will reflect optical bands differently depending on the species' biochemical and biophysical properties. Biochemical properties, including chlorophyll content and water, determine how much radiation is absorbed or reflected by the plant and in which wavelengths. Biophysical properties will control how much light is scattered and in which directions (Ollinger, 2011). Plant species and composition can therefore have different spectral signatures but are not necessarily always unique (Price, 1994). Other surface properties also impact the response, like bare ground, soil moisture (Schmidtlein, 2005), debris and, in this research, understory vegetation. Phenology and plant health can also influence biochemistry and plant structure (Ollinger, 2011; Jones et al., 1989). Optical data have been the more commonly used datasets in floristic gradient mapping, though often from hyperspectral sensors with many narrow spectral bands to pick up slighter differences in composition (Gu et al., 2015; Harris et al., 2015; Neumann et al., 2015; Schmidtlein et al., 2007, 2012). There are successful examples, however, of gradient mapping with multispectral imagery (Ohmann and Gregory, 2002; Thessler et al., 2005; Hernández-Stefanoni et al., 2012; Feilhauer et al., 2014; Adams et al., 2019), showing that high spectral resolution is not always necessary.

Image texture has been shown to characterise vegetation structure and composition at national scales (Farwell et al., 2020). Texture bands capture spatial variation in spectral responses around a pixel and indicate the local heterogeneity of spectral responses from vegetation (Haralick et al., 1973). They have been successfully used in EO-ordination models (Hernández-Stefanoni et al., 2012). The texture of spectral bands from wavelengths with important vegetation information will therefore provide information about the heterogeneity of horizontal structures of trees around a pixel.

The use of radar data is seldom used in biodiversity studies but is useful for monitoring vegetation. Radar data has limitations like speckle noise and radar shadow, but unlike optical, it is not affected by cloud cover or solar illumination issues like time of day or shadows (Herold et al., 2005). Due to its penetrative capability, radar backscatter from vegetation is determined by various structural attributes (Woodhouse et al., 2012). Radar can estimate above-ground biomass (AGB), and several studies have established these relationships (Mitchard et al., 2009; Ryan et al., 2012; Mermoz et al., 2014; Ningthoujam et al., 2018; Braun et al., 2018; McNicol et al., 2018). Radar images have been used to calculate habitat connectivity metrics (Betbeder et al., 2015, 2017) and pick out structural differences in otherwise homogeneous forest stands (Imhoff et al., 1997). Bae et al. (2019) demonstrated radar's utility in EO-ordination mapping, finding that radar was as sensitive to variation in temperate forest structure as airborne laser scanning.

The ordinations describe site-specific gradients of tree composition and so the information provided by different geospatial datasets will have varying importance between models. The results reflect this with most useful EO data for predicting tree floristic composition being inconsistent between sites. Biophysical, optical and radar data have different predictive power across sites and ordination axes.

2.4.3 EO-ordination modelling as a useful monitoring tool in agricultural-forest landscapes

With progress toward national scale data collection to monitor carbon stocks using national forest inventories, there is an opportunity to incorporate biodiversity monitoring

(Gillerot et al., 2021). The requirement for broad scale assessments of biodiversity has led to methods like EO-ordination (Thessler et al., 2005; Schmidtlein et al., 2007; Rocchini et al., 2018). Methods like this could take advantage of in-situ data collected during national inventories and use it to (re)calibrate models over time. To be used as a monitoring tool, however, comprehensive ground datasets are needed, ensuring that most community compositions and floristic gradients are captured. This may be an unrealistic expectation for most national inventories, which have lower sampling intensities (Nesha et al., 2022). The uncertainty maps show that in Rwanda and Honduras, the predictions were mostly represented by the field data. In rwanda, the predictions were understandably further from field data in areas of the landscape that were unsampled due to the absence of trees. In Uganda however, the uncertainty map shows areas where the predictions were not represented by the field data, indicating the field data did not sample the full range of tree compositions in the landscape.

To scale up the models, enough data must be collected to ensure that the full range of floristic composition is available for calibration. The maximum area the method could be applied to will be limited by what realistic volume of field data can be collected to capture the compositions and gradients. A larger area will likely include more gradients of vegetation change. In bigger landscapes, a two, or even three-axis ordination may not accurately describe floristic gradients in the data. This also limits the method's maximum landscape size, and models would need to be recalibrated in smaller spatial units.

Understanding the thematic resolution of this method is critical to applying it effectively and making appropriate inferences. The method can resolve gradients of tree composition at the scale of the inventory data. The spatial resolution of open-access satellite data necessitates plots of 0.2-1 ha, which are often affected by within-plot heterogeneity of species composition in complex landscapes. A single plot might cover multiple land uses or vegetation types. The ordination and maps do not model minor differences in tree communities but broader differences. Sites without trees cannot be included in ordinations of tree composition, so spatial models cannot predict values on land without trees. Ideally, these areas could be masked out of maps, but without accurate tree cover data, this risks erroneous inclusions and omissions.

Monitoring biodiversity requires methods sensitive to change over time (Pereira et al., 2013). Without repeat inventory data, testing this method for exploring change cannot be done. This remains a gap in EO-ordination. While changes in ordination axis values will be meaningless, because different compositions would likely result in very different orientations of data in the ordination space, interpreting time-stepped maps could help understand shifts in compositional gradients across landscapes in response to changing human activities, interventions and climate.

2.5 Conclusion

While field data are still key to accurate mapping of vegetation composition, the rapid advancement of satellite technology and machine learning has expanded the uses of inventory data. Few existing methods for mapping floristic composition capture gradients spatially, limiting our understanding of biodiversity patterns. EO-ordination research is generating methodological frameworks for these biodiversity assessments but is currently limited in applications to untransformed landscapes. This study shows that EO-ordination modelling using a fusion of data in a machine learning model can map tree floristic gradients in complex agriculture-forest mosaic landscapes. Mapping continuous gradients of species composition in these landscapes is a valuable addition to biodiversity assessments as it adds greater detail and nuance to understanding vegetation cover. The need for a spatial understanding of tree composition in agricultural landscapes is growing in importance as we look for ways to support biodiversity outside of protected areas. Mapping these facets of the landscape feeds into monitoring the EBV of community composition. Open-access data availability for this method bolsters its utility to practitioners and decision-makers with fewer resources to dedicate to wide-scale monitoring.

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Chapter 3

A Farm Biodiversity Score for consistent monitoring of biodiversity based on the measurement of trees on farms

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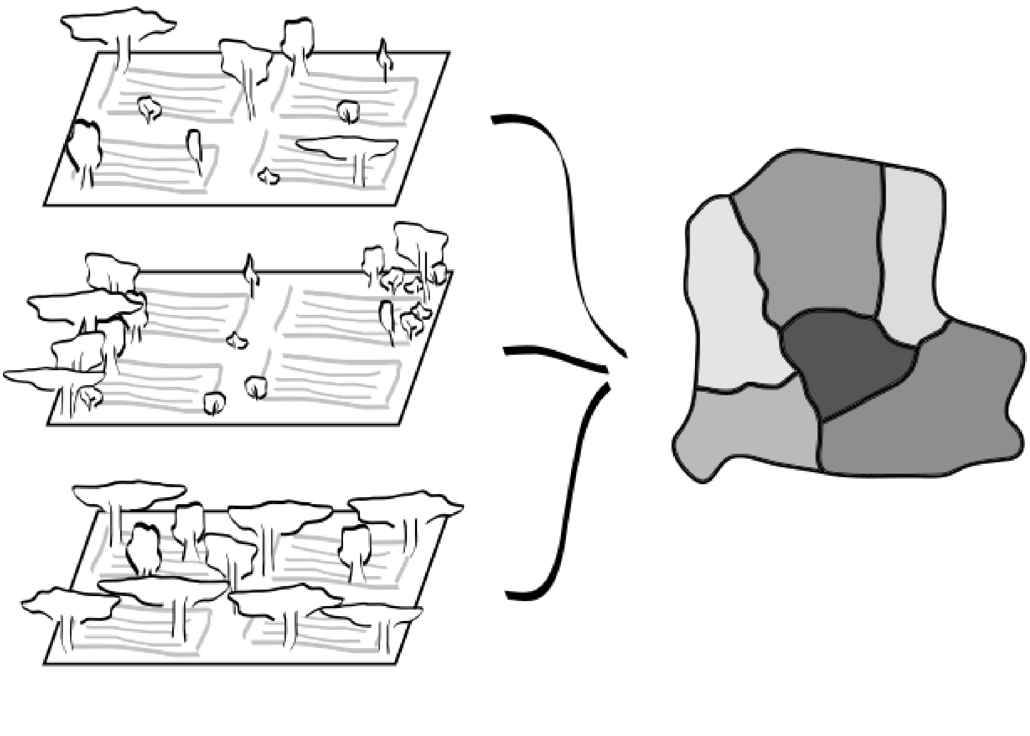


A version of this chapter has been published as an ICRAF working paper (Working Paper No. 321; Harrison et al. 2021). SBH developed the indicator with inputs from CMR and RDH. RDH and AG developed the proposal for the indicator.

Abstract

Effective biodiversity conservation efforts must include the agricultural land that covers one-third of global land area. Trees on farms are an essential aspect of how biodiversity can be maintained and enhanced on agricultural land and will be critical to meeting global biodiversity targets for production landscapes. Trees on farms benefit biodiversity by providing habitat, mitigating external resource pressures (e.g. for timber) and creating a less hostile barrier to movement between natural land covers. A lack of systematic data on the biodiversity in agricultural land means monitoring global targets is difficult. This unmet need for repeated, consistent and low-cost measurements likely contributed to the failure of Aichi biodiversity target 7. There is a clear need for indicators of agricultural biodiversity applicable at wide-scale and across different landscapes. Recent advances in satellite data and geospatial technologies make it possible to address these challenges. They have transformed land monitoring for biodiversity, but to date, this has been focused on forests and natural lands. Here we present the proof of concept for an indicator of the biodiversity value of agricultural landscapes by assessing the properties of their trees. The aim is that this indicator will be useful for planners and decision-makers to monitor agricultural land, report on biodiversity and plan informed conservation strategies. The tool uses freely available satellite data products to estimate wooded area, structural diversity and spectral diversity of agricultural lands. It combines them to ascribe a score that can be mapped at national scales. Qualitative validation shows promising results in four case studies in various agricultural contexts. The mapped scores reflect what we might expect from photointerpretation of a sample of sites across the case study areas. The tool is ready for further validation. Further areas for development include improvements in data that can come from forthcoming satellite products, as well as further qualitative validation from those with on-site expertise. This tool has the potential to be a useful and much-needed indicator for the post-2020 agenda for measuring and monitoring agricultural biodiversity.

3.1 Introduction

Globally, the conversion of natural land to agriculture is the primary cause of land use change and biodiversity loss (IPBES, 2019). Protected areas alone will not be enough to preserve our remaining biodiversity, and conservation efforts must also include the agricultural land that covers 30-40% of global land area (IPCC, 2019). These strategies should harness the potential that agroecosystems have to support biodiversity when managed to do so. Reporting on efforts to sustain or improve agricultural biodiversity is hindered by a lack of methods for monitoring it. This paper will outline and present the concept of a new remote sensing-based tool for national scale monitoring of biodiversity in agricultural landscapes based on measuring trees on farms.

The Convention on Biological Diversity (CBD) recognised the importance of sustaining biodiversity in agricultural lands by setting a target (target 7) for areas under agriculture to be managed sustainably, ensuring the conservation of biodiversity in the Aichi biodiversity targets (2011-2020), likely to be followed by target 10 in the post-2020 agenda (CBD, 2021). Broadly the Aichi targets, including target 7, have failed, with no target being fully met by 2020 (IPBES, 2019; CBD, 2020). This has been partly attributed to the way in which the goals were set, with experts saying the targets were unrealistic and progress too difficult to measure (Green et al., 2019). Sustaining biodiversity on agricultural land is also critical to the sustainable development goals (SDG), with goals to promote sustainable agriculture (SDG2) and to halt biodiversity loss (SDG15). It is therefore critical that an appropriate way of measuring agricultural biodiversity at broad scales is developed if agricultural sustainability is to be achieved in global agendas and for these goals to be measured and met, most critically in the forthcoming CBD post-2020 agenda.

Current ways of measuring biodiversity on agricultural land involve time-consuming and costly fieldwork for detailed measurement at the farm scale (Herzog et al., 2013). Field-based methods may require taxonomic expertise, specific fieldwork timing, interviews with farmers on land management and lengthy post-fieldwork sample analysis. This is not appropriate for national or global scale monitoring of targets. Satellite remote sensing has been an established tool for monitoring land cover at large scales for decades, and new technologies and methods are expanding the potential for satellite data. Several useful reviews on remote sensing for ecology, conservation and biodiversity (Kerr and Ostrovsky, 2003; Turner et al., 2003; Wang et al., 2010; Anderson, 2018) show that remote sensing data can collect a variety of useful information about biodiversity at scale with repeat measurements in a cheap and timely manner. Despite the potential, little effort has been made to develop the appropriate tools to use this data in agricultural landscapes, with much of the focus on natural and undisturbed habitat monitoring, or quantifying the damage that agriculture does (Petrou et al., 2015). Applying remote sensing data to the problems of monitoring agricultural biodiversity could offer a solution. While this approach loses individual farm-level information, this detail is not necessarily required for national or sub-national target monitoring. Landscape-level approaches better serve the aims of target monitoring, and satellite data can facilitate this.

Sustainable approaches to land management show that farms can support biodiversity while remaining productive. Research in recent decades has highlighted the link between trees on farms and biodiversity (McNeely and Schroth, 2006). Trees can facilitate greater levels of biodiversity in these agricultural landscapes. Schroth et al. (2004) outline and evidence the three key ways in which these practices boost biodiversity. First is the provision of habitat for species that are able to tolerate certain degrees of disturbance. Trees on farms can provide suitable habitat for plant and animal species that partly rely on forest habitats to survive. Introducing habitat heterogeneity, structural complexity, and diverse assemblages of trees onto farms facilitates the integration of more species into these systems. Connecting tree populations across the landscape further promotes species movement, genetic mixing and survival, both within the agricultural land and between natural habitats. The second is the reduction of pressure on nearby habitats. The hypothesis is that if the needs and resources of the farmer can be met through trees on their farm, they are less likely to exploit trees in external natural habitat patches (Atangana et al., 2014). Limited research explicitly tests whether trees on farms reduce the pressure on trees outside farms, with many locally specific factors likely to affect it. Angelsen and Kaimowitz (2004) discuss the circumstances which influence this hypothesis. This includes the farmer's land tenure, capital and labour resources. Lastly is that in mosaic landscapes of agriculture and natural or semi-natural habitat patches, the biodiversity in the non-farmed vegetation parcels is greater where the agricultural land has trees. These landscapes act as buffer zones and more permeable connective habitat between other patches. Trees on farms also provide a host of other ecosystem services that reduce biodiversity loss, like supporting soil biodiversity, erosion control and water regulation (Udawatta et al., 2019). Meta-analyses of biodiversity studies have found significantly higher species diversity in agricultural land with trees (Udawatta et al., 2019), with average species richness across all taxa roughly 60% of forest richness and some taxa like mammals and birds having over 90% of the richness found in forests (Bhagwat et al., 2008).

The Biodiversity Indicator Partnership (BIP) is an initiative to support the development of indicators for biodiversity-related targets and reporting of the CBD, Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES), and the SDGs. The BIP has produced a Biodiversity Indicator Development Framework for guidance on indicator development (Biodiversity Indicators Partnership, 2011). The framework outlines the factors that make for a successful indicator. The indicator should be scientifically valid in theory, and the concept and outputs need to be easily interpretable. It should be based on available and reliable data, be responsive to change, and be relevant to needs. Working within the existing potentials of satellite remote sensing, this paper presents the proof of concept for a new satellite-based indicator of the biodiversity value of agricultural landscapes by assessing the properties of the woody component from operational remote sensing data products. Following the BIP framework, this work presents the 'production' stage of this indicator's development, outlining the data used, the method of calculation and the reporting of outputs. This paper suggests steps needed in the 'permanence' stage, covering the refinements needed to ensure its continuity and sustainability (Biodiversity Indicators Partnership, 2011). The farm biodiversity score (FBS) proposes a starting point to appropriately fill the gap that exists in large-scale spatially explicit biodiversity monitoring of agricultural landscapes.

3.2 Methods and materials

The farm biodiversity score (FBS) assesses the biodiversity value of agricultural landscapes based on the assumption that trees on farms are a good proxy for biodiversity. The score is a composite score from three components: wooded area, structural diversity and spectral diversity, which are then weighted for areas where the positive effects of trees on farms are more pronounced. To overcome issues in global land cover products at the pixel scale, we select lands to score by delineating agricultural landscapes, defined as 8×8 km areas with a defined proportion of cultivated land, based on a land cover product. These agricultural landscapes range from fully transformed cultivated landscapes to mosaic landscapes with a matrix of cultivated and uncultivated lands. As the score is based on measuring trees, the agricultural landscapes without trees are separated and given a score of 0, while the landscapes with trees proceed to be scored. The assumption is that, while there may be an occasional tree, at the landscape level there are no trees to deliver their biodiversity value, and it cannot be scored. The agricultural landscapes with trees are then scored on three components at a 500 m pixel scale (figure 3.1). The wooded area component is a measure of the tree cover in the cropland, the structural diversity component measures the variance of tree structures in the cropland, and the spectral diversity component measures the diversity of different spectral signatures of the cropland. Together these components are a measure of the quantity and heterogeneity of trees in agricultural landscapes. On steep slopes and riparian buffer zones, where trees on farms are more important for biodiversity, the score is weighted to reflect this.

The implementation of the FBS is primarily in Google Earth Engine (GEE), a cloud-computing platform for performing geospatial analysis with a large data repository.

