MULTI-SCALE SUSTAINABLE INTENSIFICATION OF SMALL-HOLDER AGRICULTURE IN MALAWI

By

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ABSTRACT

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Malawi's smallholder agricultural production is a maize-mixed system following the unimodal rainfall system, prone to climate shocks causing variable crop yields that increase food insecurity. Smallholder farmers make decisions on crop and farm management based on resource availability as well as socio-economic and environmental factors. The government of Malawi has made efforts to improve agricultural production through fertilizer subsidies and the promotion of sustainable farm practices such as legume intercropping and crop residue management practices for soil fertility enhancement. Such efforts are part of the Sustainable Intensification (SI) of Agriculture pathway widely supported across Africa as a means to increase food and agricultural production.

The purpose of this research is to examine Malawi's agriculture through a multi-scale lens; national, sub-regional and local recognizing the spatial-temporal environmental and social drivers occurring across agro-ecologies and influencing smallholder farmers and their capacity for sustainable food production. We assess spatial patterns of Malawian productivity using decadal (2006-2017) climate, edaphic properties, and vegetation indexes, where spatially-located positive trends discrete from climate are presented as evidence of where Intensification (SI) of agriculture is taking place. Secondly, a baseline study that captures farmer demographics and farm practices from randomly stratified sites with varying agro-ecologies is carried out to better understand the contemporary Malawian farmer, the environment within which they produce food, and their overall potential for sustainable agriculture. Land Use Land Cover (LULC) change analyses and landscape quantification of agricultural intensification patterns and their underlying landscape

processes are assessed for evidence of sustainable practices. Additionally, we elucidate the landscape patterns of the SI of agriculture associated with Malawi's agricultural extension delivery system.

The main findings show evidence of positive spatial trends in Malawi's agricultural productivity that are not influenced by mesic climatic signals. This is consistent with evidence of farmer managed agricultural intensification. At the sub-regional scale, there are few land use changes in Central Malawi's Dedza and Ntcheu districts from 2014 to 2019 demonstrating the stability and maturity of this traditional agricultural landscape. However, overall land fragmentation has increased, particularly in land classified as agroforestry and shrubs/forests classes possibly indicating increased use of sustainable farming practices. Smallholders in central Malawi seek location specific agricultural advice on cropping systems and soil nutrient management recommendations. Effective delivery of advice by extension, responsive to farmer goals, could potentially boost farmer adoption of SI technologies.

This dissertation is dedicated to my parents and sisters for their love, encouragement and prayers that made it possible for me to complete this work.

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1.1 Introduction

Global food demand and production are challenged by increased population growth, climate change, global markets and natural resources deprecation (FAO 2017). Whereas most of the world population lives in urban cities, Sub Saharan Africa (SSA) holds over 55% of its population living in areas classified as rural (UN DESA). These rural regions in SSA are food provider and economic engine for most African countries. SSA population is particularly vulnerable to global challenges and also is unable to implement adaptable strategies to sustain food production (UN DESA).

To date, food security remains an unmet target for the 2015 deadline of the United Nations Millennium Development goals (UN 2014) and has been extended to the 2030 agenda under the new Sustainable Development Goals (SDGs) (D'Alessandro and Zulu 2017). In support of the Sustainable Development Goals (SDGs), government stakeholders, researchers and community advocates make competing arguments on how best to increase food production to feed the increasing global population with minimal negative impacts to the environment (Godfray et al., 2010). SSA's agricultural production faces critical challenges as millions of livelihoods are rooted in these rain-fed smallholder farming systems with scarce input resources and few contemporary practices (Hazell et al., 2007).

Some studies show that food production through sustainable agricultural practices replenish natural resources (Kates et al., 2005, Pretty, 2008). This vision of sustainable agriculture has been broadly debated in the scientific community owing to differing scientific definitions, ontologies, and application in a rapidly changing world (Pretty J.N. 1994, Petersen and Snapp

2015). Bell and Morse (2008, box 1.1) summarize sustainable agriculture as the capacity for food production with less damage to the environment. The central theme as put by Wilbanks (1994) is that "sustainability is not a state; it is a trajectory of change." The trajectory concept has led to revisiting the theories driving sustainability such as to whom and where the sustainability is directed (Pretty J.N. 1994). Some researchers argue that agricultural intensification has led to synoptic land degradation and marginalization (Bryceson 2000).

Sustainable Intensification (SI) of agriculture is a pathway that enables farmers to grow more food by utilizing available resources on the same amount of land with fewer negative environmental or social impacts (Pretty J.N. 1997, 2008, Petersen, B., Snapp, S., 2015). A review of SI of agriculture is well documented in Pretty, J.N. (1997) and challenges presented in studies by Gunton et al. (2016), and Cook et al., (2015).

Since the early 1980s, improvements in agricultural production have continued in most regions in Africa influenced by developed countries' agricultural system research and international development efforts (Feder et al., 1985). Significant advances include plant breeding for hybrid varieties, improved utilization of organic and inorganic fertilizer inputs, and farm management practices where labor availability in rural areas is maximized (Muzari et al., 2012). However, this agricultural revolution has triggered some direct and indirect effects for Africa, such as inability to reuse hybrid seeds, decreased crop diversity as traditional and perennial crops are favored by fewer farmers and replaced with short duration varieties, increasing shift to off-farm employment for income, and the degradation of arable land due to over-cultivation of maize (Leakey 2018, Waldman and Richardson 2018). Wallace and Knausenberger (1997) argue that long-term inorganic fertilizer use is costly and contributes to environmental degradation through reactive nitrogen losses, including nitrous oxide off-gassing and nitrate leaching.

There are numerous assessment frameworks that have been used to characterize sustainable agriculture (FAO 2013). Most frameworks incorporate the three traditional pillars of sustainability - Economic, Social and Environment development (WCED 1987). Assessment of agricultural sustainability requires the selection of standard indicators and representative measurements (Bell and Morse 2008). An indicator is a “qualitative or quantitative factor or variable that provides a simple and reliable basis for assessing achievement, change, or performance” (ISPC 2014). Assessment of Sustainable Intensification (SI) of agriculture requires an analysis of place-based farming using indicators at a social, economic and environmental perspective for researchers and stakeholders to understand current conditions and future trajectories (Reytar et al., 2014, Smith et al., 2017).

Recently, satellite technology for agriculture assessment has become widely used, partly due to satellite sensor accuracy, capability, and improved technical analyses that has permitted the capture of biophysical characteristics in time and space (Johannsen 1996, Jackson 1984, Mulla 2013). Many studies show integrated remote sensing in the context of global issues affecting natural systems where metrics in sustainability are applied (Atzberger 2013, Aspinall and Pearson 2000, Doraiswamy et al. 2003, Mulla 2013, Mulders 2001, Leitão 2002). Nevertheless, remote sensing products as proxy measures for SI indicators is a critical missing piece in linking sustainable intensification indicators for understanding the linkages among agricultural performances across different spatial-temporal scales.

1.2 Research problem and study significance

The knowledge gap in this study is that resilience of smallholder farming to short- or long-term shocks is not fully understood due to the lack of spatial-temporal proxy indicators that link SI indicators of agriculture in smallholder farming systems. To address this knowledge gap, we used the following objectives: (a) Develop proxy indicators to assist in understanding trends of SI of agriculture in Malawi, (b) Quantify spatial structures of SI of agriculture across time and space and (c) Identify landscape patterns of SI of Agriculture and link this to agricultural extension services delivery.

The structure of the dissertation will follow a peer reviewed paper format that will give details on the objectives, the data, methods, results, discussion and conclusion. Chapter One is a background review on Malawi's agricultural production that provides context to the historic circumstances that set the pathway for current status of Malawian food production.

Chapter Two addresses the first objective, where we develop productivity trends based on satellite dataset using biomass estimates for over a decade (2010 -2017) to identify areas where SI of agriculture is taking place in Malawi that are deemed not influenced by climate signals. We use a generalized model and the spatial distribution of agricultural production from two national surveys on agricultural production developed by the Government of Malawi. We show that productivity is a proxy indicator to show SI of agriculture across Malawi.

Chapter Three takes a broad lens to explore the local smallholder farming system in Malawi and its link to Sustainable Intensification of Agriculture. This is a baseline survey carried out in 2013 summer on randomly stratified sites in Central Malawi that gives us an understanding on farmer demographics, farm characteristics, and farm practices.

Chapter Four addresses second objective to explore what spatial structure of SI of Agriculture looks like in Central Malawi. We explore the spatial patterns found in agricultural landscapes at different scales, and quantify the different levels of agricultural landscape though a spatial-pattern-processes lens to evaluate its impacts on intensification of agriculture. We show that agricultural resilience is linked to its underlying landscape processes. Chapter Five addresses the third objective that examines SI of Agriculture as found in landscape patterns in previous chapter, then aims to link SI of Agriculture patterns to agricultural extension delivery across Dedza and Ntcheu districts.

A summary conclusion and future research recommendations are included at the end of this chapter. This study is significant as it advances food security knowledge using spatial-temporal indicators developed for smallholder farming systems. We developed novel approaches of measuring specific field observations to landscape scales indicators of SI of agriculture for Malawi that are generalizable across other regions. This research integrates interdisciplinary approaches in spatial sciences and agro-ecology to assist in understanding smallholder farming systems in international agricultural development.

1.3 Background: Malawi Agriculture Development

The third Malawi Growth and Development Strategy (MGDS III), is a five-year plan from 2017 to 2022, that offers medium-term goals of Malawi's overarching national development strategy "Building a Productive, Competitive and Resilient Nation" (GOM 2017). The first priority of MGDS III is Agriculture, Water Development and Climate Change, like most African nations, is to prioritize strategic policies geared for improving the societies livelihood, especially for those in agricultural sectors (GOM 2017). Like the majority of the African countries, Malawi's national strategic policies are focused on realigning its agricultural goals with regional, continental and international obligations and commitments to 2030 agenda on Sustainable Development Goals (SDGs) and the regional economic treaties and partnerships. (GOM 2017).