3.2.1 Creating the Farm Biodiversity Score (FBS)

There are three principal components of the FBS, plus two weighting factors; the wooded area (W) is the area of the landscape that is covered by woody vegetation; the structural diversity component (T) is the diversity of vegetation structure groups, and spectral diversity score (P) is the diversity of spectral responses measured by satellite. The sum

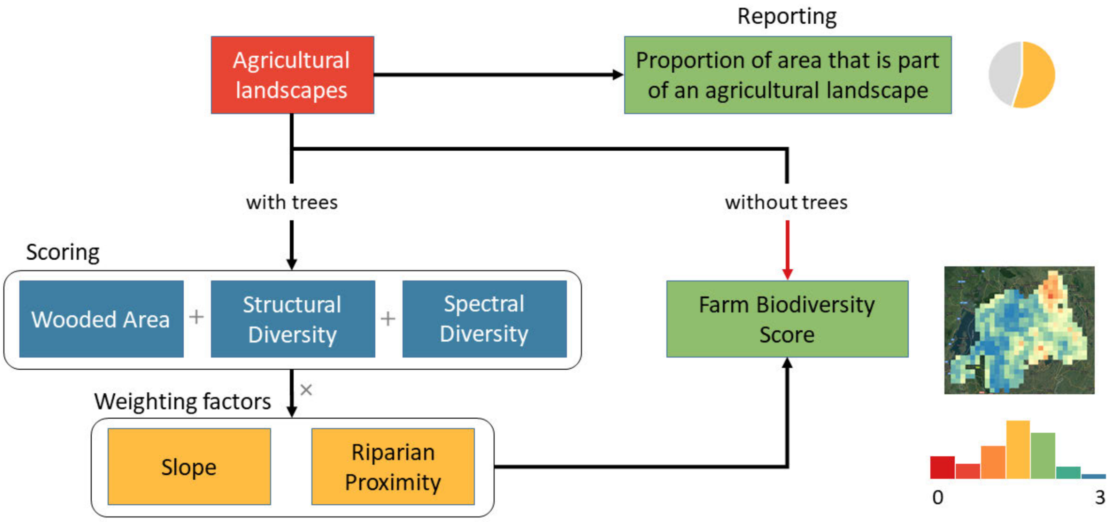


Figure 3.1: Workflow for the construction and reporting of the Farm Biodiversity Score. Remote sensing data products are used to distinguish agricultural land with trees, and these landscapes are scored based on their tree cover, structural diversity and spectral diversity. The score is weighted by slopes and riparian buffer zones.

of these components is then weighted by erosion risk and riparian buffers (s). Each component is scored from 0 to 1, so scores range from 0 to a maximum of 3.

$$FBS = s(W + T + P)$$

3.2.2 Finding agricultural landscapes

Before scoring the biodiversity, we need to delineate the agricultural landscapes. As land cover products do not classify land use, finding what land is farmed can be difficult. Land cover products classify cultivated pixels, so non-cropped farm pixels like tree cover on farms are not included in the cropland class. Misclassification of cropland is particularly an issue in areas with low cropping density, where crops have similar phenology to natural vegetation (e.g. savannah), highly fragmented landscapes and in farms with planted or remnants trees around the cropland. The cropland class in the land cover product also includes land covered with temporary crops and fallow. Because the level of omissions of agriculture from crop classifications varies greatly, we delineate agricultural landscapes instead of farms at a pixel scale. These are landscapes (at 8 km $\times$ 8 km) where the proportion of cropland, as measured by a land cover product (100 m resolution), meets a given threshold. On the ground, these are landscapes with an agricultural matrix of cultivated and uncultivated lands. The threshold of what proportion of the landscape is cropped to be defined as an agricultural landscape was generously set to be 3% by default to account for high levels of agricultural area that is not classed as cropland. This threshold can be adjusted for where the farming system may cause fewer pixels to be classified as crop, for example where shade crops and tree crops are prominent. Pasture cannot be delineated from non-grazed grasslands, and as such, the FBS is scoring the biodiversity in arable landscapes.

The FBS is based on measuring trees on farms, so agricultural landscapes without trees receive a score of 0. To find these agricultural landscapes without trees, an aboveground woody biomass data product (Globbiomass, described in the data section) is used to map the biomass across the landscapes. A threshold of what landscapes are classed as being without trees is set at 8 t ha^{-1}. As the score is a tree-based measure of agricultural biodiversity, the agricultural landscapes that are below this threshold are given an FBS score of 0. As the biomass product tends to overestimate AGB in low biomass areas, this threshold is not set at a true value but rather is based on how the data product appears to measure ground with very little or no aboveground woody matter.

3.2.3 Score elements

Wooded Area ($\boldsymbol{W}$)

Wooded area is used in the FBS as a measure of the biodiversity benefits of woody cover. Tree cover in and around farms is important for the diversity of many taxa in agricultural landscapes (Mendoza et al., 2014; Baudron et al., 2019; Socolar et al., 2019). We assume this relationship is linear, where increased woody cover reflects higher biodiversity. In reality, this relationship is far more nuanced by many factors, including climate, land management, culture and socioeconomics (McNeely and Schroth, 2006; Steffan-Dewenter et al., 2007; Perfecto and Vandermeer, 2008).

A threshold is set on the biomass dataset to define a wooded pixel. If a pixel has a value $>$25 t ha $^{-1}$, it is classed as a wooded pixel. The map is resampled to 500 m resolution (25 pixels), where the percentage of wooded pixels within this window is calculated. We then score the 500 m window based on its proportional cover of woody biomass pixels between 0 and 1 for the FBS (table 3.1). These break values were based on average quintiles from the test sites, rounded to a whole number of pixels.

Table 3.1: Wooded area thresholds and corresponding scores. A 5x5 pixel window is scored based on how many pixels have aboveground biomass $>$ 25 t ha^{-1}

Wooded pixel count	Wooded area	W score
0-4	0-16%	0.2
5-10	16-40%	0.4
11-16	40-64%	0.6
17-21	64-84%	0.8
22-25	84-100%	1.0

Structural diversity ($\boldsymbol{T}$)

There is growing research to show that many species benefit from a greater variety of vegetation structures in agricultural land. Structural complexity creates habitat heterogeneity, boosting diversity for many taxa, including birds (Laube et al., 2008; Breitbach et al., 2010; Mulwa et al., 2012) and insects (Duelli et al., 1999; Thies and Tscharntke, 1999). While the relationship may not be universal (Batáry et al., 2011; Lee and Martin, 2017), it is widely accepted (Benton et al., 2003; Fahrig et al., 2011; Reynolds et al., 2018). The focus here is on compositional structural complexity, the number of structural categories on a landscape, rather than configurational complexity which is how the structural categories are arranged within the landscape.

The biomass product is classed into ordinal groups as a proxy for vegetation structure groups (table 3.2), and the structural diversity is scored on the variance of these groups within a window of 500 m. The biomass map is categorised into groups to ensure the measure of structural complexity quantifies between-group variance and not the variance within these groups. The scoring for structural diversity is nonlinear based on the assumption that both high and low variance indicate low structural diversity and homogenous farming systems. High variance of structure classes can come from a window containing just two structure classes in a roughly even proportion to each other, one high and one low. Greater structural diversity comes from a more even distribution among all five structure classes, though this results in a middling variance calculation. The infographic in figure 3.2 highlights this relationship. The maximum variance for a set of 25 pixels in ordinal groups 1 to 5 is 4. Therefore, the T score scales variances from 0 to 2 down to 0 to 1, and variances from 2 to 4 inversely from 1 to 0.

Table 3.2: Biomass thresholds and corresponding structure group. Each pixel is given a structure class based on its aboveground biomass. Structural diversity is calculated based on these structure classes

Biomass thresholds (t ha $^{-1}$)	Structure group
0-10	1
10-20	2
20-35	3
35-65	4
>65	5

Spectral diversity (P)

The idea of spectral diversity being a biodiversity indicator is based on the spectral variance hypothesis (SVH), the idea that spectral heterogeneity across pixels indicates higher niche heterogeneity, resulting in greater biodiversity (Palmer et al., 2000, 2002; Rocchini et al., 2010a). The theory has been successfully applied to taxonomic groups including birds (Ozdemir et al., 2018), mammals (Oindo and Skidmore, 2002), and plants (William Gould, 2000; Rocchini et al., 2010b; Mapfumo et al., 2016). Most of these studies employ the idea of 'spectral species', where the pixels' spectral response are assumed to characterise a species on the ground and are the subspaces that make up the spectral heterogeneity at a landscape scale. Developing on this idea is the concept of 'spectral communities' when using coarser resolution data, so the spectral response is instead characterising a vegetation community on the ground. The method is based on an unsupervised k-means clustering of pixels to assign them to spectral communities.

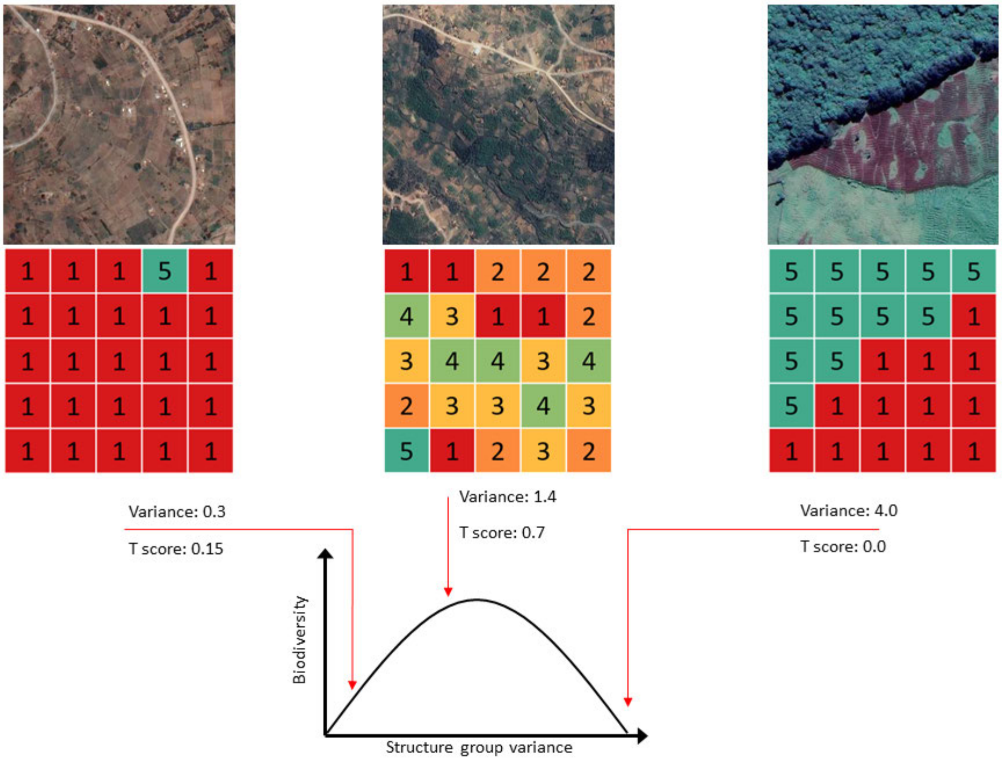


Figure 3.2: Infographic showing the assumed structural group variance relationship with biodiversity. Structural diversity is scored on the variance of pixel structure classes within a 5x5 window. The scoring is nonlinear based on the assumption that high and low variance indicate low structural diversity as shown by the example satellite data.

The Shannon's diversity of these communities is then calculated within a neighbourhood window. Rocchini et al. (2020) modelled Europe's alpha and beta diversity using this method with a time series of NDVI data. NDVI uses optical bands that hold importance for understanding vegetation, and using a time series includes information on seasonality and phenology. Following this method, the P score is calculated using the first 3 PCA axes of a time series of NDVI data. These three PCA layers are clustered into 200 clusters using unsupervised k-means clustering. These clusters represent the spectral communities. The Shannon's diversity index is calculated over a window of 10 x 10 pixels to calculate local alpha diversity of spectral communities. The spectral diversity layer is calculated in R using the biodivMapR package (Féret and Asner, 2014; Féret and de Boissieu, 2020). The result is a map at 2.5 km resolution, and the values are scaled to P scores from 0 to 1 using a minimum Shannon's index of 0.5 and a maximum of 3.3. These thresholds were set from the minimum 1st percentile and maximum 99th percentile of the spectral diversity values at all the sites where the FBS was developed and tested.

3.2.4 Weighting factor (s)

The weighting factors reflect the changing spatial importance of trees on farms depending on erosion risk and occupancy of riparian buffers in the landscape. The weighting factors will create differences in similar scoring land parcels where the trees may have greater significance.

Erosion risk

Slope is used as a simple proxy for erosion risk. Soil erosion can have detrimental effects on soil biodiversity (Pimentel, 2006) and agricultural runoff can severely affect the biodiversity of waterways (Orgiazzi and Panagos, 2018). We assume that steeper slopes are more prone to soil erosion and therefore are more important landscapes to maintain trees and doing so improves the FBS. The slope angle is calculated from the SRTM elevation product at a 90 m resolution. The slope map is then refactored into slope classes using the thresholds outlined in table 3.

Riparian buffers

It is particularly important to promote biodiversity in riparian areas within a landscape. In tropical agricultural landscapes, vegetation in riparian buffers can support more terrestrial biodiversity than surrounding farms. Similarly, riparian buffers are important for healthy waterways (Luke et al., 2019). The ideal width of a riparian buffer to support biodiversity is not uniform. A buffer of 100 m, however, would likely support multiple taxa regardless of agricultural land use or geographic location (Luke et al., 2019). The HydroSHEDS dataset maps the riparian zones for the FBS weighting factor (Grill et al., 2019). The resolution of this data means that the river vector lines are coarsely aligned to rivers on the ground, and the riparian areas were missed using a 100 m buffer. Therefore, a buffer of 500 m meters is used, which is much more likely to catch the majority of the riparian zone, albeit with a degree of inclusion error. A weight score is then assigned to each pixel based on its slope class and whether it in a riparian buffer or not as shown in table 3.

Table 3.3: Weighting factor score from slope groups and riparian buffers. The Farm Biodiversity Score is weighted by these factors to reflect where trees on farms may be more important for biodiversity

Slope °	Erosion risk	Weighting factor inside riparian buffer	Weighting factor outside riparian buffer
0 - 8	Light	0.9	0.85
8 – 12	Moderate	0.95	0.9
12 – 20	High	1	0.95
>20	Very high	1	1

3.2.5 Reporting

In reporting the FBS, statistics on the proportion of land that is classed as agricultural landscapes will be reported alongside the distribution of FBS scores and maps. The FBS can be applied at regional, national or subnational administrative boundaries and the output maps can be generated weighted or unweighted at the pixel scale (500 m), the landscape scale (8 km) or by administrative units. This flexibility means the tool can be used both for national scale reporting as this is where most targets are set (through National Biodiversity Strategies and Action Plans), but also subnational patterns to manage resources and target intervention.

3.2.6 Data

The FBS is comprised of analyses of 5 datasets: aboveground biomass, land cover, NDVI time series, elevation, and a river network dataset (table 3.4). An aboveground woody biomass data product is needed to calculate the FBS. Several datasets exist and more products are emerging in the near future. At this proof of concept stage, the 100 m resolution GlobBiomass is arguably the most appropriate dataset to use (Santoro et al., 2018). This data is a one-off from 2010, so is not operational. Its successor, CCI_biomass has more up-to-date data (2017), but GlobBiomass has the advantage of being better quality, without the erroneous data included in CCI_biomass (poorly geocoded and incidence angle striping from ALOS-2 PALSAR radar data). CCI_biomass aims to continue improving and provide updated biomass information with data additions from future missions (e.g. the BIOMASS mission), so it may be the most appropriate operational option in the future, but currently, GlobBiomass is a better quality product to use. It is important to note that all biomass products are aimed at modelling forest biomass and usually advise against using the products for analyses outside of these areas. ESA identified some of these data issues, most prominently a bias which generally overestimated in low biomass ranges and underestimated in high biomass areas. The future of biomass products is promising with biomass data from GEDI, NISAR and BIOMASS missions expected within the next few years. Operational biomass products will have improved resolution and hopefully improved accuracy.

Scoring the FBS first relies on delineating where the farms are. Land cover maps can delineate crop cover from other land cover types. However, for cropland monitoring, comparing different land cover products show dramatic differences. Pérez-Hoyos et al. (2017) looked at several land cover products for cropland monitoring and found little agreement between them, noting some stark differences including GlobCover products estimating global cropland area to be 20% higher than MODIS derived products. When comparing the products to FAO cropland statistics, the product that performed best was not uniform from country to country. Ultimately most land cover products are not reliable, especially for agricultural land, where uncertainties in classification tend to be larger than other classes. The Copernicus Global Land Cover product (CGLS-LC100 2015 Collection 2; Buchhorn et al. 2020) was used because it claims higher overall accuracy compared to other popular land cover products, and moderate accuracy for croplands (User's accuracy = 70.2%, Producer's accuracy = 83.9%). This product benefits from being operational and so is updated annually. With moderate accuracy, this is unlikely to pick up small yearly changes, but it may be important where large agricultural expansion is occurring.

A time series of Normalized Difference Vegetation Index (NDVI) from MODIS (MOD13Q1 v006; Didan (2015) for the year 2019 was used in the FBS to model spectral diversity. This NDVI product is a composite of MODIS images over a 16-day period using the best pixels available. The spatial resolution is low (250 m) but benefits from having enough pixels to produce good data in areas or times of high cloud cover. To speed up processing times, the 16-day time series was aggregated to a monthly dataset. This dataset is operational and releases up to date data regularly.

Elevation data is used to calculate slope angle for erosion risk. The SRTM dataset provides a digital elevation model at 90 m resolution appropriate for this analysis (Jarvis et al., 2008). River networks needed to be mapped in order to find the riparian areas. The WWF HydroSHEDS Free Flowing Rivers Network data was used for these purposes (Grill et al., 2019). The river polylines are calculated from a raster dataset at 15 arc-seconds ($\sim$500 m at the equator) and as such the river lines have some coarseness.