Agricultural production accounts for over 38% of Malawi's Gross Domestic Product (GDP), and provides a livelihood for 85% of Malawi's population that are mainly smallholder farmers (FAO 2015). Malawi's Government has been very intentional in the agricultural policies to improve smallholder farmer's access to fertilizer resources, by decentralization of distribution of fertilizers and market regulations thus enabling different players and sources of fertilizer instead on FISP. Two main overarching goals of Malawi's Fertilizer Input Subsidy Program (FISP) were (a) a strategy for self –sufficiency where the Government stepped in to offer the agricultural inputs such as inorganic fertilizer and maize seeds at a national level to the local farmers as a majority of smallholder farming practices were evidently lacking the minimum inputs to produce food and reduce food insecurity risks. (b) To ensure individual or household security by targeting poor farming communities, and reducing the prices of inorganic inputs and maize seeds, a majority of farmers could afford to buy at a subsidized price and that could benefit their crop production and increase yield production especially in bad climatic seasons. Potential impacts of FISP can be seen where studies have shown both benefits and challenges that FISP has brought and faced since its inception, studies have seen benefits of FISP on households (Arndt et al., 2016).

Some questions raised over the years of FISP's existence is whether local poverty has been reduced, how the farmer livelihood strategies have been impacted, and maize imports/exports in Malawi (Holden and Lunduka 2013, Dorward and Chirwa 2009), also the reevaluation of FISP has shown yield –reporting deficiencies that call into question any significant increases in food production (Messina, Peter and Snapp 2017).

Attempts were made by GOM to restructure FISP and make it cheaper and accessible through local or regional manufacturing or blending of the fertilizers, and broadening private sector participation in fertilizer and other farm input markets, reducing competition to enable open market. A review of FISP in 2018 lead to the temporary closure of the FISP programme by the GOM after underlying issues with transparency.

1.3.1 Agricultural Extension Services

The early development of Malawi Agricultural Services is traced as far back as 1907 during the colonial period and in support of the cotton export industry with the free distribution of cottonseed through the British Cotton Growers Association (Knorr et al., 2007). In the 1950s, the master farmer system was introduced to regulate extension workers and also introduce more educative and persuasive extension approaches (Kettlewell 1965). During the tumultuous period towards Malawi's independence, the Malawian leaders called for a boycott of agricultural extension and on independence in 1964, the new Malawi repealed all agricultural legislation (Ng'ong'ola 1986). In post-independence, the Department of Agriculture and Irrigation then, abandoned earlier extension regulatory systems and a sort of individual approach, a modified Master Farmer System, was used. This approach favored commercial farmers, those considered to be more progressive, and who were allowed to grow crops as tea, coffee and tobacco (Masangano and Mthinda 2012).

To increase agricultural development, a group approach was used where resource inputs were provided to farmer clubs on credit (Masangano and Mthinda 2012). The introduction of the National Rural Development Programme decentralized the agricultural system into eight agricultural divisions across Malawi (ADDs), and also sub divided these into Rural Development Projects (RDPs) that are found in the 173 Extension Planning Areas (EPAs). Several extension staff were allocated to each EPA (Masangano and Mthinda 2012).

The Block Extension System (BES) introduced extension services trainings and field visits between 1981 to 1999, this system promoted the group approach and the provision of farm inputs on credit (Knorr et al., 2007). The extension worker was given a village section that is subdivided into 8 blocks then he/she would schedule field visits. Since 2000 the District Agriculture Extension System (DAES) was introduced to ensure that services are responsive to the demands from the farmers, and also a decentralized structure that provided an interaction forum with stakeholders, both public and private collaborations were promoted. The DAES set strategies that promoted and strengthened agricultural extension and rural advisory services, such as conducting training to extension officers and enforcing standards for regulating provision of extension and advisory service through partnerships with MoAIWD, NGOs, and academic institutions such as Lilongwe University of Agriculture and Natural Resources (LUANAR), (GOM 2017).

Over the years, Malawi's Government has been very intentional in the agricultural policies and agricultural extension services for development of smallholder farmers.

The National Agricultural Policy (NAP) (2016-2020) identified essential bottlenecks in the agricultural extension services, and noted major pathways of investment in the National Agricultural Investment Plan (NAIP) (2017-2018 to 2022/23). Some of these bottlenecks include; low adoption of technologies and management practices, low productivity, and low commercialization (IFPRI 2020). Overall, improvement of Malawian agricultural extension delivery can improve farmer's livelihood when advisory services are resourced and able to offer timely information and carefully designed trainings on advanced technologies that enable farmer experimentation and feedback mechanisms (Maertens et al., 2018, Ragasa and Niu 2017).

In summary, Malawi agricultural production has been impacted many factors, such as climate change, poor resources and governance that puts Malawians at risk of food insecurity.

Vulnerable smallholder farming systems depend on seasonal rain and have inadequate resources as they continue with intensification of agriculture in marginal landscapes. In this dissertation, we propose use of long term satellite datasets and available household surveys to assist our understanding of intensification of agriculture by capturing spatial-temporal indicators of intensification of agriculture and quantifying the patterns of intensifying agricultural landscapes. Additionally, we use national and household surveys to understand the local context of smallholder farmer's adoption of strategies for sustainable intensification of agriculture. We link the landscape patterns to agricultural extension delivery. Our multiscale approach will capture this phenomenon and inform where and how sustainable intensification of agriculture manifests and at what scales.

2. SPATIAL PATTERN OF AGRICULTURAL PRODUCTIVITY TRENDS IN MALAWI[1]

2.1. Introduction

Agriculture systems offer multi-functional services that support and regulate natural services, as well as provide income, food, fodder, and fuel(Power Alison G., 2010; Simelton & Ostwald, 2019). Variation on climate and land use changes have impacted vegetation patterns and global ecosystem resilience (Foley et al., 2005; Potter et al., 1999). In many low latitude countries, climate change, population pressures, and socio-economic inequity have posed challenges to food production (Wheeler & Braun, 2013).

Sub-Saharan Africa is a vulnerable region for agriculture production. The predominant smallholder agriculture systems are rain-fed with limited use of inputs (Hazell et al., 2010). Recent studies show that shrinking farm sizes are associated with increasing population pressures, however, farm productivity trends in these areas are also influenced by socio-economic drivers and institutional policies, resulting in a wide range of agricultural pathways, from extensification to intensification (Chamberlin et al., 2014; Hazell et al., 2010). Past studies show that food production can be improved through sustainable intensification practices (Godfray H. Charles J. & Garnett Tara, 2014).

Sustainable Intensification (SI) of agriculture optimizes agricultural resource use to produce more food per unit, area of land, while conserving and protecting the environment (J. Pretty et al., 2011; J. N. Pretty, 1997). There remain conflicting scientific ontologies and sustainable

[1] This is an Accepted Manuscript of an article published by Sustainability Journal in 6 February 2020, available online at doi.org/10.3390/su12041313. Reference: Mungai, L. M., Messina, J. P., & Snapp, S. (2020). Spatial Pattern of Agricultural Productivity Trends in Malawi. *Sustainability*, *12*(4), 1313.

intensification solutions: Some researchers suggest revisiting the theories driving sustainability, while others propose consideration of 'ecological intensification' as an alternative concept in which biological processes, rather than chemical inputs, support environmentally-friendly production systems (Gunton et al., 2016; Petersen & Snapp, 2015).

Research on SI strategies mainly focuses on field experimentation and community level studies, with limited research that addresses SI practices at the sub regional through national scales, and involving biogeographic conditions across different spatial and temporal scales (Loos et al., 2014).

2.1.1 Crop Production in Malawi

Malawi is among the food insecure countries in Sub Sahara Africa. However, Malawi does have unique drivers that make it an interesting study; rainfall patterns are changing, with notable extreme weather events in past decades (Haghtalab et al., 2019; Kumbuyo et al., 2014), and has typically low nutrient soils due to inadequate resource inputs and continuous maize cultivation (S. S. Snapp et al., 1998). Socio-political factors such as colonial models of land resource management (Mulwafu, 2011), access to education, and health-HIV/AIDS combine to increase food insecurity vulnerability at both household and community levels, and these drivers vary across the country (Misselhorn, 2005).

The Malawian government has taken steps to increase agricultural production through the Fertilizer Input Subsidy Program (FISP) that provided farmers with input resources such as improved seeds and inorganic fertilizer (Chirwa & Dorward, 2013). Malawi's district based agricultural extension services system (DAESS) was involved in the promotion of FISP and innovative interventions aimed to assists farmers in improving farm productivity and livelihoods (C. M. Masangano et al., 2016). In recent years, there have been debates on whether and to what extent maize yields and productivity increased, as remote sensing productivity trends are flat or declining, and are not in line with Malawi maize yield statistics (Messina et al., 2017; Peter et al., 2018).

Additionally, since the early 2000s, the Government of Malawi has invested in smallholder scale irrigation development, implemented through the Malawi Ministry of Agriculture, Irrigation, and Water Development with partners from international donor communities (Nhamo et al., 2016). Two irrigation projects enhancing crop production in medium and small farming communities across Malawi are the Smallholder Irrigation and Value Addition Project (SIVAP) and the Shire River Basin Management Programme Project (SRBMP) (MoAIWD, 2019). As of 2014, irrigated cropland in Malawi was 4%, or 104,000 hectares; these comprise 46% estates, and 54% smallholder owned, and mainly grow maize, rice, sugarcane, and vegetables (Malawi Government, 2016).

Some studies show that smallholder farmers who have access to inputs and participate in agricultural system interventions often have improved farm productivity and are likely to practice mixed-maize systems, which include crops such as millet, root crops, pulses, and fruit trees for local consumption (Jones et al., 2014). Additionally, studies have reported that smallholder systems can increase biological and environmental resilience through application of perennial crops and legume diversification (Kane et al., 2016; Rogé et al., 2016).

Few studies of smallholder agricultural development capture long-term performance or multidimensional scaling (Gunton et al., 2016; Peter et al., 2018). There remains a knowledge gap in scaling across multiple mapping extents and political boundaries using explicit measures of agriculture intensification across time and scale. Measuring and identifying spatial-temporal patterns of intensification of agriculture is critical for the development of rain-fed smallholder farming systems, as this is linked to improving farmer livelihood and food security. The main purposes of this study are to establish sustainability indicators in a regional context and identify locations and patterns of agricultural intensification in Malawi. This study seeks to improve our understanding of agricultural intensification and associated spatial and temporal patterns. Our primary question is “where is agriculture productivity intensifying in Malawi?” Our null hypothesis is “locations with increased trends in agricultural productivity are intensifying”. To locate areas where intensification of agriculture occurs, we propose to use remote satellite imagery to develop proxies to identify productivity trends that are not influenced by good climate conditions and soils.

2.1.2 Proxies

The intensification of agriculture has a strongly spatial character. Capturing agricultural intensification patterns requires empirical analyses that embed space-time interactions (Nijbroek & Andelman, 2016; You et al., 2009). Remotely sensed time series datasets offer the requisite archival observations, allowing agricultural modeling over both space and time (Atzberger, 2013). The significance of remote sensing time series data derived indicators then is to supply information indirectly through measurements as proxies of smallholder farming system trends detected across spatial and temporal scales (Bockstaller et al., 1997; Rigby et al., 2001). A proxy is a remotely sensed derived estimate of an observed phenomenon. An example of a proxy indicator is the Normalized Difference Vegetation Index (NDVI) that is used as a biomass estimate, and thus a proxy for productivity (Anyamba & Tucker, 2005).

In smallholder farming systems, biophysical characteristics and farmer input resources, goals, and practices are among the main influencers of intensification. Long-term monitoring and spatial mapping of these drivers are best captured in remote sensed time series datasets (Dembélé &

Zwart, 2016; Pan et al., 2004; Rojas et al., 2011; Vancutsem et al., 2010). To understand this complex system of food production, we develop our geographic theory of intensification, where we observe a pixel over time for intensifying agriculture and theorize that potential areas of intensification are found in productivity scenarios presented in Figure 2.1a–d. The theoretical diagrams illustrate (a) increasing, (b) stable, (c) declining productivity trends, and (d) divergent productivity trends per pixel from a single point in production. The lines present different trajectories of productivity. For example, a farm with low productivity might increase production over time, whether through increased labor, fertilizer, or sustainable practices (A–Low). Further, this might be in response to improving, stable, or worsening climate and edaphic conditions. In Figure 2.1d, divergent trajectories might emerge from places with identical biophysical endowments as starting condition, and disentangling those trajectories and identifying those locations elucidates the manifestation of sustainable farming.

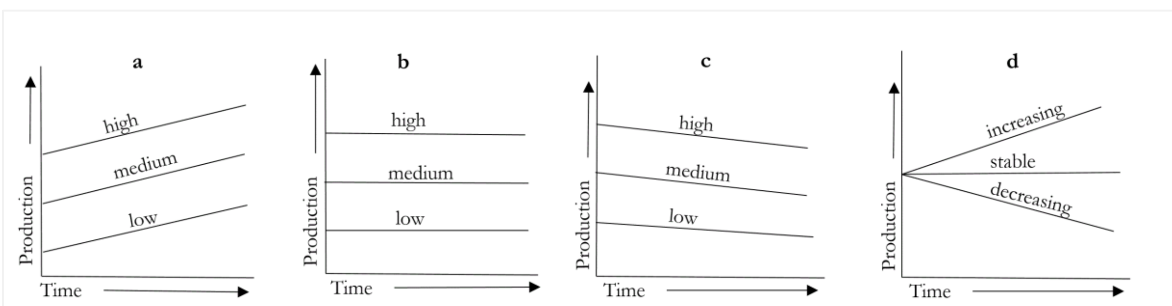

Figure 2.1: Theoretical model of trends in agricultural productivity per pixel over time. (a) Increasing productivity trends, (b) stable productivity trends, (c) decreasing productivity trends with a potential of pixel shifting from low getting medium or medium getting high where intensification of agriculture is occurring. (d) Divergent productivity trends from a single point in production.

2.2 Study Area

Malawi is a small country located in southeastern Africa. The country occupies approximately 118,480 km^2, one-fifth of which is covered by Lake Malawi (Ngongondo et al., 2011), (Figure

2.2). Malawi has complex topography along the latitudinal gradient of the rift valley, contributing to diverse geographical gradient (Dijkshoorn et al., 2016), including low Shire Valley plains (<200 m), Lake Malawi shore, middle and upper Shire (200 to 760 m), mid-elevation upland plateau (760 to 1300m) and highlands (>1300m) plateaus (Todd et al., 2016).

Malawi’s uni-modal climate is influenced by the latitudinal (north-south) shifting of the intertropical convergence zone (ITCZ) (Ngongondo et al., 2011). The rainy season starts in mid-October, peaks in January, and extends through to early March or April, while the dry season starts from May to early October (Malawi Meteorology Services). In Malawi, climate change manifests as seasonal shifts in rainfall pattern, such as the number of dry days and extreme events (Haghtalab et al., 2019; Kalanda-Joshua et al., 2011). Average temperatures range from 29 ^{o}C in October to 7 ^{o}C in February, and average annual rainfall is between 725mm and 2500mm (Malawi meteorology services). Malawi has a rapidly growing population, from 15 million people in 2012 to a projected 26 million by 2030 (*Why Population Matters to Malawi’s Development – Population Reference Bureau*, n.d.), with a majority (85 percent) of Malawians living in rural areas and making their livelihood from agricultural production (Davis et al., 2010; DESA, 2018).

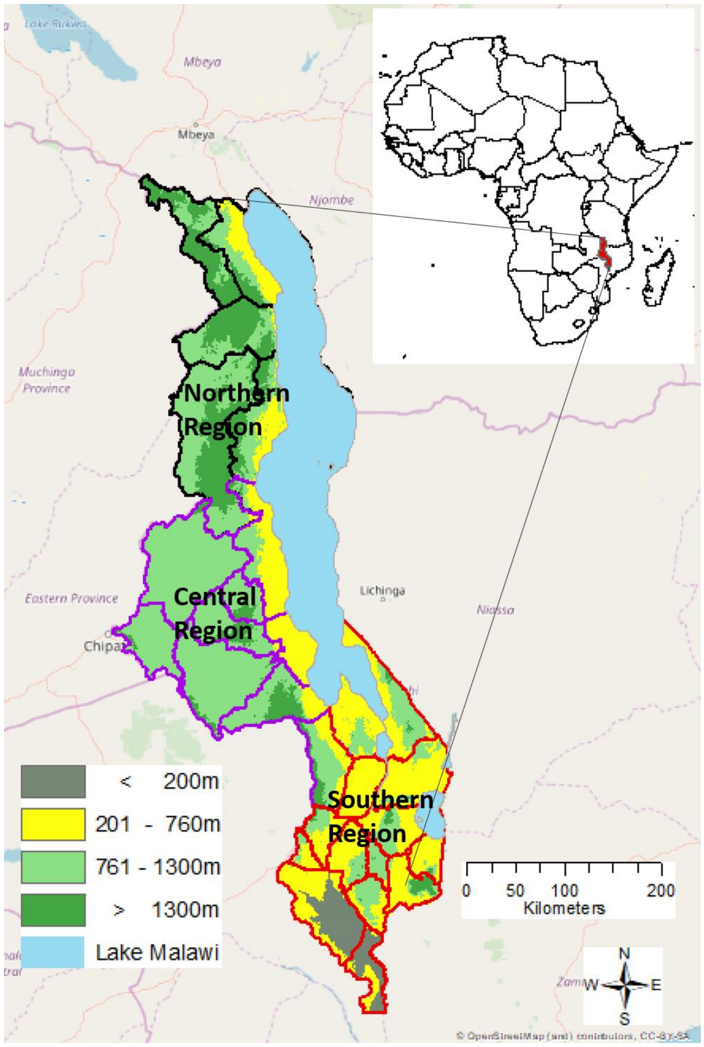

Figure 2.2: Study Area displaying three aspects: Agroecology zones based on elevation above sea level, district boundaries, and the three administrative regions of Malawi; Northern, Central, and Southern regions (District boundaries shown).

2.3 Data

The datasets used in this study include: Long term vegetation estimated from Moderate Resolution Imaging Spectroradiometer (MODIS), 16 days interval-Normalized Difference Vegetation Index (NDVI)—MOD13Q1 version 6, at 250m (https://doi.org/10.5067/MODIS/MOD13Q1.006) (Didan, 2015). Precipitation dataset is derived from MODIS-Climate Hazards group Infrared Precipitation with Stations (CHIRPS) data product at 1km resolution for precipitation (Funk et al., 2015), and MODIS-8 day Interval-Land Surface Temperature (LST) MODIS11A2.006, representing surface temperature at 1km spatial resolution (https://doi.org/10.5067/modis/mod11a2.006) (Hook & Hulley, 2015). Ancillary datasets to derive long term agriculture include: MODIS Land Cover at 500m (https://doi.org/10.5067/MODIS/MCD12Q1.006) (Friedl & Sulla-Menashe, 2019). Glob Cover 2009 land cover at 300m resolution http://due.esrin.esa.int/page_globcover.php) (ESA 2010 and UCLouvain, n.d.), FAO-Africover 2010 at 30m resolution, European Space Agency (ESA) time series 1992 to 2015 land cover at 300m resolution (*300 m Annual Global Land Cover Time Series from 1992 to 2015 | ESA CCI Land Cover Website*, n.d.), and a Malawi's soil suitability spatial distribution product from (Li et al., 2017) were used for our analysis (Table 2.1).

Table 2.1: Climatic and land cover datasets used to determine productivity trends and intensification of agriculture.

Dataset	**Time Span**	**Resolution**	**Source**
Land Surface Temperature (LST) MODIS/006/MOD11A2–8-day interval	2006–2017	1km	NASA EOSDIS
NDVI MODIS/006/MOD13Q1	2006–2017	250m	NASA EOSDIS
UCSB-CHG/CHIRPS/DAILY rainfall data	2006–2017	5km	UCSB/CHG
Malawi land suitability	[52]	-	[52]
Annual global land cover time series	1992–2015	300m	European Space Agency (ESA) website (https://www.esa-landcover-cci.org/)

Table (cont/d)

MODIS MCD12Q1 Land cover	2006–2017	500m	NASA EOSDIS
Global land cover GlobCover	2009–2010	300m	European Space Agency (ESA) website (https://www.esa-landcover-cci.org/)
FAO-Africa Cover Malawi's Land Cover Product	2010	30m	FAO GeoNetwork Website (http://www.fao.org/geonetwork/srv/en/main.home)

2.4 Methods

2.4.1 Measurement of the Spatial Distribution of Productivity

We use biomass estimates as a proxy for productivity by taking the 10-year record of mean MOD12Q1, NDVI, 16-day interval, at 250m spatial resolution during the November to April growing period for maize. This measures the onset of greenness, peak time, and maximum NDVI in one growing season (Reed et al., 1994). The mean value per pixel was computed across the growing season for each year (t) (2007 to 2017) across Malawi (Reed et al., 1994). To derive the trend and calculate the slope coefficients for each pixel, we used a linear function ($y = m+bt$), where y is dependent variable (NDVI), and (t) time as the independent variable, and apply the model over the complete time series (R. de Jong & de Bruin, 2012; Fensholt et al., 2009; Gorelick et al., 2017).