Table 3.4: Datasets used in the calculation of the Farm Biodiversity Score and the aspect of the score they are used for

Data	Dataset	Resolution	Purpose
Aboveground biomass	ESA GlobBiomass 2010	100 m	W and T scores
Land cover	Copernicus Global Land Cover	100 m	Agricultural landscapes
NDVI time series	MODIS Vegetation indices (MOD13Q1)	250 m	P score
Elevation	SRTM	90 m	Erosion risk s
River network	WWF HydroSHEDS Free-Flowing Rivers Network	-	Riparian buffers s

3.2.7 Validation and test sites

There is a lack of validation data at the scale needed to appropriately test the FBS. At this stage, the best method to check the performance of the scores is qualitative validation by cross-referencing the FBS output with what we might expect when interpreting high-resolution satellite imagery available on Google Earth. Outputs were checked across low, medium and high FBS scored landscapes. The biomass product used in this proof of concept is from 2010, and so the Google Earth image closest to 2010 was used in the validation. Only the landscape-level outputs were validated as pixel values were assumed to be noisier and include areas on non-agricultural land as per the agricultural delineation process. Some examples of this validation are presented alongside the results below.

The FBS was developed and tested in several study sites covering a variety of climates, biomes, policy contexts, farming practices and cultures. Extending up from the landscape scale in the analysis in chapter 2, the study nations are Uganda, Rwanda and Honduras. This analysis also includes the West Kalimantan province in Indonesia. The sites presented are part of the Trees on Farms for Biodiversity project funded by the International Climate Initiative (IKI) and implemented by World Agroforestry (ICRAF) in partnership with the Centre for International Forestry Research (CIFOR). The project aims to build awareness and understanding of the role trees on farms can play in biodiversity conservation.

In Uganda, approximately half of the land area is used for arable farming. Most of this is smallholder farms growing food crops and cash crops (FAO, 2015). While farming is predominantly subsistence agriculture and smallholdings, there are areas of large-scale agriculture which mainly focus on sugarcane, oil palm and rice. Most of the biodiversity loss in Uganda is related to the expansion of smallholder farming into forested areas, with conversion also occurring in savannah grasslands for maize and wetlands for rice (NEMA, 2016).

Rwanda is a small and densely populated country, with agricultural land that is estimated to be over two-thirds of the nation's total land area (Rukundo et al., 2018). In recent decades, cropland expansion has precipitated losses in forest and grassland cover of 65% and 32% respectively (1990-2015) with resultant losses in biodiversity (Li et al., 2021). Roughly a third of farmers own less than 0.2 ha of land and the agricultural mosaic is largely smallholder farms with some large-scale farms growing export crops like tea (WFP, 2018).

Forests cover almost half of the land area in Honduras, but are under threat from agricultural expansion which is estimated to be driving 80% of deforestation in the country (FAO, 2019). In terms of area, cattle ranching is by far the most extensive agricultural practice in Honduras and is the main driver of this forest loss, now covering nearly a quarter of the country's land area. Alongside this, grain cultivation in rotation and shade coffee are also widely farmed in the forest biomes of Honduras.

The rainforests in Indonesia are some of the most biodiverse in the world, containing 10% of the world's known plant species, 12% of mammal species and 17% of all known bird species (von Rintelen et al., 2017). The biodiversity of these forests is under threat from the fragmentation of habitats from agricultural expansion, primarily driven by the expansion of oil palm, of which more than 50% occurred at the expense of natural forests between 1990 and 2005 (Koh and Wilcove, 2008).

3.3 Results

This section will present the results from the four sites used to test the FBS. A Google Earth Engine app has been created to host the outputs where they can be viewed and interacted with. The web app can be found at `https://samharrison1606.users.earthengine.app/view/fbs`. A selection of these maps is presented in the results section here, with more sites available to view in the Earth Engine app.

3.3.1 Uganda

In Uganda, 78.8% of the country was part of an agricultural landscape, almost all of which had trees. Figure 3.3 shows the unweighted FBS at the pixel scale for Uganda. The highest scoring areas in Uganda are across a central belt of the country, with the cropland here generally scoring around 2. The scores get patchier in the north where farms with some of the poorest scores are punctuated by areas of higher-scoring agricultural landscapes. There are a small number of landscapes that were classed as unwooded with a score of zero. Scores were also high on areas of the east and west borders of the country, where farms are located on the slopes of mountains or mountain ranges.

Figure 3.4 shows a selection of high-resolution images and their respective scores. These images, alongside further qualitative validation in this method, show that the FBS scores

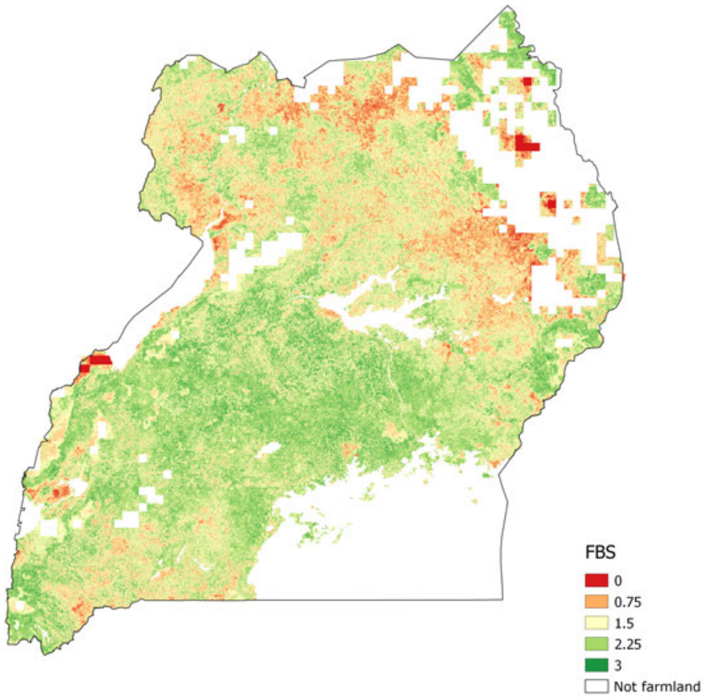
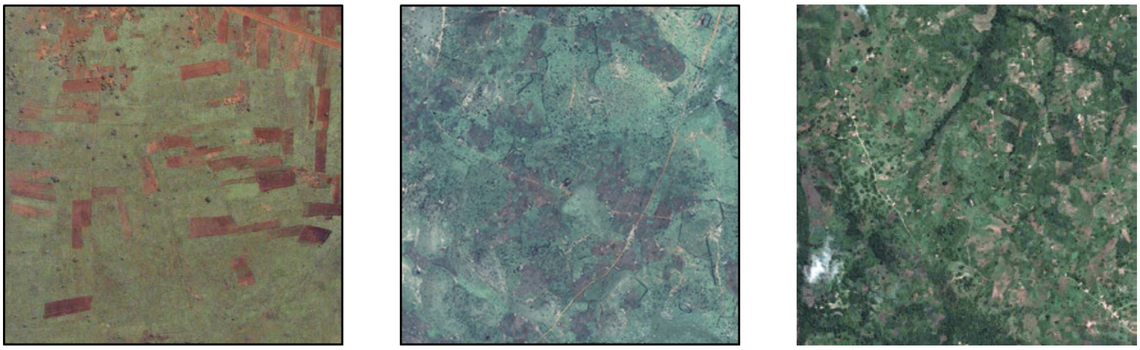


Figure 3.3: Farm Biodiversity Scores (Unweighted) for Uganda at a pixel scale (500 m)

generally reflect what we might expect from the satellite images. The low-scoring farm (figure 3.4a) has no woody cover (W score: 0) with little structural diversity (T score: 0.12), and while the spectral diversity (P score: 0.48) may pick up fields at different planting stages, it is not enough to give the area a high score. Figure 3.4b shows greater woody cover (W score: 0.4) but little diversity in its structure (T score: 0.22), with the spectral variance (P score: 0.57) accounting for half the overall score. The high-scoring landscape (figure 3.4c) has a greater woody cover with a W score of 1 and more diversity in structure with various tree densities (T score: 0.83, P score: 0.77).

3.3.2 Rwanda

Almost all landscapes in Rwanda are agricultural landscapes with only 9% of the land not part of these landscapes. None of the agricultural landscapes were without trees at the landscape level. Figure 3.5 shows the national pattern having an east-west divide



(a) Low (0.6) (b) Medium (1.2) (c) High (2.6)

Figure 3.4: Example photointerpretation validation showing a range of landscapes in Uganda and how they score in the FBS in brackets

with higher FBS landscapes in the west. The administrative units map shows that there is an appreciable difference in the mean FBS between the highest-scoring (Gakenke, 2.2) and lowest-scoring districts(Nyagatare, 1.2); this was the greatest difference between 2nd administrative units across all the study areas.

Validation here showed similar outcomes as for Uganda with the scores reflecting what we

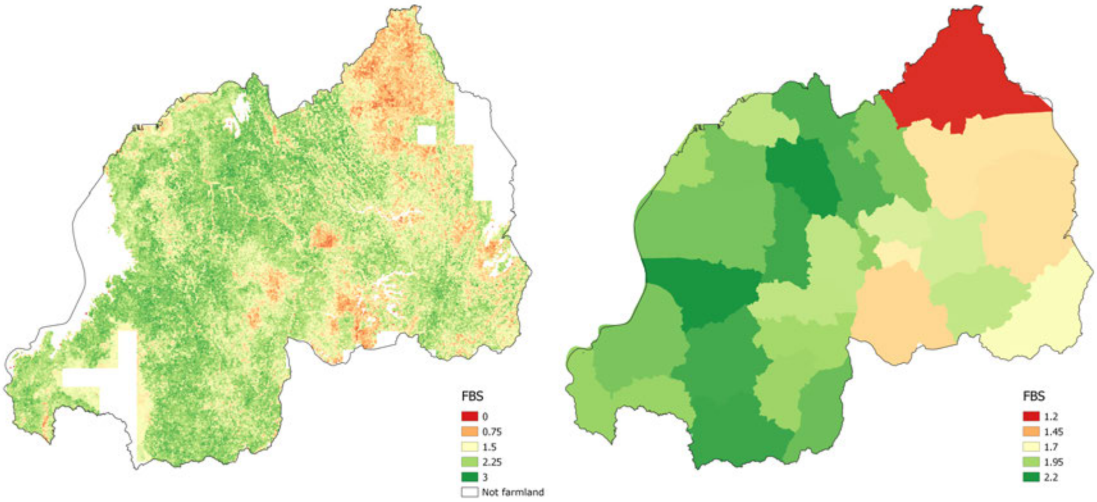


Figure 3.5: Farmland Biodiversity Score (Unweighted) for Rwanda at pixel scale (left) and aggregated to the 2nd administrative units (right)

would expect when interpreting the high-resolution images. A sample of these images is shown in figure 3.6. The high-scoring landscape shows greater woody cover and variability in structure among small fields, while the lowest-scoring landscapes, had little woody cover, mostly as part of boundaries for large fields.

(a) Low (0.7) (b) Medium (1.4) (c) High (2.5)

Figure 3.6: Example photointerpretation validation showing a range of landscapes in Rwanda and how they score in the FBS in brackets

3.3.3 Honduras

Almost all of the agricultural landscapes in Honduras were landscapes with trees, and made up 81% of the land area. Figure 3.7 shows the FBS aggregated at the landscape scale. In contrast to Uganda and Rwanda, there does not appear to be a dominant national pattern in score distribution, instead, the scores are generally more even and the spread of values is smaller, with fewer values at the extreme ends. The exception is the low scoring landscapes in the south of the country.

Figure 3.8 shows various landscapes in Honduras and the respective FBS scores. Figure 3.8a shows large-scale tree cropping in northern Honduras, perhaps of oil palm, which has an FBS of 1.0, with a W score of 0.60, T score of 0.26 and P score of 0.14. The higher scoring image (figure 3.8b) shows a lower intensity mixed system with high woody cover (W score: 1) and a variety of structures and mix of agricultural land uses (T score: 0.74, P score: 0.86) combining for an overall score of 2.6.

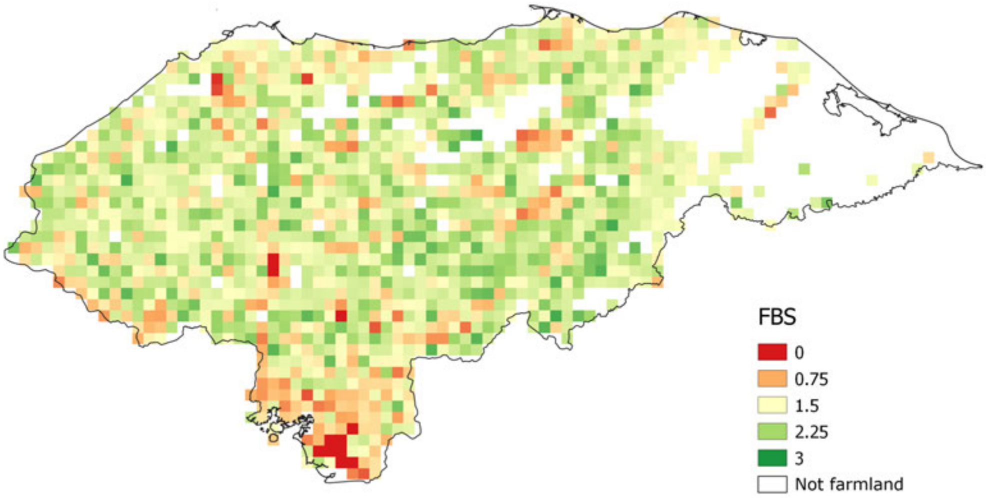


Figure 3.7: Farmland Biodiversity Score (weighted) at the landscape level for Honduras

3.3.4 West Kalimantan

The least farmed of the study sites was West Kalimantan, with 60% of the land being part of an agricultural landscape, all of which had trees. The agriculture here is predominantly large-scale oil palm plantations. The FBS score at the landscape scale for

(a) A low scoring (1.0) tree crop plantation

(b) a high scoring (2.6) low intensity system

Figure 3.8: Example photointerpretation validation for two different farming systems in Honduras and how they score in the FBS in brackets

West Kalimantan is relatively uniform around the mean FBS of 1.85 (SD = 0.16), with little spread of values as shown in figure 3.9. When aggregated to regencies (second administrative unit), the range of means was small, from 1.4 to 1.7, further showing the homogeneity of the scores.

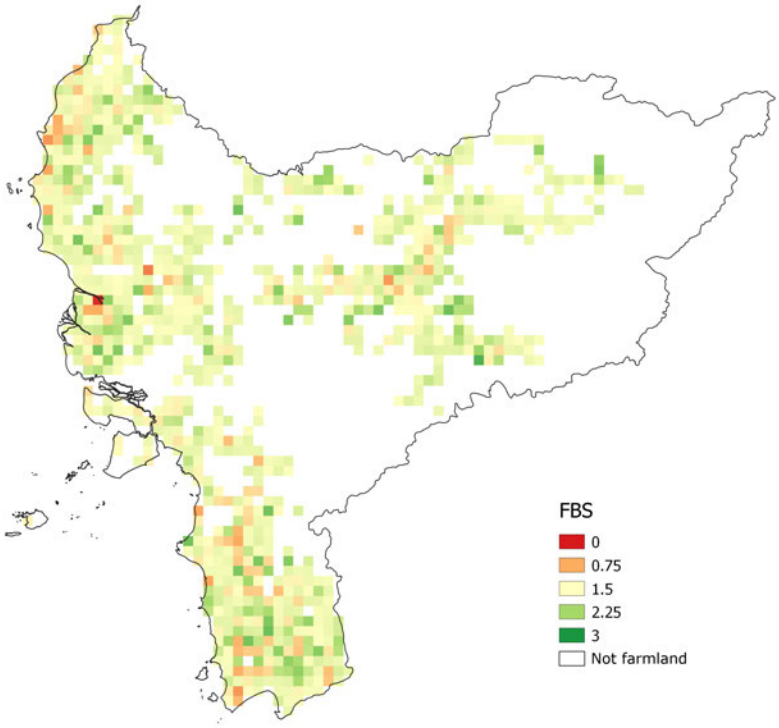


Figure 3.9: Farmland Biodiversity Score (weighted) at the landscape level for West Kalimantan, Indonesia

This site is the most difficult to validate as persistent cloud cover means clear images for the years around 2010 are rare. The landscapes with the highest scores were those where the large scale palm plantations were yet to reach, or in the early stages of clearance (figure 3.10c). The type of oil palm plantation that is now widespread in the region scores around 1, and figure 3.10a shows a plantation landscape like this that scored 0.7. Smallholder systems (figure 3.10b, displayed more variation in tree cover and scored closer to the average for the region.

(a) A low scoring (0.7) high-intensity oil palm plantation

(b) A mid scoring (1.9) smallholder oil palm system

(c) A high scoring landscape (2.6), possibly in clearance

Figure 3.10: Example photointerpretation validation for three different farming systems in West Kalimantan and how they score in the FBS in brackets

3.4 Discussion

These results showcase the concept of a new remote sensing-based approach to estimating farm biodiversity by assessing the properties of trees on farms. The FBS shows encouraging potential at this stage, with mapped scores reflecting what we expect from photointerpretation of a sample of sites across the case study areas.

As the approach taken here includes all land within an agricultural landscape, there will likely be areas of uncultivated land included in the analysis. For example, in Northeast Uganda, the climate is generally drier and the land much more sparsely cultivated than in the south, so the proportion of uncultivated land in these landscapes may be higher. Including these larger areas of uncultivated land in the landscape may affect the landscape level scoring. Where the uncultivated areas of the mosaic have greater tree cover and diversity than the farmland, it will inflate the score. Where the uncultivated areas in the mosaic have patches of both greater and lower-scoring land, as is the case in Northern Uganda, the effect is difficult to quantify. Increasing the cropland cover threshold for what is considered an agricultural landscape may reduce some of these inclusions, but may risk losing agricultural landscapes elsewhere.

In Rwanda, there was an east-west divide in FBS scores, with the highest-scoring landscapes in the west. This greatly reflects a climatic divide in the country, with the driest regions in the east being the lowest-scoring landscapes (Jonah et al., 2021). As the indicator is based on cover and heterogeneity of trees, the climate will have a significant impact on the score, affecting the species present and size classes of trees.