This linear trend technique allows per pixel comparison between NDVI and other datasets to examine long term trends, unlike using a nonlinear approach, since nonlinearity would not allow clear pixel comparisons between datasets (Fensholt et al., 2009). One caveat here is that our linear function does not take into account model assumptions of serial correlation (Rogier de Jong et al., 2011). However, the Mann–Kendall test was used to compute serial correlation on mean annual NDVI time series, and a Theil–Sen (TS) slope estimator was computed on mean annual NDVI to identify significant trends (Kendall, 1948; Theil, 1992). This method handles seasonality more efficiently than the trend-over time linear model (Forkel et al., 2013; Verbesselt et al., 2010).

Additionally, Mann Kendall's decomposition function separates deterministic series from the original data time series and breaks down the data seasonality from the trend, and remaining or random data as the annual anomalies (Forkel et al., 2013). The observed NDVI trends from the maize growing season over time are classified into high, minimal change, and low trends using equal interval classification in ArcGIS to determine NDVI signal attributed to high, minimal change, and low pixel values. We use minimal change term for precision in our analysis, pixels with minimal change are referred to as stable; these two terms are used interchangeably in the study. Stable production can be an indicator of sustainability as climate or other conditions decline.

2.4.2 Biophysical Drivers

We calculate average values on the MODIS 11A2 -8-day interval temperature and precipitation time series from the growing season (November to April) over 2006 to 2017, to derive the trend and slope coefficients for each pixel, as previously described with the NDVI dataset above. A linear function is developed on both the temperature and precipitation datasets ($y = m+bt$), where y =the dependent variable as the (LST_Day_1km band) for temperature, and precipitation estimates for precipitation, while (t) = time per year over a ten-year period, independent variable.

2.4.3 Malawi Land Cover

Malawi's agricultural lands were identified using four different land cover products: FAO-Africover 2010 product at 30 m resolution, European Space Agency (ESA) 1992 to 2015-time series land cover at 300m resolution, Glob-Cover 2009 land cover at 300 meters to look at intensification aggregates, and the MODIS Land cover from 2000 to 2013 at 500 meters that uses land cover assessment from five global land cover classification systems.

We resample all low spatial resolution land cover data sets to the finest spatial resolution of 30m using nearest neighborhood sampling method, and use a binary reclassification for the agricultural classes, and nonagricultural classes. The four land cover layers are summed, resulting in a combined output with five agricultural class categories 0, 1, 2, 3, and 4. The '0' category are pixels classified as non-agriculture based on the combined land cover class product, while "1" is some agriculture, and '2, 3, 4' pixel categories have increasingly reported agricultural cover, and are representative of Malawi's agricultural land area of 50,236 km^2, which differs only slightly from the FAO 2010 cropland area of 55,720km^2 (*2019 | FAO | Food and Agriculture Organization of the United Nations*, n.d.).

2.4.4 Land Suitability Spatial Distribution

Most of the agricultural land in Malawi is degraded or of marginal quality due to continuous cultivation and expansion onto hill slopes (Li et al., 2017). To characterize agricultural suitability, we used the spatial distribution of land suitability product developed by (Li et al., 2017), which addresses land favorable for cultivation based on topographical conditions, that is; terrain, soil erosion risk, and soil characteristics such as texture, soil organic carbon (SOC), pH, depth, drainage, erosion potential, Cation Exchange Capacity (CEC). We rate the land's ability for agricultural production by reclassifying the soils into: Suitable soils for crop cultivation (that represent highly suitable, moderately suitable classifications in (Li et al., 2017)) and poor soils (marginally suitable, and unsuitable soils in (Li et al., 2017)).

2.4.5 Spatial Distribution of Productivity, Soil Suitability, Precipitation, and Temperature

The spatial distribution of agricultural production incorporating climate and edaphic conditions is derived via a two-step process. In the first step, multiple datasets; NDVI (productivity), soil suitability, and climate pixel values calculated from above section are imported into ArcGIS. Each dataset; NDVI, soil suitability, and climate values are reclassified into categories, that is; NDVI increasing, minimal change, decreasing trends (1,2,3), temperature increasing/decreasing trends (1,0), precipitation increasing/decreasing trends (1,0) and soil suitable and unsuitable classes (1,0). These multiple datasets are combined to derive their spatial information using spatial analysis combine feature in ArcGIS environment, where a total of 40 unique combinations are realized.

The 40 unique realization layer is superimposed on agricultural layer, and all non-agricultural areas are masked out. Figure 2.5 shows the 40 combinations of the four variables (productivity (P), rainfall (R), soil (S), and temperature (T)) we analyzed. In the second step, we identify locations of potentially intensifying agriculture, we query for pixels where increasing productivity is not driven by good climate and suitable soils from the 40 unique realization layer from step one above.

We use high spatial resolution satellite imagery from Google Earth Pro to carry out a visual inspection of identified intensifying agriculture pixels above. The intensifying pixels' layer was rendered in Google Earth Pro, we used archived Landsat satellite images of 30-meter resolution found between 2013 to 2016 for Malawi growing season and dry season captured to determine the land use in the "intensification" pixels. We randomly zoomed into locations in the north, central, and southern Malawi, where these increasing productivity pixels seem to be located, that is mostly in mountainous, forested, or flood plain areas.

2.4.6 Agricultural Input Resource Management

To explore social drivers of agricultural production, and disentangle these social drivers from intensification, we present farmer reported yields and input practices as reported by farmers interviewed in two cross sectional instrument surveys: Third Integrated Household Survey—2010-2011 and Fourth Integrated Household Survey—2016–2017 Living Standards Measurement Study (LSMS), respectively, implemented by the Malawi National Statistical Office (National Statistical Office (NSO)., 2010, 2016; *NSOMALAWI*, n.d.). These surveys were used to monitor and evaluate the Malawian households for poverty and vulnerability, to assist with evidence-based policy formulation for strategic national development (*World Bank 2020*, n.d.). The Integrated Household Surveys—IHS3 was implemented in March 2010– March 2011 using 12,271 households and Integrated Household Survey—IHS4 was implemented April 2016–April 2017 using 12,447 households.

We developed a database to be able to manage these data subsets and also linked each data subset using a unique identifier. We created queries to minimize data errors from the surveys, where we considered only the data where (a) farmers reported plot yields greater than 0 and less than 10,000 kg/hectare and also reported use of fertilizer inputs greater than 1000 grams. The 2010–2011 survey sample size was filtered to 9939 samples, similarly, 2016–2017 survey sample size was filtered to 10,757 households. Additionally, in both datasets, only maize crop information was included. The farmer reported plot yields units for both surveys were standardized to yields in Kilograms units using 2009 world bank crop conversion standards. In both surveys, we considered the agricultural management questions that asked farmers the use of organic fertilizer (Yes/No) and use of inorganic fertilizer (Yes/No) per plot. Additionally, in both surveys, farmers were asked to rate how they perceived the soil quality on their plots, as good, fair, or poor.

Household geographic coordinates used in both surveys are offset approximately five kilometers from the actual physical household location for privacy reasons, and their plot geographic coordinates were recorded as distances from displaced plot location to displaced house location. The outputs from the database on both survey datasets above were used to create distribution maps (layers) in ArcMap software. Distribution maps created were for farmer reported yields, organic and inorganic inputs use, and soil quality responses, respectively. We overlay each layer over the identified potentially intensifying agriculture layer from section 4.5 above.

Our models are interpreted using regions as depicted in study area figure 2.1, and for ease of reference, we also distinguish locations based on their topographical features.

2.5 Results

2.5.1 Descriptive Statistics of Trend Analysis

The dominant trend apparent in Malawian agriculture is one of decline. Figure 2.3, shows the mean NDVI correlation coefficient of −0.31, significant at 0.05 level. NDVI trend declined at a value of −0.003 per year over growing season period between 2006–2017. Further examination of trend using the Mann Kendall test shows a tau value of −0.0633, and an overall trend is negative, and the trend is worsening at a magnitude of −0.0002 for annual NDVI, significant at 0.05 level. The mean seasonal rainfall also shows a declining trend by −13.8 mm per year over the 10 year growing season period, with a correlation coefficient of −0.331, significant at 0.05 level (Figure 2.4). Mean temperature displays an increasing trend of 0.1 Celsius per year over 10–year period, with a correlation coefficient of 0.26 at 0.05 significant level (Figure 2.5).

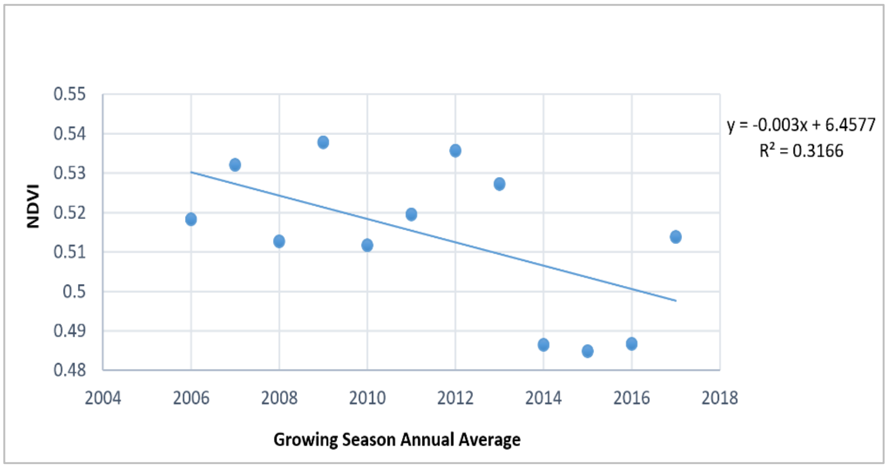

Figure 2.3: Annual mean trend over time including regression coefficient of MODIS-NDVI 2006 to 2017-time series for Malawi's main growing season (November–April).