Larger commercial farms are more common in Honduras than in Rwanda and Uganda, where agricultural land is mostly smallholdings. Using satellite images to validate the FBS performance in Honduras picks up how the score fares in these landscapes. Some of the lowest-scoring landscapes are in areas where woody cover may be high, but the large-scale growing of tree crops means there is little structural or spectral variation. The non-wooded agricultural landscapes that scored zero in the south of Honduras are areas dominated by large-scale commercial agriculture with few or no trees. Elsewhere in the country, the zero-scoring landscapes are those located in and around large towns and cities. The mix of land covers in the low-intensity systems boosted the scores, with forest patches among pasture or cropland providing more varied structure and spectral variation.

In West Kalimantan, agriculture is predominantly oil palm plantations, much of it large-scale. This poses an interesting test for the FBS. Much of this agriculture is not classed as cropland by land cover products as perennial woody crops are instead classed as forest/shrub. As such the crop threshold was set to its lowest possible value (a single 100 m pixel within the 8 $\times$ 8 km landscape) in order to make sure as much of the agricultural land was analysed. The dominance of this one crop and one agricultural system is likely the reason for the more restricted spread of FBS values.

The land cover products in West Kalimantan that could not delineate oil palm crops as agriculture led to the indicator failing to pick up areas of agriculture in the province, particularly smaller-scale oil palm farms in the forest-farm mosaic landscape. This is likely to reduce the overall scores for West Kalimantan as these mosaic landscapes would likely score much higher than the large plantations. Setting the crop threshold to the lowest possible value helped to pick up more agricultural landscapes, but there were still areas that were not delineated and thus not scored.

These promising results show the FBS can be a viable indicator for agricultural biodiversity. Existing biodiversity indicators for agricultural land are predominantly at the farm-scale (Herzog et al., 2013) and there are few existing indicators for agricultural biodiversity at national scales. One of the few existing indicators focuses on agrobiodiversity, which is the variety of species used in agriculture, including crops and livestock. The Agrobiodiversity Index (Jones et al., 2021) is based on 22 indicators including the diversity of species in the production and consumption of agriculture. The index provides a single score for each country with available data. Another proposed national scale indicator of biodiversity is the percentage of cropped landscapes with at least 10% natural land (BIP, 2021). This provides a more spatially disaggregated approach, but is a coarse indicator with little detail and a sole focus on land cover. The 10% target may also be too low to be meaningful to conservation or restoration (Garibaldi et al., 2021). The FBS adds to the few available indicators. It focuses on the wider biodiversity and the spatially disaggregated outputs can help guide and focus national policy to target specific areas. The method can be parameterised for local conditions and the outputs too can be interpreted with local context.

3.4.1 Next Steps

Avenues for improvement to the FBS are outlined below and cover the 'permanence' stage of the Biodiversity Indicator Development Framework (Biodiversity Indicators Partnership, 2011), which are the steps needed to ensure the continuity of the FBS.

Foremost is the need for further validation. A search for appropriate datasets for quantitative validation has yielded little in the way of comparative biodiversity metrics for agricultural land across nations. Subnational datasets are also scarce, with few countries having available data. There are some datasets like the Pan-European Common Bird Monitoring Scheme (PECBMS), which collates bird diversity data from most European countries' national bird surveys, many of which sample birds in agricultural lands. Efforts have been made in recent years to set up common bird monitoring schemes in Africa (Wotton et al., 2020) for both inside and outside protected areas. A comparable multinational dataset is likely to be an unrealistic request. A more realistic approach to improve the method through validation is expert elicitation to gather further qualitative feedback from those with on-the-ground expertise and knowledge of agricultural biodiversity across a large scale.

A useful facet of a monitoring tool is the ability to map not just spatial patterns but temporal changes too (Biodiversity Indicators Partnership, 2011). In further development and testing of the tool, the detection of FBS change over time should be assessed through repeat analysis at multiple time steps and by looking at areas of known change in intensification or intervention. This would require a regular time series of biomass and land cover.

Potential additional modules

Additional components could be included as optional for specific uses or planning purposes. Landscape connectivity, for example, is an important aspect of biodiversity in agricultural areas, facilitating movement and genetic mixing across landscapes and between intact habitats. Producing useful and informative maps of connectivity in agricultural landscapes requires significant research and modelling efforts that are outwith the scope of this study. Appropriate methods need to be selected based on target species and available data. Parameters for connectivity analysis require expert understanding of habitat type permeability to target species (Luque et al., 2012). Research into developing informative connectivity metrics for agricultural land is ongoing (Correa Ayram et al., 2016; Keeley et al., 2021), and these could optionally be included in the FBS.

Parameter / threshold fine-tuning

The FBS is based on many assumptions on a variety of window sizes, thresholds, classes and cluster parameters. Performing some sensitivity analysis on this could help improve the model and our understanding of the importance of some of these parameters. For biomass thresholds, an idea for more informed thresholds could be based on potential biomass from climate and elevation data. The empirical data on potential biomass from climate alone is scant, with a few datasets on potential biomass for some biomes using sophisticated models (Exbrayat et al., 2017). Local understandings in the nations or regions the FBS is applied to could help make a more informed threshold choice based on potential biomass by biome or climate.

Biome- or ecoregion-specific parameters could help improve the scoring and make it more locally relevant. An ecoregion weighting could also be used to account for the rarity of ecosystems, i.e. trees on farms in rare wooded biomes may have more importance than those in more abundant biomes.

The structural diversity layer should be tested and refined based on local applications. The variance around the structural classes is currently used to measure structural diversity. While this seems to work well in many cases, it may not always be the best measure. Using this calculation, certain configurations of biomass data within the window can lead to high structural variance scores while having a relatively homogenous structure. Some further testing and development, and comparisons to other structural diversity metrics like entropy or dissimilarity metrics (Masisi et al., 2008; Haralick et al., 1973) could improve this. The biomass class thresholds should be tested in more locations as the current classes may be biased toward wetter biomes. In low biomass biomes, much of the land may fall in fewer structure classes leading to a low score. More classes for low biomass pixels could help to reduce this bias as an alternative to the potential biomass approach mentioned above. Tree height data from GEDI (Potapov et al., 2021) could offer an alternative, as tree height heterogeneity can be a measure of vertical vegetation stratification (Larue et al., 2019).

The output of spectral variance analysis is currently at 2.5 km from a 10-pixel window of 250 m data. This may be too large a pixel size to pick up some homogenous farms where the surrounding landscape is spectrally diverse. To reduce the scale of the spectral diversity, finer resolution input data will be needed. NDVI data at a smaller spatial resolution exists or can be calculated (e.g. from Sentinel-2 or Landsat) but lacks the temporal resolution or the 16-day 'best pixel' data quality that MODIS has. As with much of the data used, there is a compromise to be made. Higher-resolution data is also likely to result in longer computing time and a greater computer power requirement. Large-scale spectral variability analysis is a relatively new method (Féret and de Boissieu, 2020; Kacic and Kuenzer, 2022), and any subsequent literature may help shed light on the sensitivity of some of the parameters like window size or number of clusters.

Weighting

Improvements to the weighting factors should include sensitivity analysis. At the moment, the score can be reduced by a fifth if the land is not sloping and not riparian. Exploring how these parameters alter wider scale scoring and patterns could help adjust these factors accordingly. The slope is currently used as a proxy for erosion risk. Much more sophisticated erosion models exist and this simple proxy could be elaborated to include some of the detail included in erosion models. For example, the commonly used and adapted USLE model uses a slope-length factor instead of the slope angle alone (Wischmeier and Smith, 1978). Including the upslope length along with the slope in the weighting would make it a more accurate reflection of erosion risk. Other erosion risk factors that could be included are soil type and climate.

Data improvements

The FBS could be improved when newer, up-to-date and/or operational biomass datasets become available. The GlobBiomass dataset used here compromises recency for better quality data, as such the qualitative validation can be tricky where there have been significant changes in the past decade. An up-to-date biomass product could provide a more up-to-date FBS, but with poorer quality data, the score may be affected. As and when new data becomes available, this can be incorporated into the FBS for operational and recent biomass data, for example, newly released GEDI data (Dubayah et al., 2020; Duncanson et al., 2020), and NISAR and BIOMASS missions which are expected to be operationally released in the next few years (Dubayah et al., 2020; Duncanson et al., 2020; Quegan et al., 2019). For any new biomass dataset used, the thresholds that are applied to the biomass data should be reconsidered and tested in a range of landscapes, as each dataset will perform differently in these landscapes.

Similarly, recently released GEDI data has also been used to produce a global forest height map (Potapov et al., 2021). This could be explored as a dataset for structural diversity scoring instead of biomass. This dataset is currently at a prototype stage with known data issues but will be updated and refined over time. Although the data should still be applicable outside of forests, it has been designed for forest height mapping and not tree height in general.

As mentioned above, an alternative dataset for the spectral analysis could improve the spectral variance layer. Sentinel-2 data may offer a solution and could be used to generate a time series of vegetation index at the resolution needed, but data quality control will be needed to make sure the images are cloud-free.

Land cover products continue to be an issue. In drier biomes, overestimation of agricultural landscapes is likely as natural vegetation here is confused with cropland (Pérez-Hoyos et al., 2017, 2020). In forest biomes, underestimation of these landscapes is likely, as wooded farms in a mosaic of forest remnants are confused with forest classes. A possible solution to this would be to use locally specific land cover maps where possible. These may be made by government agencies, NGOs or researchers with ground data to have tailored a land cover or land use map to the specific area. However, these are not always available or willingly shared.

Make it operational

After further development of the FBS, it would be made far more useful if it were reworked into an operational web tool, app or dashboard for planners or land managers to view and interact with the outputs. This may also allow the user to tweak the parameters of the FBS based on their own assumptions of the land in which they are applying the tool.

The FBS is currently modelled in Google Earth Engine, with the spectral variance layer being calculated in R using the biodivMapR package. Calculating the spectral variance layer requires computing power which may not be accessible to all potential users. Making the model operational could require this spectral variance analysis to be rewritten into a cloud computing platform with links to Google Earth Engine, which could be possible with Google Colab. If the operational biomass layers are not available through Google Earth Engine, this platform could be used to get data and make it available for analysis in Earth Engine.

3.5 Conclusion

Recent advances in remote sensing data and technologies are creating new opportunities for the conservation of biodiversity. The ability to use and analyse recent data means we can map the current state of environments and observe changes going forward. The application of these technologies in an accessible tool needs to be fully realised in agricultural biodiversity if we are to gauge our progress towards global agricultural biodiversity targets set in the post-2020 agenda. While there are aspects of farm biodiversity this does not account for, like inputs, livestock grazing and other management practices, the FBS indicator presented here is a promising proof of concept. With further testing and development, the indicator could be an invaluable tool for decision-makers. It could provide relevant information to a range of users on the spatial patterns and temporal changes of trees on farms and their contribution to agricultural biodiversity.

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Chapter 4

Socioeconomic determinants of trees on farms: regional variation and regularities in Uganda

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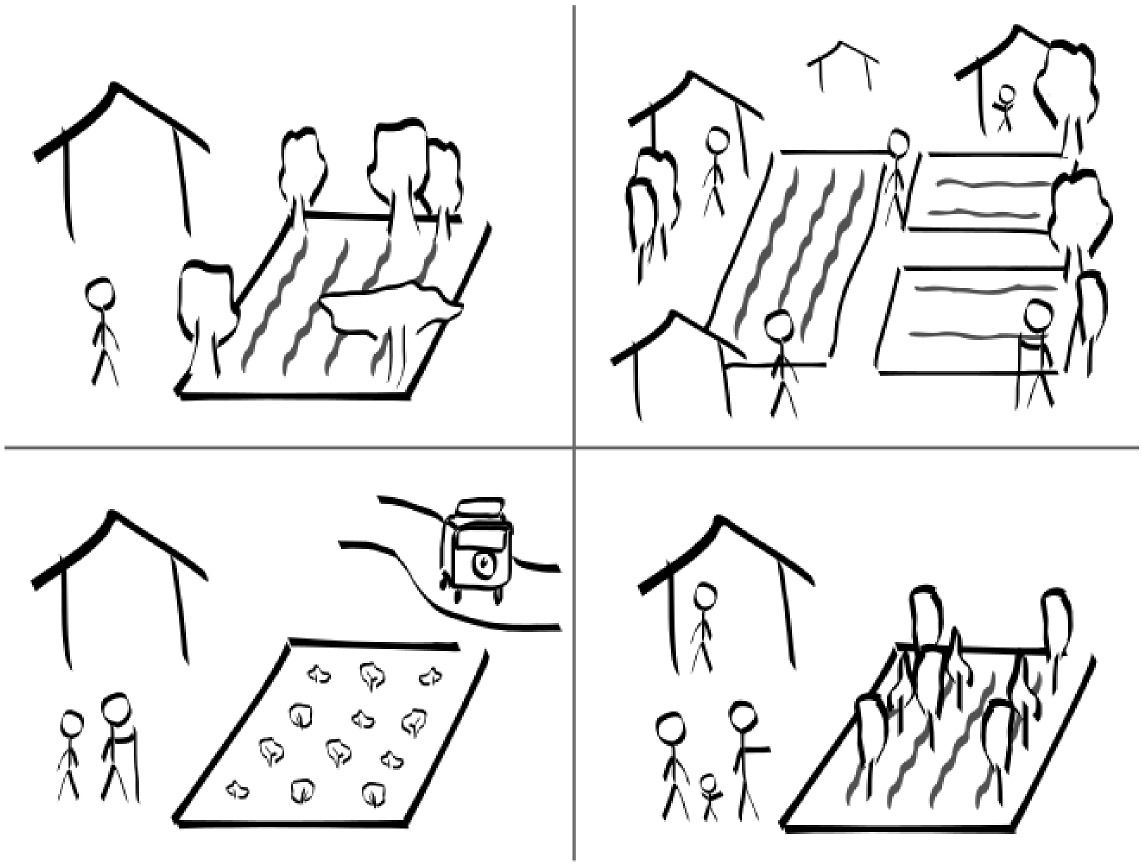

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Abstract

The adoption of agroforestry is an important aspect of improving rural livelihoods, developing climate-smart agriculture, and benefiting the wider environment. We know the adoption of agroforestry depends on many factors, including a number of socioeconomic and biophysical conditions. Current research in understanding the determinants of adoption is focused on context-specific case studies but broader scale patterns in the determinants of agroforestry adoption remain elusive. To ensure effective and informed policy and action, more generalisable information is needed. Combining earth observation products, census and household survey data, this study explores the relationships between hypothesised determinants of agroforestry adoption and tree cover on farms regionally in Uganda. The results show that on average across all regions, travel time to cities was the most important determinant of tree cover, but there is significant regional disparity in which factors are most important as well as inconsistent directions of the relationships. This spatially explicit information can help improve agroforestry adoption through better extension services and interventions that are tailored to regional circumstances, tackling the most important barriers in each region.

4.1 Introduction

Agroforestry is promoted across the tropics by governments and non-state actors as an important tool to help tackle environmental degradation and promote development (Bettles et al., 2021). The various benefits of agroforestry have been well-documented. They include economic benefits to farmers like diversified livelihoods (Kalaba et al., 2010; Anderson and Zerriffi, 2012; Mbow et al., 2014), increased crop yields and provision of fuelwood or fodder (Kuyah et al., 2019; Idol et al., 2011; Nair, 1985). The delivery of other ecosystem services from trees on farms has also been well studied and includes improvements to soils and water (Barrios et al., 2013; Jose, 2009; Kuyah et al., 2016), and boosting biodiversity in what can otherwise be a hostile habitat to many species (Schroth et al., 2004; McNeely and Schroth, 2006). Trees on farms have also been given attention for their carbon sequestration potential, and make up a large portion of carbon projects and forest landscape restoration, for their potential to provide both climate and development benefits (Anderson and Zerriffi, 2012; Zomer et al., 2022).

Furthermore, as part of a larger group of agricultural innovations, agroforestry is a part of the development of agriculture, especially in sub-Saharan Africa which has not experienced the same agricultural revolutions seen elsewhere in the Global South. Despite the benefits and promotion, adoption of agroforestry remains relatively low in sub-Saharan Africa (Zomer et al., 2014; Meijer et al., 2015; Mbow et al., 2014).

Climate is generally understood to be the main driver controlling tree cover in Africa with soil and disturbances like fire and herbivory also altering tree cover in complex ways (Staver et al., 2011; Bucini and Hanan, 2007; Sankaran et al., 2005; Good and Caylor, 2011). However, in transformed agricultural landscapes with substantial human management, the climate-tree cover relationship can be altered (Zomer et al., 2009; Brandt et al., 2020). Where decisions are made on planting or maintaining trees on farms, socioeconomic factors can have a significant bearing on tree cover through the adoption of agroforestry practices (Pattanayak et al., 2003; Amare and Darr, 2020).

Existing research on agroforestry adoption shows that many factors affect whether a farmer might adopt agroforestry, and it is often socioeconomic as much as environmental (Wells et al., 2020; Place et al., 2012). Pattanayak et al. (2003) defines five general categories of determinants of adoption: farmer preferences, resource endowments, market incentives, risk and uncertainty, and biophysical factors. Preferences include how risk averse a farmer is, and their attitudes to new technology, often inferred by proxies like farmer age, gender or education. Resources are the means available for implementing a new technology and include income, assets, labour availability, and savings or access to credit. Market incentives affect the costs associated with adopting agroforestry, as well as the price of commodities from trees or alternative land uses. Risk and uncertainty capture unpredictability in circumstances, for example, extension services and communication with other farmers may provide certainty for new adopters of a technology, while insecure land tenure is a source of uncertainty. Biophysical factors other than climate may include soil quality, erosion risk and farm size.

Research focuses mainly on local case studies within a country, confined to certain localities or intervention projects (Miller et al., 2017). Global analyses have explored the extent of tree cover and biomass on farms using existing remote sensing data (Zomer et al., 2009, 2014, 2016), but little has been done to link these large-scale spatial analyses to socioeconomic characteristics. Some studies and reviews have compared adoption between case studies (Pattanayak et al., 2003; Mercer, 2004; Meijer et al., 2015; Miller et al., 2017; Wells et al., 2020) and these collectively show inconsistency and a large number of insignificant determinants or contrasting relationships with adoption. This suggests that contextual factors are moderating the relationship the determinants have on agroforestry adoption. This poses a problem when trying to extrapolate results beyond the case study, as some factors are moderated by local factors and we do not know what relationships apply more broadly. Continuing research in this way can be useful for generating contextual generalisations about what might determine adoption (Meyfroidt et al., 2018). It cannot, however, help our understanding of how widespread or important different determinants are (Amare and Darr, 2020). There have been no national-extent fine-grained analyses of these relationships that give a broad understanding of the patterns of factors affecting agroforestry adoption.