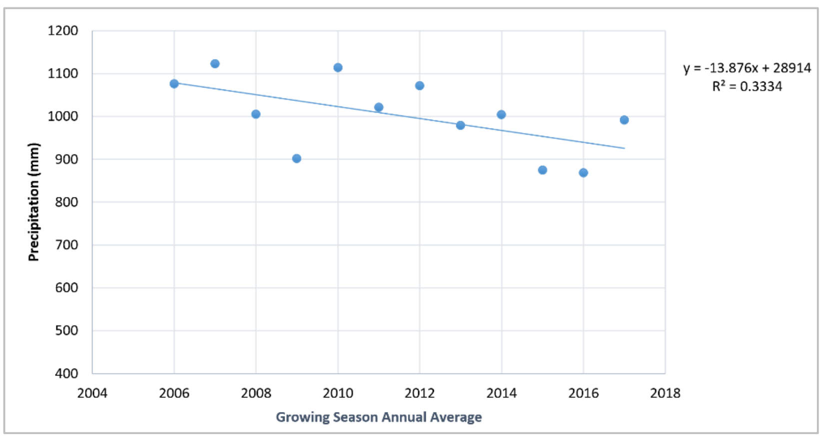

Figure 2.4: Annual mean trend over time including regression coefficient CHIRPS-Precipitation 2006 to 2017-time series for Malawi's main growing season (November–April).

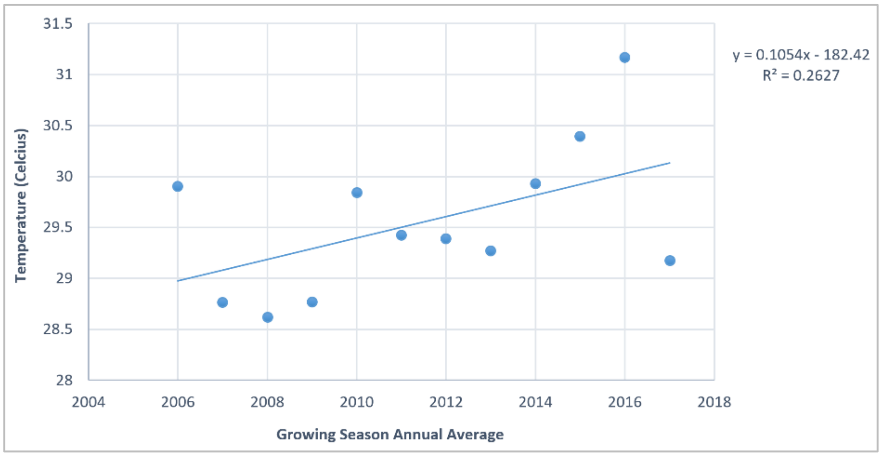

Figure 2.5: Annual mean trend over time including regression coefficient MODIS-Land Surface Temperature 2006 to 2017-time series for Malawi's main growing season (November–April).

Decomposition of NDVI time series is shown in Figure 2.6. The top section is the original data series, the next is a seasonal component that illustrates the expected vegetation growing pattern from start to end of growing season, the third section is a trend component that captures distinct increases or decreases in NDVI value; declines are visible in 2009, 2012, and 2015 that coincides with observed flooding and drought events (*MALAWI PDNA 2015 DRAFT REPORT*, n.d.). The remainder or noise component, which is the difference of the original data minus the seasonal component and direction of change-trend is shown in the last section of Figure 2.6.

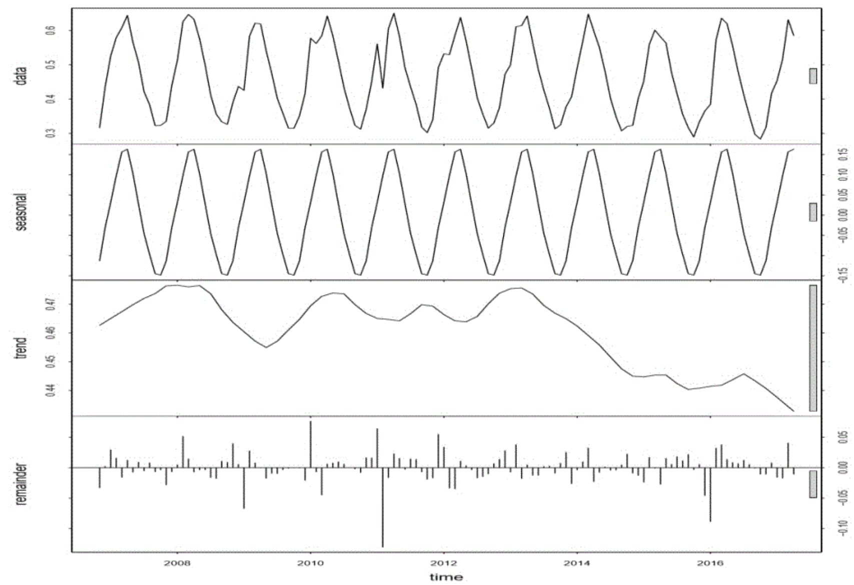

Figure 2.6: Mean NDVI growing season time series decomposition for Malawi. First part of graph is the original data series, second part is the seasonality component of the data, trend part of the data and remainder—that is the original data minus the seasonal and direction of change (trend). The plot has solid bars on the right hand side that show the data range and assist with comparisons.

2.5.2 Spatial Distribution Pattern Analysis

The spatial distribution map highlights the growing season NDVI slope coefficients per pixel that range from 2.5 (increase), −1.7(decrease) over 2006 to 2017 (Figure 2.7a). NDVI pixels in green color have increasing high slope coefficient values, these are found in the high to mid-altitude plateau areas, circled in the figure, while pixels in orange located mostly in lakeshore plains and upper Shire valley show decreasing low −1.7 value slope coefficients. Precipitation displays a latitudinal trend with increasing rainfall moving from south to north (Figure 2.7b). Land surface temperature exhibits decreasing trends in the northern regions and mountainous areas like Dedza in the central region and Mount Mulanje found in the south, while increasing temperature trends are found towards central and southern plains, respectively (Figure 2.7c).

Malawi's dominant soil texture is well-drained loamy clay sands that have adequate to low nutrient levels (S. S. Snapp, 1998). Overall, sandy clay loam is found across 78% of the country, with the remaining soils; 10% sandy loam, 8.4% sandy clay, and 4% blend of clay loam soils (Li et al., 2017). Figure 2.7d displays Malawi's soil suitability map, illustrating that unsuitable soils are coincident with high slope areas, for example, in the Nyika highlands located in the northern region, the rift valley escarpment in the central region, and the Shire highlands in the southern region. Suitable soils are found in mid-altitude plateaus and lake plains, such as Nkhata bay.

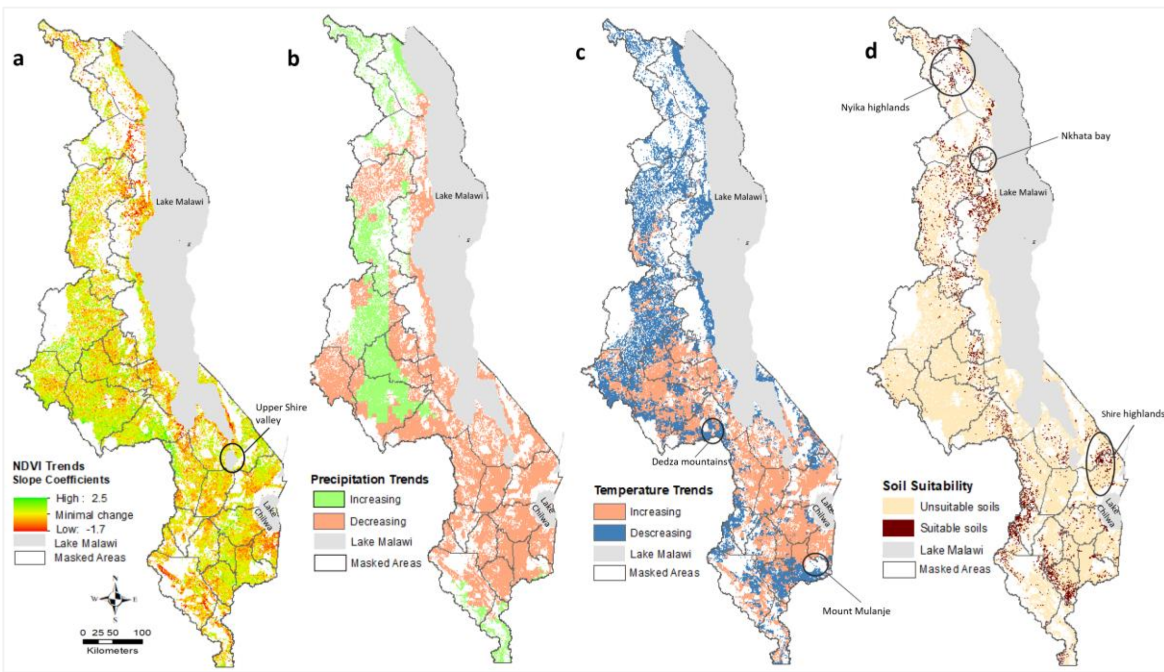

Figure 2.7: (a) Malawi's NDVI slope coefficients, few high pixels are seen scattered, while the majority of pixels dominate the landscape. (b) Precipitation trend displaying the latitudinal (north–south gradient); with increasing pixels shown in green color, while decreasing pixels are in orange color. (c) Land surface temperature trend displaying a latitudinal (north–south) increasing pixels (orange) and decreasing (blue). (d) Spatial distribution of soil suitability data source from (Li et al., 2017). In all the figures above, agriculture land cover is shown, while all other land cover types are masked out in white color.

Figure 2.8 shows the spatial distribution map of pixel-by-pixel combinations of NDVI, rainfall, temperature, and soil suitability, and their percentage pixels in each category. Here, the northern region has more high productivity pixels as indicated by NDVI, while others are scattered across Malawi, in high plateau areas of Dedza mountains, and the southernmost tip of Malawi (lower Shire valley). Overall, 21% of agricultural lands are associated with an increasing agricultural productivity trend. This could be largely attributed to higher levels of precipitation (900mm to 1200mm) in these high elevation areas, in contrast to the lower precipitation (725 mm to 800mm) and higher evapotranspiration in the lowlands. About 35% of agricultural lands are associated with no changes in productivity. These areas are found primarily in the central and southern regions. About 43% of all agricultural lands present decreasing productivity trends. These lands are predominantly in the southern region. Less than one percent of pixel combinations show increasing productivity trends associated with suitable soil pixels, with either decreasing rainfall and temperature trends, or vice versa.