Wide-scale agroforestry adoption is evidently growing in attention from governments and non-state actors alike (Place et al., 2012; Bettles et al., 2021). Promoting agroforestry is part of most sub-Saharan African countries' nationally determined contributions to the Paris Agreement (Rosenstock et al., 2019). It is also included in many nations' agricultural policies including in the national adaptation plan for the agricultural sector in Uganda, the focus country of this research (MAAIF, 2018). If these policies are to be successful, understanding the factors that affect whether a household is likely to adopt the practice is critical in designing effective and efficient extension services, agroforestry projects, forest landscape restoration or other interventions. If we can determine which groups are not adopting, we can begin to address the barriers for these groups. Furthermore, not accounting for these factors could undermine the long-term sustainability of these plans or lead to poor use of resources and time. Farmer's experiences of new technology impact their attitudes and perception of risk (Meijer et al., 2015; Pattanayak et al., 2003; Amare and Darr, 2020), and poorly designed programmes that fail create a negative perception of agroforestry or agricultural innovations more generally, hampering future extension efforts (Nath et al., 2005; Höhl et al., 2020).

This research conducts national-scale regional analyses of socioeconomic factors affecting tree cover on farms in Uganda, a country with a diverse range of farming practices and rates of agroforestry adoption. Using population census and household survey data, alongside land cover and tree cover data products, the relationship between household socioeconomic features and tree cover on farms is explored to assess if more general relationships can be drawn at scale. As the relationship between the predictors and response is not uniform across case studies, the relationships are considered within broad agroecological zones separately. The research is guided by the following research questions:

1. How much do socioeconomic factors explain tree cover on farms in Uganda, and which factors are most important?
2. Do the relationships between tree cover on farms and socioeconomic factors vary spatially?
3. How much influence does climate have on tree cover on farms?

4.2 Methods and Materials

4.2.1 Trees on farms data

A national scale map of tree cover on farms (TCoF) was created as an indication of agroforestry adoption. Percentage tree cover from the 2016 MODIS (MOD44B; DiMiceli et al., 2015) dataset was the product used for tree cover. This was then masked to a cropland data layer to map tree cover on farms. Agriculture as a land use includes all land used for cultivating plants and livestock, but as land cover data products generally delineate cropland rather than agricultural land inclusive of pastureland, the analysis uses just cropland, land used for annual and perennial crops. In this study therefore, 'tree cover on farms' refers to forms of agrisilviculture, the land use practice combining crops and trees.

Land cover products in Africa generally do a poor job at picking out agricultural land and share low levels of agreement despite individual products claiming high levels of accuracy (Pérez-Hoyos et al., 2017, 2020). In order to generate an improved cropland map, an ensemble of eight land cover products was used (table 4.1). Products with data within 5 years of the census (2014) were chosen, and resampled to the same resolution (100 m), and agreement between these products was mapped across Uganda. Land was assumed to be cultivated where all products were in complete agreement. Then land where all but one product were in agreement was included. The process continued until the total area of cultivated land met the FAO statistic on cropland area in Uganda (9.1 million hectares; FAO, 2021). Where land cover products delineated mosaic cropland, these were included if the mosaic included >40% crop cover. The land cover products used are found in table 4.1.

Table 4.1: Land cover products used in generating a 'consensus' approach cropland map

Product	Year	Sensor(s)	Agency	Definition(s) used
Copernicus Global Land Service	2015	PROBA-V	ESA	Cultivated and managed vegetation/agriculture (cropland) - Lands covered with temporary crops followed by harvest and a bare soil period (e.g., single and multiple cropping systems).
C3S Global Land Cover	2015	MERIS, SPOT	ESA	Cropland & Mosaic cropland where natural vegetation (tree, shrub, herbaceous cover) <50%
CCI Land Cover Sentinel 2 prototype	2016	Sentinel 2	ESA	Cropland
GlobCover	2009	MERIS	ESA	Post-flooding or irrigated croplands & Rainfed croplands & Mosaic cropland (50-70%) / vegetation (grassland/shrubland/forest) (20-50%)
Global Food Security-Support Analysis Data	2015	Landsat, MODIS, AVHRR	USGS	Cropland
Globeland	2010	Landsat, HJ-1, GF-1	CNSA	Cultivated land - lands used for cultivating crops.
Land Cover Scheme	2014	ENVISAT, IKONOS, Landsat, MODIS, VIIRS, SRTM, WorldView, GeoEye, Sentinel 2, RadarSat	SERVIR / USAID	Cropland
MODIS Land Cover Type Yearly MCD12Q1	2014	MODIS	NASA	At least 60% of area is cultivated cropland & Mosaics of small-scale cultivation 40-60% with natural tree, shrub, or herbaceous vegetation.

From the eight land cover products, where four or more were in agreement amounted to just under 8 million hectares. To reach 9.1 million hectares, part of the area where 3 products were in agreement was used. To establish the most likely cropped area here, 3 datasets on the fractional cover of cropland were used (table 4.2)

Table 4.2: Fractional cropland cover products used in generating a 'consensus' approach cropland map

Product	**Year**	**Sensor(s)**	Agency
MapSPAM percentage cropland	2017	Combination of global, regional and national land cover datasets	IFPRI
Global Land Cover - SHARE	2013	"Best available" high resolution national, regional and/or sub-national land cover databases	FAO
Copernicus global land cover fraction	2016	PROBA-V	ESA

This consensus map performs well from qualitative validation using photointerpretation and appears better than the individual land cover products. The tree cover product is then masked to the cultivated areas only. The primary assumption with this product is that tree cover on farms constitutes some form of adoption of agroforestry, be that active planting or passive preservation of remnant trees.

4.2.2 Socioeconomic data

Literature on the factors affecting agroforestry and agricultural innovation adoption was reviewed, developing the basis for determinants included in the models. Several factors are unmeasurable latent variables with no appropriate proxy or lacked data and so were omitted, including information on extension services and membership of farmer or community groups. The remaining factors were cross-checked with available socioeconomic data and the most appropriate variables or proxies were chosen from the census data, household datasets, or auxiliary geospatial datasets. The final set of socioeconomic determinants included in the analysis are found in table 4.3.

Much of the data to quantify the socioeconomic variables were available in Uganda's 2014 national census at the parish level (n = 7457), the smallest administrative unit. However, some socioeconomic factors were unavailable in the census and were generated at the parish level from small area estimation methods using household survey data from the 2016 Demographic and Health Surveys (DHS; UBOS and ICF, 2018b). The DHS Program collects household survey data nationally in over 90 countries. In Uganda, the 2016 DHS survey collected data from 20,880 households (UBOS and ICF, 2018a).

Small area estimation

Detailed spatial community data are important information for many stakeholder groups in the development sector from NGOs to policymakers. Census data often provides nationwide socioeconomic information for lower administrative boundaries. These census datasets are often readily available, but frequently lack the variables of interest to many practitioners (Amoako Johnson et al., 2012). Not all socioeconomic factors affecting agroforestry adoption were available from the national census data and so household survey data were used. Small area estimation techniques have been increasingly used to fill in the detail that census data cannot deliver. These statistical methods use census data alongside sample survey data to provide estimates of variables of interest in small areas (Rao and Molina, 2015). They harness the spatial coverage of census data, and the thematic detail from survey sampling to provide these estimates. The Fay-Herriot method for small area estimation was used and implemented using the emdi package for R (Kreutzmann et al., 2019). The Fay-Herriot model is one of the most commonly used small area estimation models and is essentially an area-level linear mixed model with a random effect for area (Fay and Herriot, 1979). A relationship is derived between direct estimates for parish-level variable means from the household survey data and a set of variables from census data with random area effects to make predictions in non-sampled parishes. The quality of the small area estimates was assessed by calculating a goodness-of-fit test (Brown et al., 2001) and the correlation between the model and direct estimates. Further information on the Fay-Herriot model can be found in appendix A.1

Important variables that were not available in the census were scaled up using small area estimation. These variables were; the proportion of households in the parish who owned land, the average household head education level, the average area of land owned by households, the average number of livestock owned and the DHS wealth index. The DHS calculate a wealth index from some of its variables, based on ownership of certain household items, including television, bicycle and car, as well as housing characteristics like building materials, hygiene facilities and water sources. The area of land owned and the number of livestock owned were not included as variables in the final models as the small area estimation models did not produce good estimates. Furthermore, some variables were dropped due to colinearity with other variables (table 4.3). Where small area estimation-derived variables were colinear with census variables, the census variables were selected for data quality. After dropping colinear variables, only one small area estimation variable was used; the DHS wealth index. While the regression models used are robust to colinearity, the importance and partial dependence are affected by colinear variables.

4.2.3 Climate data

While the focus is understanding the relationship between TCoF and socioeconomic characteristics, the analysis was repeated including climate data to understand the comparative explanatory power. Nineteen bioclimatic variables (WorldClim v2; Fick and Hijmans, 2017) were used and transformed through principal components analysis, with the first three principal components being used in the model. These three components accounted for 85% of the variation in climate data for Uganda. These spatial principal components were then averaged within each parish.

4.2.4 Regression

The relationship was explored within six broad agroecological zones. There are 15 agroecological zones in Uganda characterised by 10 separate farming systems, with different soils, climate, and socioeconomic contexts (MAAIF, 2018). These 10 zones were aggregated to 6 zones across the country: Northeast, Northwest, Southeast, Southwest, Pastoral Rangelands and Highland Ranges (table 4.4).

Table 4.3: Socioeconomic data used in the models of agroforestry adoption

Data variable for parish	Factor	Dataset
Proportion of households headed by a man	Gender	Census
Proportion of females that are literate	Education	Census
Proportion of population over 18 in work	Off farm income	Census
Proportion of households that rely on subsistence farming	Off farm income Land ownership	Census
Average household size (number of people >15 years old)	Labour availability	Census
Proportion of household heads >60 years old	Age of household head	Census
Mean household DHS Wealth Index score	Wealth	DHS with SAE
Proportion of households with a member that has a functional bank account	Wealth	Census
Mean travel time to town	Market integration	MAP [1]
Population density	Land pressure	Census
Small area estimation variables not included in the models:		
Land ownership	Correlated with proportion of households that rely on subsistence farming	
Household head education	Correlated with female literacy	
Area of land owned	Poor small area model estimate	
Livestock owned	Poor small area model estimate	

[1] Malaria Atlas Project (2015)

A random forest regression model was used in each of these zones using the same variables (Breiman, 2001). Random forest models are useful for understanding relationships especially when you do not need to extrapolate information. They do not assume linearity, useful here as the relationships are complex dynamics with several factors potentially moderating the relationship with tree cover. It is not always clear in the literature what factors might be considered drivers of adoption and what factors are moderators of other drivers. Random forest models are useful here, the model considers interactions without the need to specify them. Additional information can be derived from random forest

Table 4.4: Agroecological zones used in the analysis of agroforestry adoption. The six agroecological zones in this analysis are based on the ten agroecological zones from MAAIF with some zones joined together. The models were run for each agroecological zone separately

Agroecological zone	**No. of parishes**	**Agroecological zones from MAAIF**[1]
Northeast	798	The northeastern drylands and savannah grasslands
Northwest	991	The northwestern savannah grasslands and para savannah
Southeast	2258	Kioga plains and Lake Victoria crescent
Southwest	1707	Western savannah grasslands and southwestern farmlands
Pastoral Rangelands	590	Pastoral Rangelands
Highland Ranges	1113	Highland Ranges

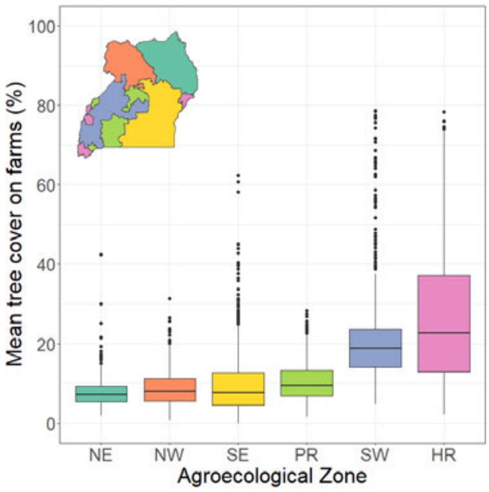
[1] MAAIF (2018)

models including the importance of each variable in the model. In turn, the values of each variable in the out-of-bag sample are shuffled and the percentage change in the model's mean square error is recorded as a measure of the importance of that variable. Partial dependence can also be extracted from the model, which shows the way in which each predictor variable affects the dependent variable. It tells us for any given value of a variable what the average marginal effect is on tree cover.

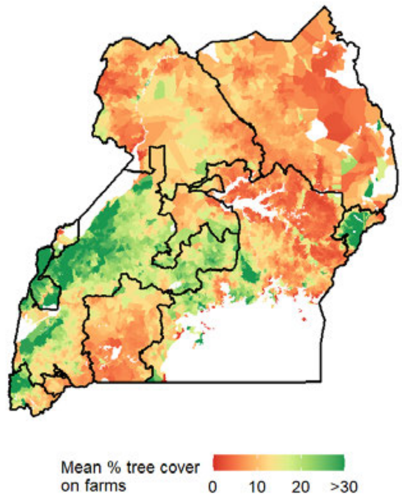
4.3 Results

4.3.1 Trees on farms in Uganda

The extent of tree cover on farms in Uganda is variable across the country (figure 4.1). The mean TCoF is 14%. Median tree cover in the highland ranges and southwest farmlands is greatest at 23% and 19% respectively and with greater range than other zones. These areas encompass large areas of land that are part of montane forest ecoregions. The lowest tree cover is in the North, where the climate is generally drier with yields from the main crops some of the lowest in the country and more households engaged in rearing livestock (UBOS, 2020).



(a) Mean tree cover on agricultural land in parishes boxplots by agroecological zone



(b) Tree cover on agricultural land by parish. Black boundaries are agroecological zones

Figure 4.1: Parish level mean tree cover on farms in agroecological zones of Uganda. MODIS tree cover data was cropped to agricultural land based on an ensemble of land cover products and then averaged over each parish area

4.3.2 Model explanatory power

The ability of the socioeconomic variables to explain the variation in TCoF differs considerably from zone to zone (table 4.5). Socioeconomic predictors alone could explain between 21-46% of the variance in TCoF. The model had the least explanatory power in the Northeast agroecological zone and explained the greatest variation in tree cover in the southeast. While these models, which include many of the major drivers identified from case studies, show some significant results, much of the variation in TCoF remained unexplained.

4.3.3 Variable importance and relationships

The factors that are most important in the models vary between zones. On average, the most important variables across the models were travel time to cities (access to markets), population density, female literacy and household size (figure 4.3). The result also shows that factors that have the most explanatory power in some zones have minimal power in others.

Agroecological Zone	Variance explained by model: Socioeconomic model	Variance explained by model: Socioeconomic and climatic model (% increase)
Highland Ranges	0.39	0.69 (77%)
Northeast	0.21	0.29 (38%)
Northwest	0.36	0.60 (67%)
Pastoral Rangelands	0.30	0.72 (140%)
Southwest	0.27	0.56 (107%)
Southeast	0.46	0.59 (28%)

Table 4.5: Variance in tree cover on farms explained by the models of agroforestry adoption by agroecological zone

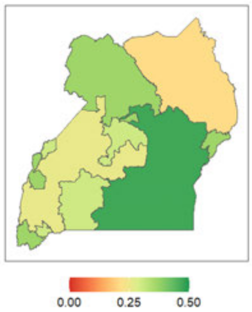


Figure 4.2: Mapped variance in tree cover on farms explained by the socioeconomic model

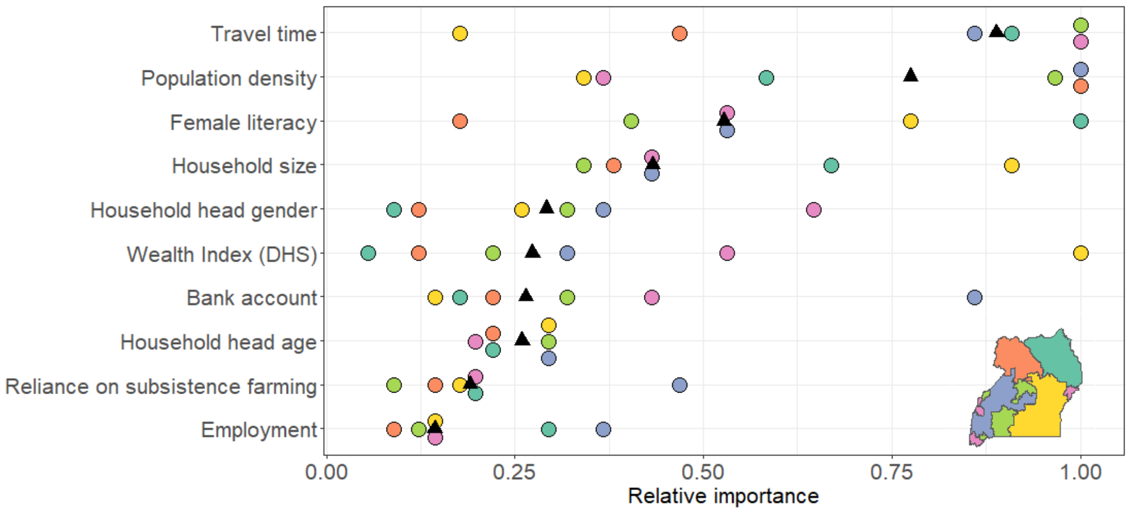


Figure 4.3: Relative importance values in each agroecological zone. Median values are presented in black

While travel time was on average the most important variable in explaining tree cover, it was relatively unimportant in the Northwest and even less important in the Southeast. A number of relationships are exhibited in these models. Figure 4.5 shows the partial dependence plots from the random forest models, showing the dependence between tree cover on farms and the top determinants, marginalising the values of all other input features. In the Highland ranges, tree cover increases sharply with increased time to cities to about 50 minutes where it levels off and decreases moderately. A negative, roughly linear relationship exists in the Southwest farmlands, where tree cover decreases with increasing distance from cities. The effect sizes are smaller in the other zones but remain important. In the Pastoral Rangelands, tree cover is relatively stable until a travel time of about 100 minutes where it increases and levels off at a few percent greater tree cover.