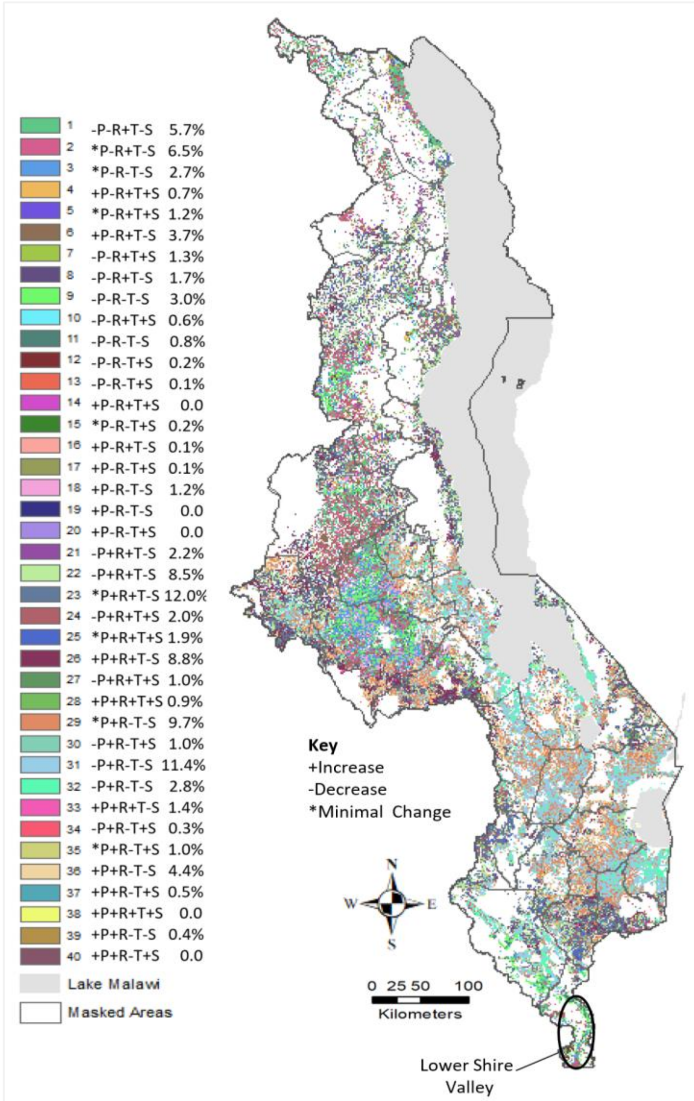

Figure 2.8: Spatial distribution of all pixel by pixel possible combinations of the four maps from figure 2.5 of variables under study NDVI (P), Soil (S), Temperature (T), and Rainfall (R). Agriculture land cover is displayed; all other land cover types are masked out.

Figure 2.9a, b display scenarios queried from above pixel by pixel combinations; (a) decreasing productivity trends, poor climate, and poor soils (b) stable productivity, poor climate, poor soils (c) increasing productivity, poor climate, poor soils. The pixels selected are not a composition of increasing precipitation and suitable soils, which takes 62% of all the pixels, but the remaining 38%-pixel combination as potential locations where agriculture is intensifying.

From these remaining pixels; 7% are located in sites that were associated with trends of decreasing productivity, lower rainfall trends, and poor soils. These sites are primarily located along Lake Malawi shore. Another 23% of sites were associated with trends of decreasing productivity, poor soils, and increasing rainfall, and were located in the central and south-west tip region of Malawi (Figure 2.9a). Another 7% of sites were associated with stable productivity trends, decreasing rainfall, and poor soils are found scattered in central and along Lake Malawi shoreline (Figure 2.9b).

These sites may represent sites of intensification. Drivers may include various social or biophysical factors, including a shorter cultivation history and forest border effect. Decreasing trends can be associated with temperature-induced drought stress in these regions based on the different years of irregular rainfall or heavy downpours that flooded areas close to water bodies, based on the Government of Malawi floods and drought alerts in April 2016, and flooding incidents in 2017 (*Malawi 2019 Floods Post Disaster Needs Assessment Report - Malawi*, n.d.; *Malawi Drought 2016 PDNA*, n.d.). Figure 2.9c displays increasing high productivity trends in areas with decreasing rainfall, and unsuitable soils, 0.07% of these pixels are found in the south-east lower areas in the floodplains of Shire river and Lake Chilwa, while in the central regions, the pixels are adjacent to forest cover masked areas.

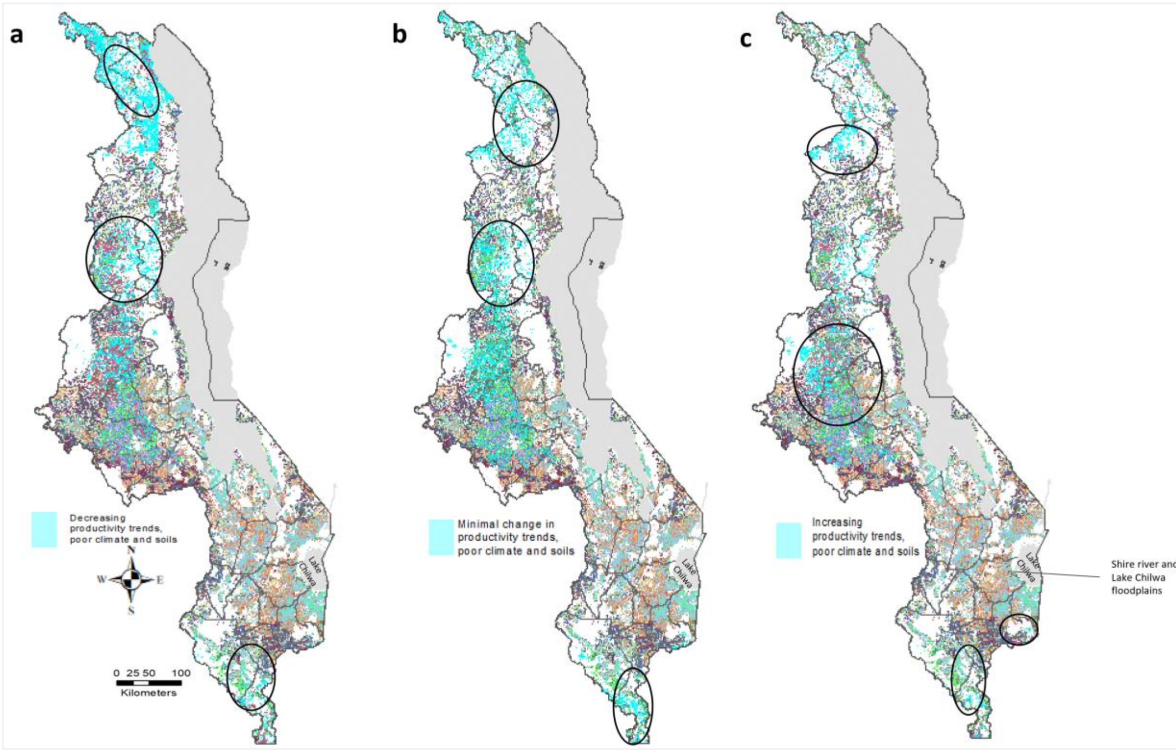

Figure 2.9: NDVI trend pixels in cyan color, some illustrated in circles, three most likely scenarios on poor climate and soils from above figure 2.6 pixel by pixel combinations. (a) Decreasing productivity trends, poor climate, and poor soils. (b) Minimal change in productivity, poor climate, poor soils. (c) Increasing productivity, poor climate, poor soils, deemed to be intensifying areas.

Figure 2.10a, b displays the Malawi farmer reported yields in Kilogram per Hectare (Kg/Ha) during 2010–2011 and 2016–2017 from the national LSMS-IHS3/4 surveys overlaid on the intensifying areas layer. In 2010–2011 surveys, 61% of farmers reported yields below 1000Kg/Ha. Of these households, 37% are located in the southern region, while the central region has 14%, and the northern region has 10%. Households with yields between 1000–2000Kg/Ha make up 25% of farmers, and are found in few areas in the north at 10%, and in central region at 14%, while 13% of farmers were found in the south region. Households with yields between 2000–3000kg/Ha make up 8% scattered across Malawi. Households with yields greater than 3000 Kg/Ha are sparsely distributed across Malawi, and make up less than 6% of households. These high productivity farms are mostly located in the southern and central regions.

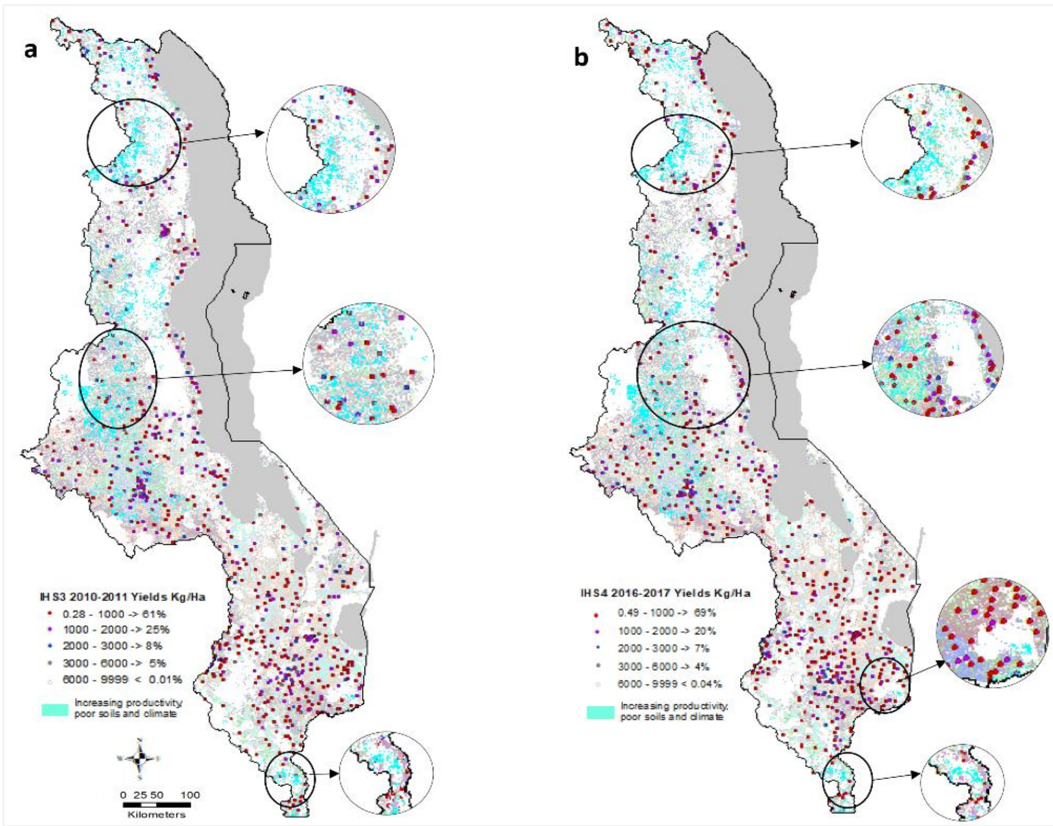

Figure 2.10: Geographic distribution of (a) households that reported yields for 2010–2011 growing season (source data: LSMS-IHS3 (n = 9,939 households); (b) households that reported yields for 2016–2017 growing season (source data: LSMS-IHS4 (n = 10,757 households) overlaid in the areas predicted to intensify with increasing productivity and poor climate and soils.