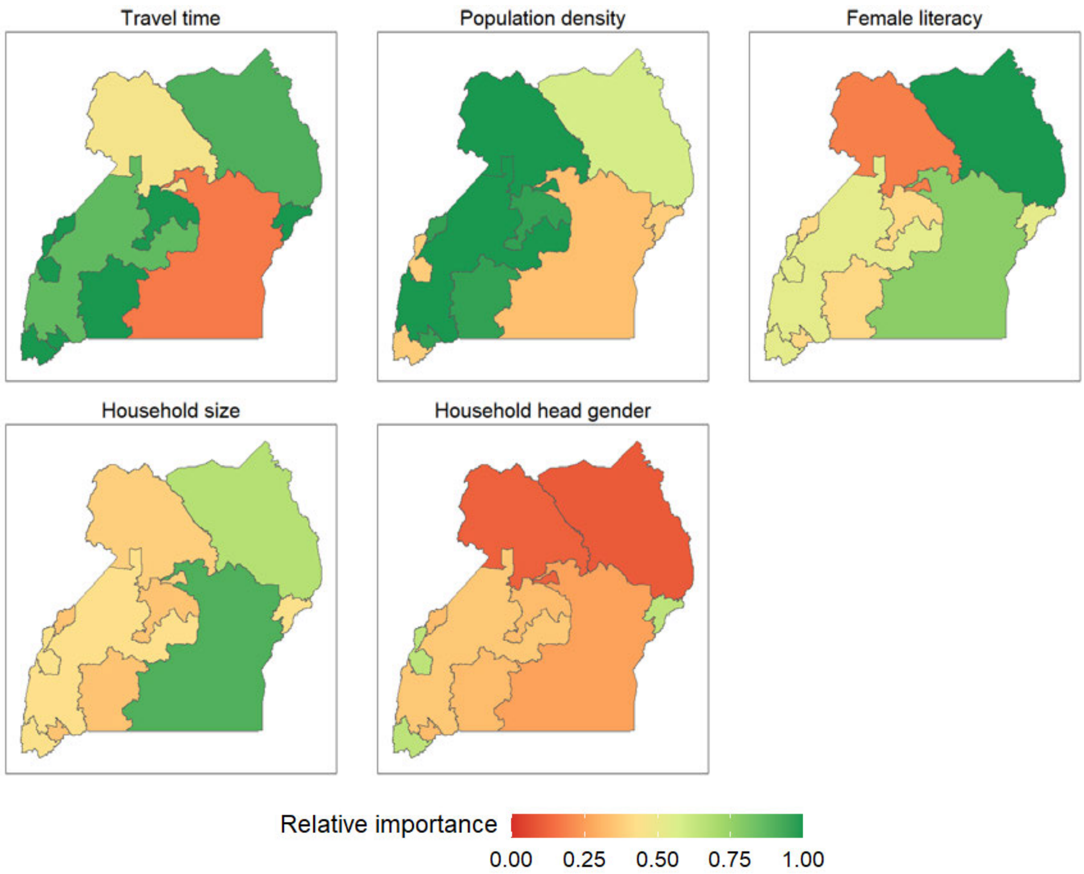


Figure 4.4: Relative importance for the five most important socioeconomic variables in explaining tree cover on farms. Outputs for all the variables can be found in appendix A.2

Population density was important in most zones, especially in the regions in the east of the country. The relationship is similar in most of these areas; tree cover is highest in the areas of low population density, decreasing with increasing density and levelling off. The relationship is relative to the population densities found in the zone, with levelling off occurring by around the midpoint in a region's range of population density.

Education was also relatively important in several areas, with female literacy being the most important variable to explain tree cover on farms in the Northeast. It was far less important in the Northwest and the Pastoral Rangeland. In the Highland ranges, the relationship is roughly linear with tree cover on farms decreasing with increasing female literacy. A similar relationship is present in the Southwest farmlands, albeit after a threshold at around 60% literacy. In the Northeast, where it is the most important factor, tree cover on farms increases with literacy across the parishes with low literacy rates and is roughly stable once mean literacy is around 20%.

Household size was an important factor in zones in the east of the country as well as in the Highland ranges. The relationship was generally similar in each zone, with tree cover decreasing in parishes where the average number of adults in a household was greater.

The results here show that at this scale, household head gender is less important than most other variables in all locations except in the Highland ranges where it was relatively important. In this zone, the proportion of tree cover on farms increases quite considerably in parishes where more households are male-headed.

It is also notable that the effect of factors is relative to the average zone tree cover, and the effect size is indicative of the variance explained by the model as a whole, with effect sizes smaller where the model had less explanatory power. The partial dependence plots for all variables can be found in appendix A.2.

4.3.4 Climatic explanatory power

When climate variables are included in the models, the model can explain more variation in tree cover by an average of 24% across all zones (table 4.5). However, the increases in models' predictive power is uneven between zones. The inclusion of climatic variables

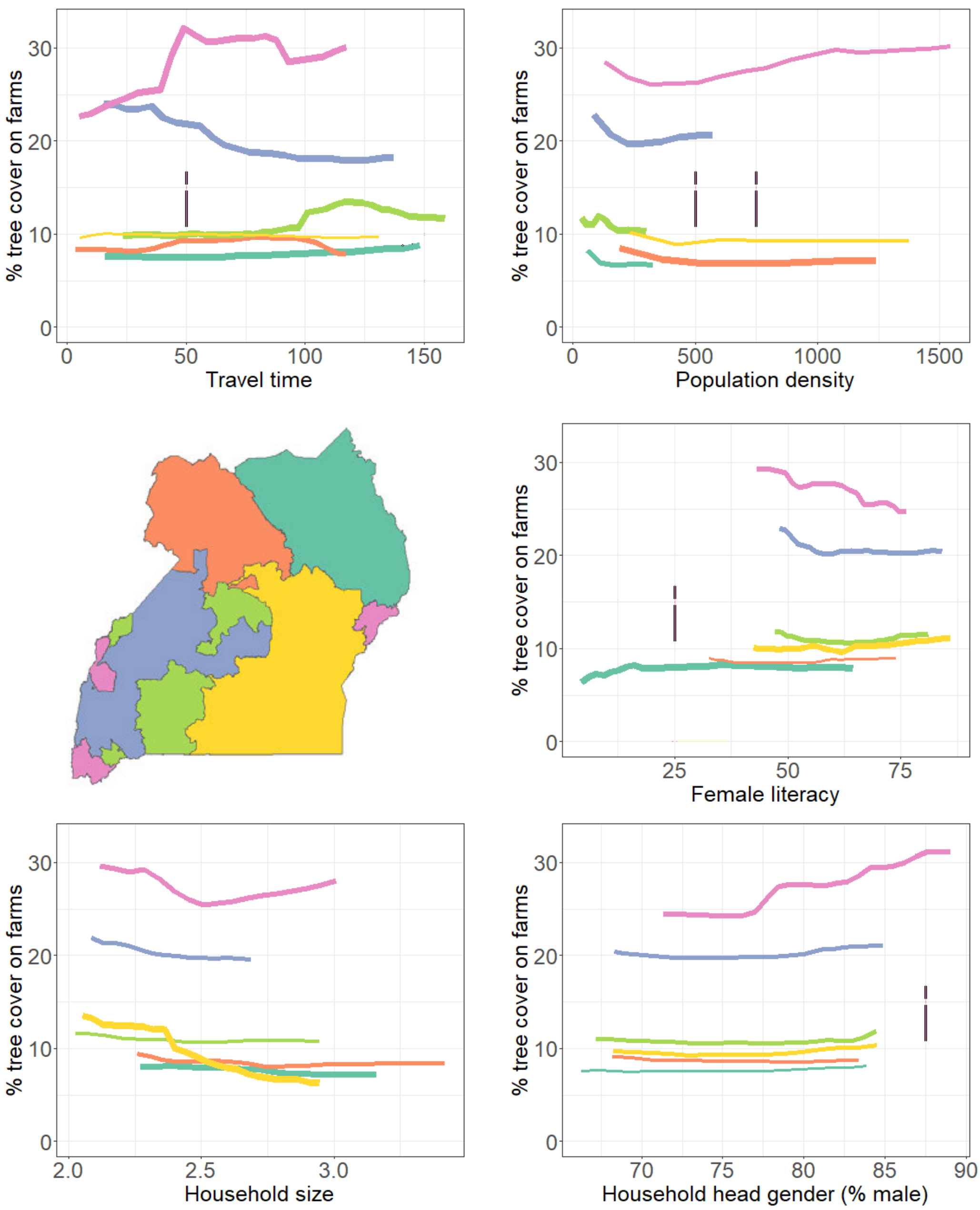


Figure 4.5: Partial dependence plots for four important variables with lines coloured by agroecological zones, with coloured key map. Partial dependence plots show the way in which each predictor variable affects the dependent variable. It tells us for any given value of a variable what the average marginal effect is on tree cover. Line thickness corresponds to the importance of the variable in the model, and lines are clipped to exclude the bottom and top 5% of data. Outputs for all the variables can be found in appendix A.2

more than doubles the model's explanatory power in the Pastoral Rangelands and the Southwest farmlands. It has a much smaller effect in the Northeast and Southeast agroecological zones.

4.4 Discussion

The results show that the socioeconomic links to tree cover on farms vary greatly within Uganda. The explanatory power, important variables and the nature of relationships vary from zone to zone. This reflects what we see in case study literature, where determinants are not consistent and moderated by local contextual factors. Exploring the effects of moderating factors spatially across a national scale has not been considered in this way before. We know that when thinking about extension, intervention or the diffusion of agroforestry adoption, one size does not fit all. These results show that our understanding of some determinants can be generalised across a region, which can help us design better extension or intervention at a national level and guide local studies to understand adoption.

4.4.1 Spatial variability in the importance of socioeconomic determinants of tree cover on farms

We found that the set of socioeconomic variables and models used here could explain different levels of variance of tree cover on farms across the six agroecological zones in this study. This shows that socioeconomic characteristics have different explanatory power over tree cover depending on the location, likely moderated by other factors. Few studies consider adoption at multiple sites separately using the same variables, but we see differing model performances where they do. Geographic effects like village (Wells et al., 2020) or country (Miller et al., 2017), included in models of adoption show that there are place-specific factors operating at multiple levels that impact how much the household characteristics can explain. This study shows that these patterns also exist at the regional scale with parish-aggregated data, and can be explored nationally.

The results also show that much of the variance remains unexplained. This highlights the complexity of agroforestry adoption, with the drivers and moderators likely to be very diverse at this scale, many of which may be unmeasurable. This scale of analysis does not take into account what form the trees on farms take. Agrisilviculture is practised in a variety of ways, including scattered trees among cropland, homegardens, alley cropping, shade cropping and more. These practices require different inputs or management, are more suitable for certain farming systems over others, and so the type of system will therefore moderate the effect of various socioeconomic drivers on adoption. It is clear that the process is complex and that lessons are hard to transfer. However, it is important to understand the opportunities and barriers to adoption that we can quantify at a broader scale.

It is important to highlight the factors that could not be included in this set of socioeconomic variables. From case study literature, we would expect aspects of extension to be important, like extension methods, time spent with services or number of visits by extension stakeholders (Pattanayak et al., 2003; Feder and Umali, 1993; Mercer and Pattanayak, 2003), as well as membership of community/farmer groups (Meijer et al., 2015; Adesina et al., 2000; Dhakal and Rai, 2020; Mercer and Pattanayak, 2003), the land size (Pattanayak et al., 2003; Owombo and Idumah, 2017; Mwase et al., 2015; Feder and Umali, 1993) and in some cases number of livestock (Pattanayak et al., 2003; Nkamleu and Manyong, 2005). These factors either lacked data or could not be accurately modelled with small-area estimation methods. These missing data are significant, especially information on extension which is likely to have a large impact on agroforestry adoption at the regional scale by exposing farmers to agroforestry practices, skills, advice and resources (Amare and Darr, 2020). Extension services are likely to be an important moderator of many other socioeconomic drivers; for example, moderating the effect of education by improving access to knowledge; providing equitable advisory services to men and women may moderate some of the effects of household head gender; farmers in more densely populated areas or farmers with lower education levels might be more likely to experiment with new technology if extension services inform them on the risks and benefits of certain practices. It is likely that individual government and non-state extension services keep data on their activities to assess the impact of extension. The detailed spatial distribution, intensity and remit of extension services nationally is critical information for the efficiency of pluralistic extension, and would help in monitoring the national impacts of all extension services on agroforestry adoption.

The model in the Northeast explained the least variance in tree cover. A number of factors make this region of Uganda different. Conflict in Northern Uganda had resulted in over 1.8 million Northern Ugandans living in IDP camps by 2005 (Russo, 2007). Largely as a result of insurgencies by the Lord's Resistance Army (LRA) (in areas of both the northeast and northwest agroecological zones) but also in part, in the Northeast, due to persistent raids by Karamojong warriors (Stites and Howe, 2019). While some violent cattle raiding still occurs, most of the displaced people have returned back to re-establish their farms in the past 10-15 years (Joireman, 2018). This region also has the highest density of livestock in the country with rearing livestock being a primary livelihood for many farmers here (UBOS, 2020). Lastly, the region displays the least variation in tree cover on farmland in the country (figure 4.1). As such other factors might be more important in the Northeast in explaining the little variation of trees on farms. Access to extension here is the lowest in the country (UBOS, 2020), with 7% of agricultural households in Karamoja (a subregion fully within the Northeast agroecological zone) receiving extension services in 2018, and 4.5% of agricultural households in Serere (partially within the Northeast agroecological zone). As the public sector extension services are demand-driven and farmer-led (Rwamigisa et al., 2018), it may be the case that the extension that does occur in these areas is focused on livestock. Furthermore, communication and relationships are critical for the diffusion of technologies, and while conflict has reduced, disputes have arisen among returning farmers where land boundaries and ownership are unclear which will have impacts on the diffusion of technologies between farmers (Joireman, 2018).

4.4.2 Climate explained more tree cover variation in some areas than others

When climate variables are added, the models had extra explanatory power but not evenly across all models, suggesting that climate has an inconsistent influence on the tree cover in these heavily managed landscapes or an effect in moderating other factors. Climate will affect adoption in a number of ways. It will limit what trees can be grown where and affect the survival of seedlings. Climate will also affect other biophysical characteristics like soil quality or erosion risk that might make trees harder to maintain or increase their appeal for adoption. Most studies on factors affecting agroforestry adoption do not include climatic variables as often these will not vary significantly across a study region (Pattanayak et al., 2003). Wells et al. (2020) found that climate water deficit explained as much variation in aboveground biomass on farms as extension services or household material wellbeing in restoration projects. In a study of 5 sub-Saharan countries, geoclimatic variables including precipitation and temperature were found to explain about 31% of the variation in the adoption of trees on farms (Miller et al., 2017). Results here support these findings from previous studies but showcase the variability of climatic influence nationally in Uganda.

Knowing where climate has a greater impact when designing and implementing interventions is important. In areas more sensitive to climate, it becomes more critical to ensure the interventions and advice are appropriate to the local conditions to ensure success. Understanding where a changing climate might have a bigger impact on efforts for extension or intervention is also important when thinking about the longevity of intervention or behaviour change. More detailed climate analysis could help pick apart the bounds and conditions that are important here.

4.4.3 Towards a generalised but contextual understanding of the determinants of agroforestry adoption

Across the country, travel time, population density, literacy, and household size were the most important variables in explaining the variance of TCoF, though this was not consistent across zones. This suggests that, while there are factors that are generally more important, the socioeconomic characteristics important to agroforestry adoption are context specific. It is important to understand these patterns when designing national extension services or interventions as one size does not fit all. These patterns may be dictated by a number of local moderating factors that alter the influence of a specific driver. We see this in literature from local studies, where variables of importance in one place are not relevant in others. What this research shows is that shifting patterns of adoption drivers are also operating at the regional scale, with regionally important variables differing across the country.

Travel time was one of the most important variables in most zones, but the direction of its impact was inconsistent. Mercer (2004) found that stage of the diffusion of agroforestry (eg. early adoption, majority adoption etc.) was a moderating factor on the impact of access to markets. Infrastructure drivers became more important in later stages of adoption when many farmers have already adopted agroforestry and there is a more developed market for tree products. Transportation challenges will also inhibit the ability to access markets to sell tree products where there is demand (Sebukyu and Mosango, 2012; Fouladbash and Currie, 2015). This is the relationship we see in the Southwest farmlands, a zone with some of the highest TCoF, suggesting later-stage adoption with more commonplace agroforestry practices. It suggests that in this area, providing market access where travel times are currently long, could have a significant effect on the diffusion of agroforestry or the success of interventions. Travel time may also moderate other drivers. Farmers may be less likely to adopt with increasing travel time to population centres as they may have less access to extension, exposure to new technologies, ideas or required inputs (Nkamleu and Manyong, 2005).

If demand for tree products is low, market access incentivises farmers to maximise cash crops to sell in the short term, reducing the likelihood of adoption (Zerihun et al., 2014). Exposure to new technologies and ideas can expose farmers to agroforestry knowledge, but may also introduce farmers to other agricultural innovations and technologies that compete for land use, leading to reduced adoption (Beyene et al., 2019). Proximity to population centres could also indicate land pressure and small plot sizes where it may be harder for farmers to give up land to plant trees. In these areas, we can see that proximity to population centres presents some barrier to adoption, and it highlights the need for understanding these barriers to design effective extension services and interventions. There are elements of access to markets that the travel time dataset does not capture as a proxy. The travel time dataset estimates travel time to the nearest city, but there are smaller towns and markets not accounted for by the dataset, and farmers may sell products from their farm instead of a market. These aspects of market access not described by the data may affect the realtionship the predictor has with tree cover.

Population density was included as a proxy for land pressure, and it had a similar relationship in all areas where it was important. The parishes with the lowest population density had the highest TCoF. This relationship may exist because with more people, there is 'less room' for trees (Zomer et al., 2009). High land pressure may also indicate smaller field sizes, and farmers may be more risk averse to adopting new technologies and lack the land space for experimentation (Adesina et al., 2000). The results, however, show the relationship is mostly only present among parishes with the lowest population densities. This could suggest that high population density may not be a barrier, but that low population density may be an opportunity to foster experimentation with new technologies. This relationship could also be due to mosaic landscapes being included in the land cover data. In the process of establishing agriculture and clearing trees, population density is lowest at the earliest stages, and so these mosaic landscapes may have the fewest people and the tree cover in natural vegetation patches is counted as part of the agricultural landscape.

Education levels are usually linked to access to knowledge on farming practices indicating exposure or understanding of agroforestry. Higher education levels of household heads are also likely to improve their ability to weigh up the risks and benefits of adopting a new innovation and their ability to understand and manage unfamiliar technology (Doss and Morris, 2001). In agricultural innovation diffusion, the education levels of adopters are thought to be more important in earlier stages (Feder and Umali, 1993). Our results here might reflect this diffusion in stages, with literacy being the most important variable in the Northeast farmlands, where recent returns to farmland and access for extension may place farms in this area early in the diffusion process. This highlights a need or opportunity for co-development of education and agricultural extension. We also see an inverse in other places where literacy is still somewhat important in explaining variation in tree cover, like the Highland ranges and Southwest farmland. The processes operating here are unclear and warrant more detailed research to build our understanding of how co-occurring educational development will impact agroforestry extension efforts.

We might expect the gender of the household head to impact TCoF, but it is relatively unimportant in all zones except in the Highland ranges where it has a relatively large effect. There are a number of reasons why male-headed households might be more likely to adopt. Male-headed households are likely to have greater access to resources, credit, land tenure, extension services, and education among others (Kiptot and Franzel, 2012). Women who are household heads will often have responsibility for other domestic duties like resource collection, childcare or cooking and may not be able to allocate time to learning and managing a new technology (Miller et al., 2017). The results show that gender is not important in most places, suggesting that the effect is minimal at this scale. This does not necessarily mean the effect of gender is minimal at finer scales, within parish household differences could still be significant and should be considered. Gender may not be a factor in driving the parish-level mean tree cover on farms, but it could well drive within parish differences. Furthermore, this result does not show the distribution of labour in tree maintenance, which often falls to women in male-headed households (Kiptot and Franzel, 2012). Where we do see gender having an impact on adoption, female-headed households are less likely to adopt. Barriers to adoption by women should be examined locally and relevant action should be taken to address these barriers by, for example, ensuring equitable access to extension services, community women's groups and microfinance.

Household size also had an important impact on tree cover and a similar relationship is seen in all areas. Parishes with greater average household sizes had less tree cover on farms. We do not see here the expected relationship that the increased labour availability associated with larger households translates to greater adoption (Pattanayak et al., 2003), especially in the early stages of adoption where planting and management are more labour intensive (Franzel et al., 2001; Miller et al., 2017). This may be moderated by the type of agroforestry, with labour constraining certain tree cultivation practices more than others (Miller et al., 2017). The proxy measurement of household size for labour availability also simplifies labour, ignoring the labour that can be used from outside of the household, including communal labour and hired labourers (Mercer, 2004; Chitakira and Torquebiau, 2010)

There are policy implications for these understandings. National policies and institutions have a considerable impact on adoption (Miller et al., 2017), and without policy providing incentives or resources, the level of adoption is often lower (Place et al., 2012). Promoting agroforestry is included as a medium to long-term action point in Uganda's agricultural adaptation plan (MAAIF, 2018), although with little detail or urgency. Regional institutions exist through the National Agricultural Advisory Services (NAADS) to provide government agricultural extension services. Regional patterns on factors affecting adoption could inform the planning of these extension services by, for example, improving market access in the Southwest, ensuring extension services address barriers to women adopting agroforestry in the Highland ranges, or tailoring advice to larger households in the Southeast to address the obstacles they face. These results provide information to avoid the pitfall of adopting a "best practice" blueprint, not tailored to the context (Davis et al., 2021).

Context-specific understandings of adoption are still critical. People are not passive participants in adoption and decisions are not just the output of a set of household-level conditions. Decision-making takes place in a system with a complex network of actors operating from local to national scales. How these actors interact and communicate, the personalities of stakeholders involved at all levels, and the relationship dynamics between these actors all play a part in the local context (Amare and Darr, 2020). It is impossible to take this system-level approach at regional and national scales as the requirements for this type of data are hyperlocal. Regional analyses, however, can help us understand what lessons are more generalisable and what moderating factors are operating at broader scales.

4.5 Conclusion

Previous research at the local level has been context-specific and the lessons learned have been hard to generalise. This research uses national-level datasets to draw some more generalisable understandings of agroforestry adoption in Uganda. Understanding how contextual factors moderate some determinants and the effect they are likely to have on tree cover on farms helps focus extension services or design more appropriate and effective interventions. If we understand the barriers to adoption or the opportunities that certain types of households exploit, they can be more explicitly addressed. While local context is undoubtedly important, the national scale data allows relationships to be explored regionally, assessing how adoption dynamics vary across the country and facilitating more specific interventions. The approach would be applicable across sub-Saharan Africa where appropriate census data are available.

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Chapter 5

General discussion and conclusions

Trees on farms contribute significantly to livelihoods whilst supporting biodiversity and increasing carbon storage in agricultural landscapes. Trees on farms have been identified as a land use that can help tackle environmental degradation, development issues and the climate crisis, and meet global targets in these areas. Despite this, it is relatively understudied when compared to forests or agricultural production. This is especially the case with research conducting spatial analyses and using Earth observation data, particularly in tropical agricultural systems. However, these geospatial approaches facilitate the study of these landscapes at much broader scales than ground data and have the potential for drawing conclusions with more general applicability. In this thesis, I contributed to this understudied field by developing and applying methods and tools for monitoring agriculture-forest mosaic landscapes using remote sensing and other geospatial datasets at various scales.

First I showed that remote sensing can map gradual transitions in tree species composition in complex agricultural landscapes. Next, I showed that geospatial methods can be used to monitor the contributions of trees on farms to national biodiversity commitments. Finally, I explored the relationship between socioeconomic and climatic determinants of agroforestry adoption and tree cover on farms regionally across Uganda. I found the determinants of trees on farms varied from area to area, not just in magnitude but sometimes in direction too.

In this chapter, I will discuss the contributions of this thesis to addressing the initial research aims, broader questions around the monitoring of agroforestry landscapes, and the further work identified by my findings.

5.1 Addressing research aims

5.1.1 To test the efficacy of an EO-ordination modelling approach for mapping tree floristic gradients in complex agriculture-forest mosaic landscapes

Community composition is an essential aspect of biodiversity (Pereira et al., 2013) because it describes the abundance and diversity of species, functional traits and ecological interactions. The importance of trees on farms for biodiversity means that tree floristic gradients are important features of agricultural mosaic landscapes. Being able to map and monitor composition efficiently is, therefore, a critical step in understanding the biodiversity in agricultural landscapes and in reporting on biodiversity targets. EO data and geospatial analyses can help with this efficiency at scale. Despite recent advances in monitoring biodiversity from EO data, current methods for mapping composition are seldom applied or tested in agricultural landscapes, with a greater focus on high biodiversity areas like forests and more untransformed ecosystems. Many methods are not applicable or operationally efficient in these complex landscapes, and common methods like land cover mapping are thematically coarse and do not describe the fuzzy vegetation patterns presented. EO-ordination methods can help but have not yet been applied to agricultural-forest mosaic landscapes like those in chapter 2.

Therefore, in chapter 2, I aimed to apply an EO-ordination modelling approach to test its efficacy as a monitoring tool in agricultural-forest mosaic landscapes. The results showed that it is possible to map tree community composition in agricultural-forest mosaic landscapes, with all ordination axes across the three study sites predicted with an RMSE $<$20% and with R^2 $>$0.5. The EO data that were most useful in predicting tree floristic composition varied between the three sites. This suggests that the fusion of EO data types in this approach has provided a wide enough range of information on the trees to capture the different compositional gradients that the ordination axes are describing. The novel inclusion of radar data in this research proved to be a useful addition and shows that its inclusion in EO-ordination models should be considered in future applications of the method. Previous applications of the method have not proven that it can be used as an operational tool in tropical agricultural landscapes using open-access datasets. This is because previous work has been confined to more homogeneous or forest landscapes or using cost-prohibitive hyperspectral or airborne imagery. The research in chapter 2 showed that EO-ordination modelling could be a useful monitoring tool in these landscapes, but will require a substantive field based data set as well.

Chapter 2 adds to a growing body of work on EO-ordination methods (Feilhauer et al., 2014, 2011; Gu et al., 2015; Harris et al., 2015; Neumann et al., 2015; Schmidtlein and Sassin, 2004; Schmidtlein et al., 2007; Schmidtlein, 2005; Schmidtlein et al., 2012; Feilhauer and Schmidtlein, 2009; Hernández-Stefanoni et al., 2012; Ohmann and Gregory, 2002; Thessler et al., 2005), and extends the method beyond its previously tested capabilities, using a fusion of open-access optical and radar data and on landscapes as heterogeneous and intensely managed as tropical agricultural landscapes.

5.1.2 To develop a proof-of-concept indicator for national monitoring of the biodiversity of agricultural land based on trees on farms

Extending beyond the landscape approach in chapter 2, chapter 3 aimed to provide a tool that could be used to monitor and compare the biodiversity value of trees on farms at subnational and national scales using only EO data products, without the need for prohibitively-extensive field plots. National reporting on biodiversity targets requires aspects of biodiversity to be measured at national scales. Targets that are not measurable are likely to fail, and this likely contributed to the failure of many of the Aichi biodiversity targets, including target 7, which covered agricultural sustainability (Green et al., 2019).

The purpose of this research was to propose an indicator that could be used as a proxy for the contribution of trees on farms to biodiversity. The indicator used free and open-source global datasets to ensure it had wide geographic coverage. It was developed and applied in four countries across the tropics to showcase the concept. Following the criteria for a useful indicator (Biodiversity Indicators Partnership, 2011), the chapter outlines the scientific basis for the indicator, the accessibility of the data, the interpretation of the output, the relevance to users, and the use case for the indicator. The index was calculated for four case studies, and outputs at the pixel, landscape, and 2nd administrative unit levels are presented. The qualitative validation proved promising, with mapped scores reflecting what we might expect from photointerpretation of a sample of sites across the case study areas. The next steps for the index include furthering the validation with experts, assessing the validity of the indicator for temporal change quantification and testing additional modules to the index like connectivity metrics. The Farm Biodiversity Score has been submitted by World Agroforestry (ICRAF) to the Biodiversity Indicators Partnership (BIP) and the application is pending. The BIP have still proposed the FBS to the United Nations Convention on Biological Diversity (CBD) as an available indicator for monitoring post-2020 biodiversity goals (World Agroforestry, 2020; BIP, 2021). As I write, the 15th Conference of the Parties (COP15) to the CBD is underway to determine the post-2020 agenda and its indicators.

5.1.3 To determine the national patterns of the determinants of agroforestry adoption

In this chapter, I addressed a gap in the agroforestry adoption literature. Research on the factors affecting the adoption of agroforestry practices is almost exclusively based on case studies or research with restricted spatial scope. In order to design and deliver effective and resource-efficient national or regional extension services and agroforestry interventions, understanding more general patterns in the determinants of adoption is critical. To address this gap, I used national-level census and household survey data alongside EO-based estimates of tree cover on farms to explore the relationship between various socioeconomic characteristics and the adoption of agroforestry in Uganda.

Exploring the spatial patterns of the determinants of agroforestry adoption, I showed that socioeconomic characteristics explained different amounts of the variation of tree cover on farms depending on location within the country. The most important variables in the models varied from region to region. In some cases, the direction of the effect of a factor changed based on location. This indicates that modifying factors alter how socioeconomic determinants affect agroforestry adoption.

This research adds something new to the existing literature on agroforestry adoption by taking a regional approach across a country using national-level data, instead of focussing on a case study. The results confirm the site-to-site variability seen in the literature, possibly due to local modifying factors. These contextual modifying factors may include the presence of extension services, the phase of agroforestry adoption, or the type of agroforestry practice adopted which alter the effects that determinants have on the likelihood of agroforestry adoption.

5.2 Broader conclusions

5.2.1 Implications for policy and practice: Methods

The methods applied or developed in this thesis for monitoring aspects of biodiversity in trees on farms are transferable, and similar analyses can be done elsewhere. The landscape level analysis has ground data requirements, but the rest of the thesis findings rely on data that are freely available. the methods allow analysis at various scales in different locations, from the landscape, sub-national, national and international levels.

As I write, the parties to the CBD are developing the post-2020 global biodiversity framework (GBF) to replace the Strategic Plan for Biodiversity (2011-2020) and the Aichi targets within them (CBD, 2021). The draft GBF, published in July 2021, includes 21 targets to achieve by 2030, including a target to "ensure all areas under agriculture, aquaculture and forestry are managed sustainably". Policymakers have been responsible for setting National Biodiversity Strategies and Action Plans (NBSAPs) as contributions to the global targets through mainstreaming biodiversity into economic sector policy (Whitehorn et al., 2019). The Biodiversity Indicators Partnership (BIP) encourages the incorporation of indicators in NBSAPs for measurable biodiversity monitoring. Current NBSAPs are expected to be reviewed and aligned with post-2020 targets. The analysis in chapter 2 is included in a protocol of data collection and analysis (Harrison et al., 2019), developed to monitor agricultural sustainability under Aichi Target 7, and applies to the equivalent target (target 10) under the draft GBF. The BIP promote the use and development of biodiversity indicators to make measurable progress in biodiversity protection for biodiversity-related goals from CBD, the UN SDGs, and global assessment report like those of Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES).

The approach taken in chapter 4 combines census and household survey data with EO data products to explore the relationship between people and their environment. This hybrid approach has been used to explore various other interactions, like poverty and forest cover (Sunderlin et al., 2008), livelihood capitals (Berchoux and Hutton, 2019), female literacy and environmental metrics (Watmough et al., 2013b), and crop intensification and deforestation (Pelletier et al., 2020). The method had been applied to explore the economic contribution and determinants of trees on farms at national-level patterns in Sub-Saharan Africa (Miller et al., 2017). The research in this thesis shows the method is applicable for determining the subnational patterns and could be applied elsewhere. Depending on the country's available data, the balance of census and household survey data may need to be adjusted. Almost every country conducts regular population and housing censuses, and the DHS has one of the most extensive databases of household surveys in developing countries with survey data from 90 countries (The DHS Program, 2022). The World Bank Living Standards Measurement Study (LSMS; World Bank 2022) and the UNICEF Multiple Indicator Cluster Surveys (MICS; UNICEF 2022) are other programmes with extensive household survey datasets and could be used to supplement analyses where other datasets may be lacking.

5.2.2 Implications for policy and practice: Results

Effecting change in agricultural systems to simultaneously address the goals of biodiversity conservation, rural development, carbon sequestration and food production requires a holistic view. Trees on farms can meet many of these goals, but for them to be effective requires an understanding of the country, regions and landscapes. Mapping out where trees on farms have greater or lesser biodiversity value can help focus conservation efforts in specific areas. Within these areas, promoting species that match existing tree compositions will not improve biodiversity. Instead, promoting appropriate species that improve species or functional diversity alongside livelihood goals can be more effective for biodiversity. In promoting these practices, understanding the barriers to adoption can help improve uptake, making efforts to tackle them more successful and efficient.

At the landscape level, understanding the distribution of common tree species present or absent across the landscape provides a basis for planning interventions. The tree species on farms and their uses can also tell us about the livelihood strategies and types of ecosystem services from trees on farms people choose. All agroforestry designs must be appropriate for the location, people's capacities, and needs. Environmental objectives are important in promoting agroforestry but should not override farmers' priorities, and interventions need to meet farmers' needs (Gassner and Dobie, 2022). The tree species that are advised, encouraged, or germplasm provided must be carefully planned as such. This requires an understanding of the current species utilised in the landscape, and the results from chapter 2 show this can vary considerably in the landscape.

At the regional or national level, understanding where agricultural biodiversity is lower can help focus policy and interventions to boost biodiversity in specific areas and monitor the impact. Encouraging greater tree species diversity, structural diversity or tree cover through intervention helps meet biodiversity goals, among others. Promoting the adoption of these practices requires an understanding of the factors influencing uptake. National agricultural or forest policies and local extension services can target context-specific barriers to adoption and use locally-relevant determinants of adoption as opportunities to facilitate greater tree cover on farms. The results of this work are relevant to the designing and planning of interventions and extension services both at the policy level, and on the ground, especially in Uganda, where this thesis had a particular focus. For example, by improving market access where travel time is seen to reduce agroforestry adoption; ensuring extension services address barriers to women adopting agroforestry where the gender of the household head is an important factor; or tailoring advice to larger households where the results show they might face extra barriers to agroforestry adoption.

5.2.3 Remote sensing and agroforestry systems science

This thesis aimed to bring remote sensing data and methods to the study of agroforestry landscapes. These complex socio-ecological landscapes have been little studied with EO data and geospatial analysis. The thesis has also sought to bring these complex transformed agricultural landscapes to the field of remote sensing for biodiversity, which is often focused on intact or untransformed habitats.