In the 2016–2017 survey, 69% of farmers reported yields below 1000 Kg/Ha. Of these households, 37% were located in the south, while 22% are in central, and the remaining 10% are found in the north. 20% reported yields were between 1000 to 2000 Kg/Ha, evenly distributed throughout the central and south regions, with less than 0.5% in the northern region. 10% farmers reported yields greater than 3000 Kg/Ha, and these were also mostly located in the southern and central regions (Figure 2.10 a, b).

In 2010–2011 surveys, 77% farmers reported having applied inorganic fertilizer in their plots. Not surprisingly, the majority were located in the southern region of Malawi with the poorest soils (Figure 2.11a). Likewise, in 2016–2017 surveys, 68% farmers reported applying inorganic fertilizer, again most commonly in the southern region (Figure 2.11b).

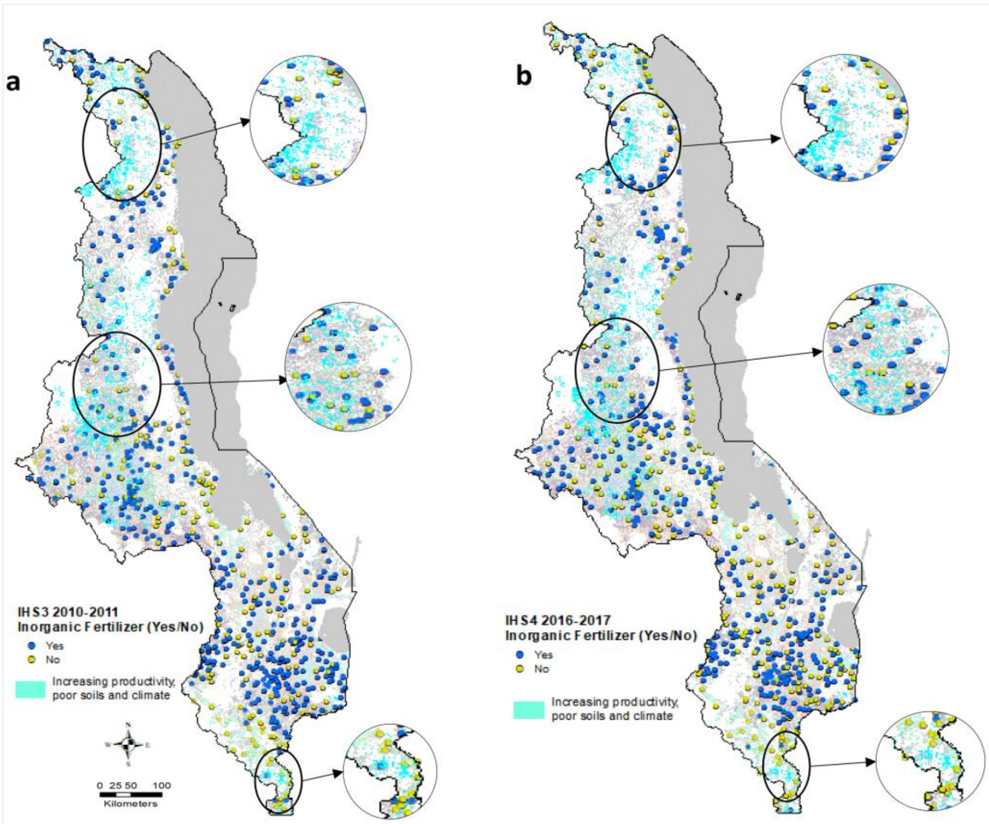

Figure 2.11: Spatial distribution of households that reported Yes or No to applying (a) inorganic fertilizer to their fields for 2010–2011surveys (source data: LSMS-IHS3 (n = 9939). (b) Households that reported applying inorganic fertilizer to their fields for 2016–2017 surveys (source data: LSMS-IHS3 (n = 10,757), overlaid in the areas predicted to intensify with increasing productivity and poor climate and soils.

Figure 2.12a, b shows the spatial distribution of farmers who reported using organic fertilizer in their plots across Malawi. A proportion of farmers 24% in 2010-11 survey, and 20% of farmers in 2016-17 survey reported applying organic fertilizer, and overall livestock presence as a source of organic fertilizer is low, especially in the southern region (Figure 2.10).

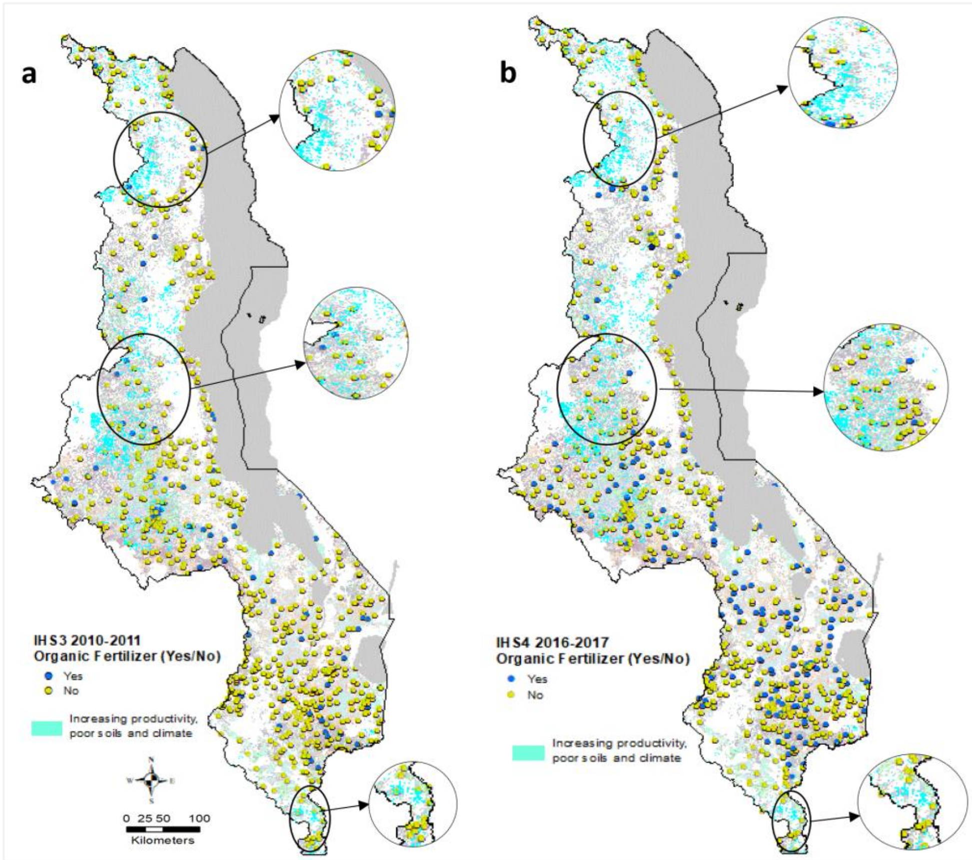

Figure 2.12: Spatial distribution of (a) households that reported applying organic fertilizer to their fields for 2010–2011 growing season (source data: LSMS-IHS3 (n = 9939); (b) households that reported applying organic fertilizer to their fields for 2016–2017 (source data: LSMS-IHS3 (n = 10,757). Overlaid in the areas predicted to intensify with increasing productivity and poor climate and soils.

Farmers reported their perceptions of their plot soil quality using three categories: Good, fair, and poor ratings. In 2010–11 surveys, 44% of farmers perceived plot soil quality to be good, 44% perceived their soil quality to be fair, while 12% replied poor for plots' soil quality (Figure 2.13a). In 2016–2017 surveys, 50% of farmers rated their plots' soil quality to be good, while 36% perceived their plot soil quality to be fair, and 14% perceived their plot quality to be bad (Figure 2.13b). In both surveys, only 16% of farmers in the northern region rated their plots' soil quality as bad, and 21% of farmers found their plots to be fair, while 20% of farmers reported their plots' soil quality as good. In contrast from the north, over 50% of farmers in the south rated their plots' soil quality between bad or fair (in both surveys), whereas in the central region, 30% of farmers rated their plots' soil quality as bad or fair, and a small percentage rated the soil quality as good (Figure 2.13a, b).

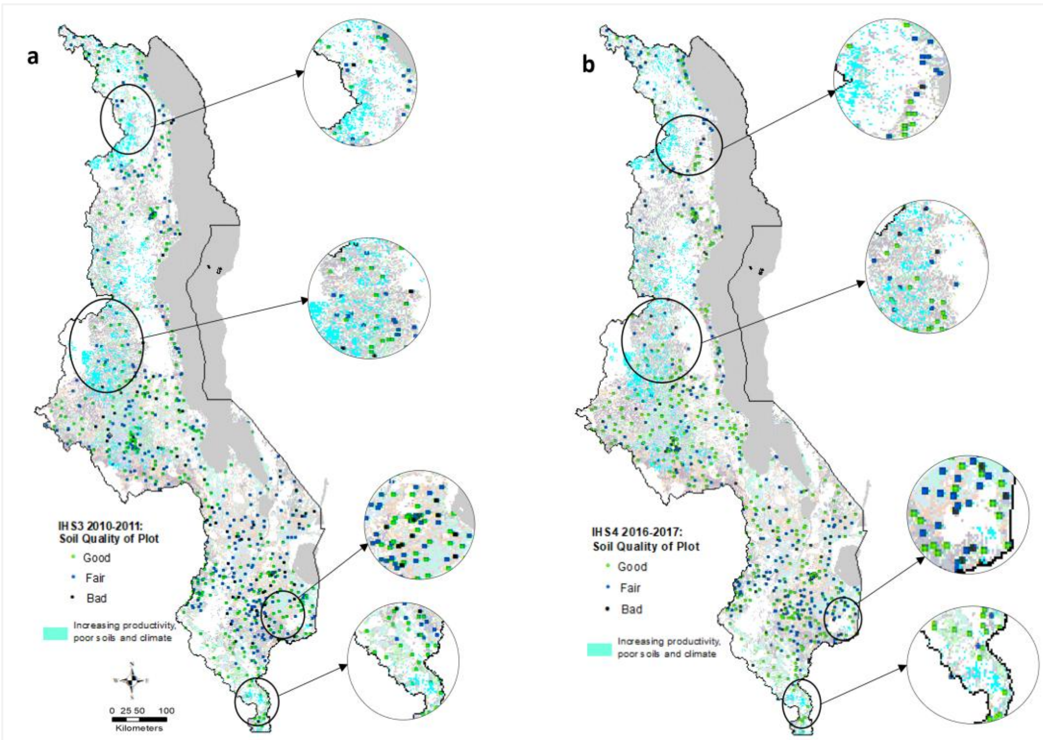

Figure 2.13: Spatial distribution of farmer response to whether the soil quality was (Good, Fair, or Bad). (a) Farmer responses on soil quality of their plots in 20102011 surveys (source data: LSMS-IHS3 (n = 9939). (b) Soil quality of their plots in 2016–2017 surveys (source data: LSMS-IHS3 (n = 10,757). Overlaid to areas predicted to intensify with increasing productivity and poor climate.