Biodiversity field surveys are often challenging to scale up for fine-grain landscape or national biodiversity assessments. Collecting the large quantities of data needed can be expensive, labour-intensive, time-consuming, and requires specialised knowledge and skills. Essential Biodiversity Variables (EBVs) are a set of measurements essential for national to global monitoring, researching, and managing of biodiversity (Pereira et al., 2013). The work in this thesis on biodiversity aims to add to the methods enabling the measurement of EBVs. Satellite remote sensing can enable field measurements to be scaled up. There have been several useful reviews on remote sensing for ecology, conservation and biodiversity monitoring (Kerr and Ostrovsky, 2003; Turner et al., 2003; Wang et al., 2010; Anderson, 2018; Rocchini et al., 2018). However, much of the literature is focused on the biodiversity of natural or intact ecosystems, and few studies employ satellite remote sensing for measuring biodiversity in tropical agricultural systems. This research helps add these missing landscapes to the remote sensing of biodiversity literature.

EO data can support sustainable rural development in several ways and can provide assessments of rural poverty and development (Hargreaves and Watmough, 2021). Many aspects of the environment and natural landscape that people live in are associated with their wellbeing. The idea that these environmental features can be assessed from EO data has been used to explore these links with rural poverty and literacy or predict aspects of wellbeing (Okwi et al., 2007; Watmough et al., 2013b,a; Zhao et al., 2019). Testing the links between agroforestry and aspects of human wellbeing using EO data has been assessed at a national scale (Miller et al., 2017). This thesis contributes to the small but growing field of applying satellite Earth observation to determine the links between the environment and socioeconomics.

5.3 Building on this research

The EO-ordination modelling was tested in three different agricultural-forest mosaic landscapes and showed promising results. Still, in order to be sure the method works across other different types of transformed agricultural landscapes, it could be tested at more sites, following the same method for data collection (Harrison et al., 2019) and analysis. The study sites capture three different tropical agricultural-forest mosaic landscapes, but all had relatively high land-use intensity and trees were simultaneously integrated with crops. The method could be tested in mosaic landscapes with less land-use intensity and rotational agroforestry systems, such as improved fallows or slash-and-burn agriculture. The datasets used two axes of the ordinations, but these outputs could be compared to the same analysis conducted with 3-axes. Mapping three axes of ordination could improve model predictive accuracy, but it may be more difficult to interpret the outputs in three-dimensional space. The tradeoffs between any model accuracy gains and interpretability should be explored. While the results showed the EO-ordination method chosen was successful for these sites, comparing the applicability of the NMDS ordination chosen with other appropriate ordinations would be interesting to assess if some ordination methods outperform others depending on the site and field data characteristics. Isomap is an ordination approach previously used in heterogeneous landscapes using high-resolution hyperspectral imagery on smaller scales and could make for an interesting comparison at these sites (Feilhauer et al., 2011; Harris et al., 2015)

In further work, the outputs from chapter 2 could also be linked to some beta diversity metrics. On the same basis as the spectral variation hypothesis (SVH), that spectral heterogeneity is indicative of environmental heterogeneity (Palmer et al., 2002), the spatial variability of the ordination values (a proxy for species assemblage) within a local neighbourhood or kernel of pixels would be an assessment of beta diversity of that neighbourhood (Rocchini et al., 2018).

The Farmland Biodiversity Score is a proof of concept tool, and there are several avenues for the development of the tool, detailed in the chapter. These included: repeated analysis to assess the validity of the indicator for temporal change quantification; incorporation of additional optional modules to the index, like landscape connectivity metrics; nationally specific parameter tuning, which would allow users applying the index to adjust the parameters based on more nationally appropriate assumptions; and index weighting according to separate erosion risk models. These developments could cement the validity and applicability of the score, tailor it better to local contexts, and prove its utility for monitoring biodiversity over time. Building on this research alongside the EO-ordination modelling, the FBS could be compared to metrics of beta diversity calculated through the variability of ordination values in a moving window.

A qualitative analysis of determinants of agroforestry in Uganda would complement the quantitative spatial analysis of agroforestry adoption well. Engaging with stakeholders at multiple levels across Uganda would add greater depth and understanding to the outputs of this research. The idea could be tested that moderating factors (Oldekop et al., 2021) might be affecting which determinants are more or less important in various places, and the relationship they have to adoption. What these moderating factors might be could become clear through interviews or workshops with farmers, extension agents, non-state intervention programmes, regional or national extension planners (NAADS representatives), researchers from the National Agricultural Research Organisation (NARO), including the Forest Resource Research Institute (NaFORRI) and the Zonal Research Institutes (ZARDIs), as well as government representatives from the ministry of agriculture.

5.4 Looking forward

The twin biodiversity and climate crises need addressing urgently and need to be addressed while supporting the social and economic development of a growing global population. The future of land use is central to many of these challenges. The coming years leading up to 2030 are critical for these global challenges; the post-2020 GBF will have goals set for 2030 (CBD, 2020), the SDGs and 2030 agenda also have a 2030 target (United Nations, 2015). The Paris climate agreement requires global warming not to exceed 1.5°C, requiring a 55% emissions reduction of 2018 levels by 2030 and net zero by 2050 (UNEP, 2019). Because of this, trees on farms will be in increasing focus globally.

Promoting agroforestry often requires effective incentive systems to encourage the uptake of the practice. Farmers who are expected to contribute to global environmental goals through adopting agroforestry may reasonably expect access to funding, for example, through carbon financing schemes or global funding in other payment for ecosystem services (PES) schemes (Gassner and Dobie, 2022). Financing for PES schemes has grown dramatically in recent decades (Salzman et al., 2018). In 2018, the global budget for PES schemes, including those for biodiversity, and forest and land-use carbon sequestration, was estimated at US$ 36–42 billion annually. With the promotion of agroforestry to meet goals and the payments for incentives often come monitoring requirements. The use of remote sensing and Earth observation in this is increasingly important. Methods and data like those used in this thesis allow governments, non-state actors and funders to track progress at landscape and national scales to meet these goals.

Climate change is affecting agricultural and forest ecosystems worldwide, and agroforestry systems are not likely to be untouched (Luedeling et al., 2014). The results from this thesis have shown that climate can impact the types of species grown on farms (chapter 2), the biodiversity of trees on farms (chapter 3), and the level of adoption of trees on farms (chapter 4). Climate change is likely to affect these aspects of agroforestry systems, and these changes in these systems can be better understood through monitoring methods like those used here.

The most recent estimates of global expansion of tree cover on agricultural land are 3.7% from 2000 to 2010, constituting a 2% increase in agricultural land with $>$10% tree cover (Zomer et al., 2016). This is not uniform across the world. This same period saw reductions in tree cover estimates on agricultural land in West Africa, Tanzania, Ethiopia, Brazil and Nepal, and larger than average increases in China, northern India, and regions of Argentina and Mexico (Zomer et al., 2014). The progress in including agroforestry in land use policies is uneven globally, with some countries making greater progress at recognising the potential for agroforestry in ‘green growth’ policies (Noordwijk et al., 2019). Lessons can be learnt from countries leading in this regard. Mainstreaming agroforestry in international agendas to tackle poverty, mitigate biodiversity loss, and sequester carbon will facilitate the growth of agroforestry practices globally.

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Appendix A

Chapter 4 appendix

A.1 Small area estimation

Model outputs

Average household wealth index score in a parish

Details from the small area estimation for the wealth index score in each parish implemented by the emdi package in R are as follows:

Fay-Herriot model for small area estimation (Empirical Best linear unbiased predictions - EBLUP) was used. This is an area-level model. We make direct estimates of the domain means and variances from the DHS data, taking into account sample weighting. Then build the model of the direct estimates against the census data. The goodness-of-fit test (Brown et al., 2001) was calculated.

$\bar{Y}_d = \beta_0 + \beta_1 X_{d,1} + \beta_1 X_{d,2} + ... + \beta_1 X_{d,p} + \tau_d$

Mean value ($\bar{Y}$ eg wealth index) of the domain(d) = intercept (β_0) + fixed effects (β 1,2,..,p) at the domain (d) + local effect (τ_d). As the mean value is an estimate (mean from the sampled households in the parish), we add an error term. The error is assumed to be zero, but has a variance which is calculated from the DHS sample data.

Fixed effects:

- percent of the parish population with an O-level qualification
- percent of parish households who own a radio
- percent of parish households with permanent roofing material

- percent of parish households with permanent flooring material
- percent of parish households who own a TV
- percent of parish households who get water from a borehole
- percent of parish population who use the internet

	coefficients	std.error	t.value	p.value
(Intercept)	-135525.90	7273.64	-18.63	0.00
O-level	512.42	1263.27	0.41	0.69
radio	1108.41	167.63	6.61	0.00
roof	599.57	100.35	5.97	0.00
floor	822.70	305.93	2.69	0.01
tv	1512.68	804.27	1.88	0.06
borehole	-144.82	81.20	-1.78	0.07

loglike	AIC	BIC	KIC	R2	AdjR2
-6239.33	12494.66	12528.63	12502.66	0.71	1.00

The null hypothesis, which can be accepted, is that the EBLUP estimates do not differ significantly from the direct estimates. The correlation between synthetic part and direct estimator is 0.84.

Brown test		
W.value	Df	p.value
146.9	516	1

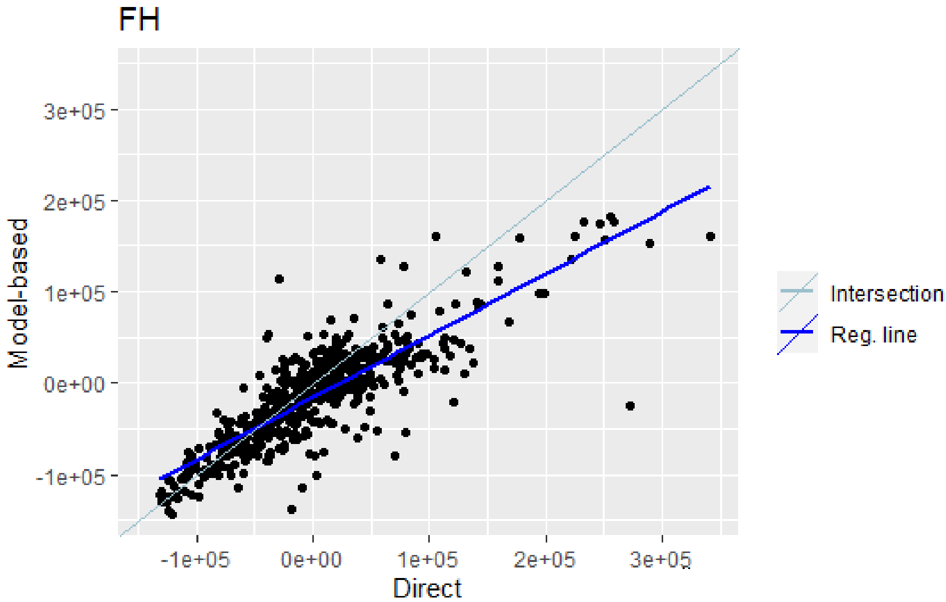


Figure A.1: Correlation between the DHS estimated parish mean and the Fay-Herriot small area model estimate

Model evaluation for the small area estimates for the variables which could not be accurately modelled.

Average number of cattle owned by households in a parish

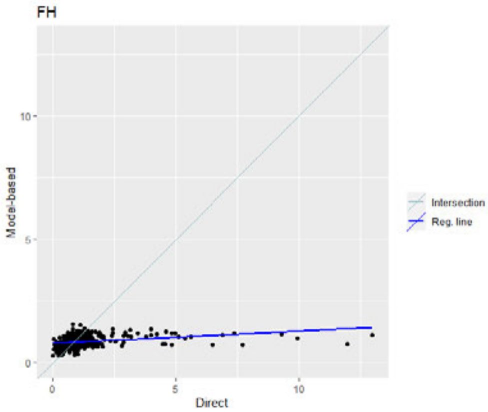
Brown test		
W.value	Df	p.value
573.5224	514	0.03515754

Null hypothesis can be rejected - EBLUP estimates differ significantly from the direct estimates. Correlation between synthetic part and direct estimator is 0.36.

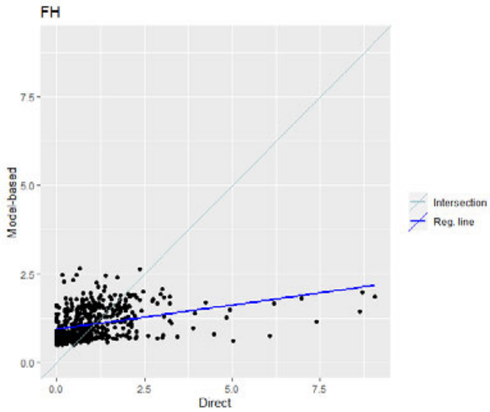
Average hectares of land owned by households in a parish

Brown test		
W.value	Df	p.value
122.4334	516	1

Null hypothesis can be accepted, EBLUP estimates do not differ significantly from the direct estimates. But the correlation between the synthetic part and the direct estimator is 0.31, and the compare plot shows poor performance



(a) Hectares of land owned



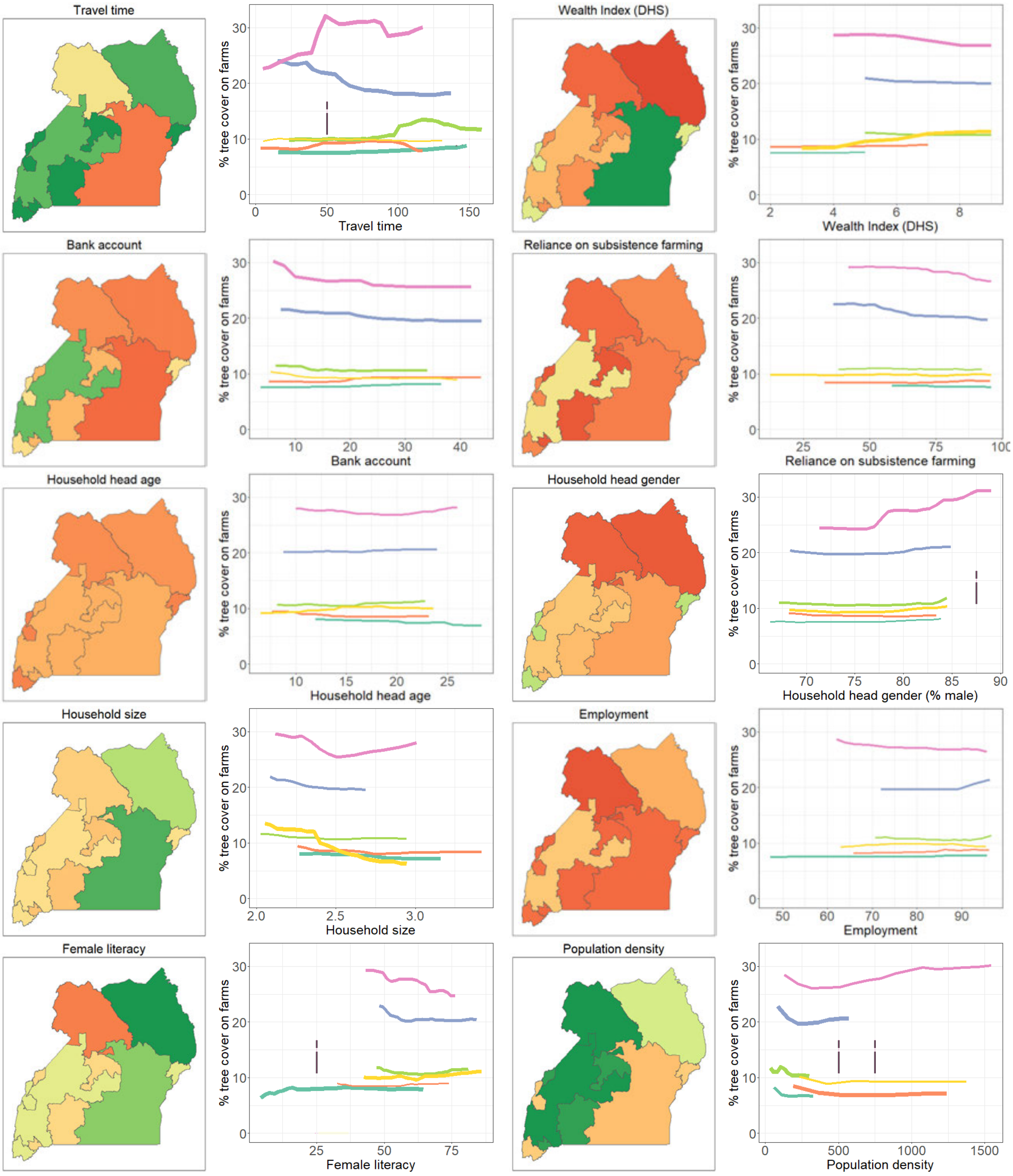
(b) Number of cattle owned

Figure A.2: Correlation between the DHS estimated parish mean and the FH model estimate for variables which could not be accurately modelled

A.2 Full results from the socioeconomic model

Table A.1: Relative importance of each variable in the socioeconomic models of agroforestry adoption

	Agroecological zone					
Variable	1	2	3	4	5	6
Household head gender	0.10	0.11	0.36	0.65	0.33	0.26
Household head age	0.23	0.21	0.30	0.19	0.29	0.29
Employment	0.29	0.08	0.36	0.15	0.13	0.14
Bank account	0.18	0.21	0.85	0.43	0.31	0.14
Reliance on subsistence farming	0.20	0.14	0.47	0.20	0.09	0.18
Wealth Index (DHS)	0.06	0.13	0.32	0.54	0.22	1.00
Female illiteracy	1.00	0.18	0.53	0.53	0.40	0.77
Travel time	0.91	0.47	0.87	1.00	1.00	0.17
Population density	0.58	1.00	1.00	0.37	0.97	0.34
Household size	0.67	0.38	0.43	0.44	0.35	0.91


Travel time
% tree cover on farms
Travel time
Wealth Index (DHS)
% tree cover on farms
Wealth Index (DHS)
Bank account
% tree cover on farms
Bank account
Reliance on subsistence farming
% tree cover on farms
Reliance on subsistence farming
Household head age
% tree cover on farms
Household head age
Household head gender
% tree cover on farms
Household head gender (% male)
Household size
% tree cover on farms
Household size
Employment
% tree cover on farms
Employment
Female literacy
% tree cover on farms
Female literacy
Population density
% tree cover on farms
Population density