Figure 2.14 visualizes the pixels identified as intensifying (defined by increasing productivity, poor climate and soils) in Figure 2.9c. Here, we show land cover during the main growing season—wet season—and the dry season where imagery was available for assessment of the land use in these intensifying pixels. The image data suggest land use with mixed cropping, or under-irrigation. The temporal imagery on these intensification pixels show that the land use (agricultural management activity) identified in these pixels may suggest that these management activities are associated with intensification.

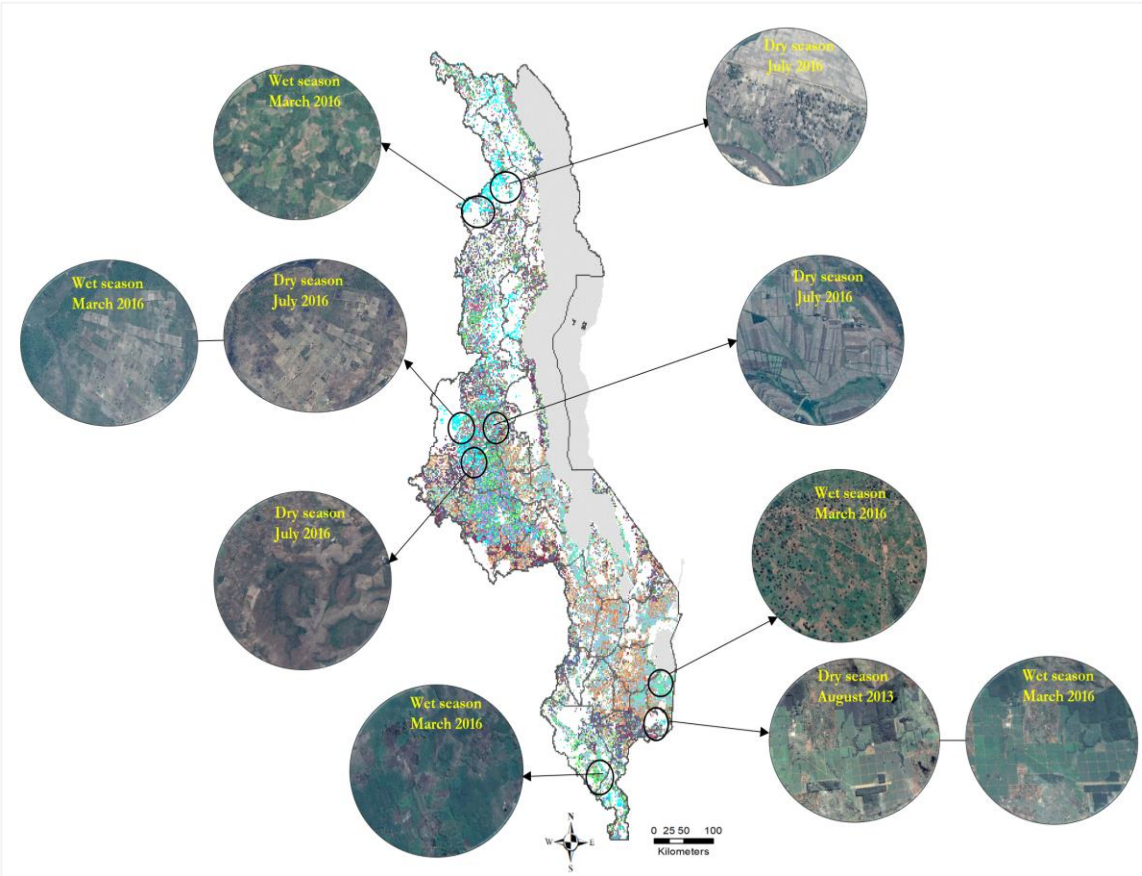

Figure 2.14: Land use and land cover of available cloud-free satellite imagery of selected intensifying pixels as viewed using Google Earth Pro application. Satellite imagery is Landsat 30m resolution. The circles in the map represent the areas in which the imagery was taken (Source: “Malawi”, Google earth, 2013, 2016 imagery, August 01 2019).

2.6 Discussion and Conclusion

2.6.1 Malawi’s Productivity Trends

There are few biophysically based longitudinal studies that consider productivity over time, and we know of no other that addresses this in smallholder agriculture in Africa. This critical aspect of agricultural sustainability is evaluated here based on spatial-temporal patterns of intensification of agriculture for maize crop growing season (November to April) from 2006–2017 using generalized models on Malawian farmland productivity trends. We hypothesize that locations with increasing trends in agricultural productivity are intensifying, and specifically highlight areas where productivity trends are increasing and not fully explained by climate trends and soil conditions. Our results partly agree with the (Galford et al., 2016) study, showing spatial distribution of Malawi's productivity trends as influenced by climatic factors and agricultural input resources.

Increasing productivity in some locations (Figure 2.9c) with suboptimal climate and soils for maize is evidence of intensifying agriculture across Malawi. We have observed that farmers with farms in these marginal environments are intercropping with legumes, growing a significant number of trees for green manure, or adopting other climate and soil resilient strategies. Previous studies for Malawi that show mixed cropping systems with tree species are widespread, especially in the northern and central regions, nitrogen-fixing trees such as *Gliricidia sepium, Sesbania sesban, Tephrosia vogeii*, and *Faidherbia albida*, that improve soil fertility, are common (Coulibaly et al., 2017; Kaczan et al., 2013; Kwesiga et al., 2003; Thangata & Alavalapati, 2003).

Additionally, increasing productivity located close to or within forested areas may suggest forest cover conversion to agriculture. In such areas, few farmers practice shifting cultivation—letting the soil rest in natural forest regenerations or in some cases; slash and burn practices are carried out (Kaczan et al., 2013).

Intensifying agriculture located close to lakes and river plains may be further explained by supplemental irrigation. Since early 2000, the government of Malawi has increased supplemental irrigation schemes for small scale farming (Kumwenda et al., 2015). Within the lakes and river catchments, ongoing, low-cost, community-led irrigation scheme projects promote sustainable intensification and allow small scale farmers to cultivate diverse crops such as rice, vegetables, or sugarcane through the dry season (Mwase et al., 2014; Nhamo et al., 2016; *Publications | Agwa | Food and Agriculture Organization of the United Nations*, n.d.).

Remote sensing imagery captured intensifying agricultural areas that have mixed cropping and agroforestry practices, and also showed farming landscapes likely involving irrigation. The findings are consistent with studies that note that land access to input resources may boost productivity in changing climates (Campbell et al., 2014; Hammond et al., 2017; Mbow et al., 2014). Our findings also show decreasing productivity trends, especially in the southern region, correlate with a rainfall gradient that follows a north to south pattern (Davenport & Nicholson, 1993). The decreasing productivity across Malawi suggests that the landscape is homogenous in terms of vegetation types and cropping systems; areas with sparse vegetation have effect vegetation apparent reflectance lost due to the soil or bare areas, while in drier areas, the vegetation reflectance values are not expected to change much over time (Chavula et al., 2011; Fensholt et al., 2009). Decreasing trends that occur during main growing season, suggest crop failure due to erratic weather across Malawi, as prior extreme weather events, as reported in earlier years 2009, 2012, and 2015, subsequently affected crops in the main growing season (*Malawi Drought 2016 PDNA*, n.d.). In 2015–2016, Malawi's main growing season experienced late onset of rains, and a prolonged dry spell, possibly driven by El Nino conditions that impacted crop development (World Bank, 2016).

2.6.2 Malawian Spatial Distribution

Low productivity was observed in surveys as well as remote sensing. The general spatial observation of lower yield reported in the south is also reflected in FAO statistics, however, the amount is 50% less from farmer reported survey data here. In the southern region, farmers reported maize yields are less than 2000 kg per hectare in both surveys, and we attribute this to the fact that farming in the southern region is challenged by dense local populations, and livestock populations competing for the same small land sizes for sustenance.

The central and northern regions have dissimilar opportunities and challenges relative to those found in the south. Land resources are abundant in the northern region due to lower population density, and thus flexible to crop diversification. Additionally, the majority of land ownership in Malawi is through customary laws, while the rest is either public or private lands (Kishindo, 2004). In the central region, farmers typically cultivate small to medium size landholdings, and thus may be involved in cash cropping (e.g., tobacco, cotton, and horticulture), also farmers own small livestock such as goats, pigs, and chickens for food and manure (*Productivity and Survival Ability of Goats in Smallholder Crop/Livestock Farming Systems in Malawi*, n.d.). In the northern region, there are livestock farmers who own cattle and have bigger landholdings, and most of these farmers are from medium to high income households (U.N. Malawi, n.d.).

From both IHS surveys, the majority of farmers reported soil quality as fair or bad. This is likely an indicator of crop health and yield performance history. Previous studies have shown that continuous cultivation in smallholder farming is a major factor contributing to soil degradation, leaving soils depleted of nutrients (S. S. Snapp et al., 1998). The majority of households in central and southern Malawi reported using inorganic fertilizer, however, few households reported using organic manure for soil amelioration, as this resource is linked to ownership of livestock (Tittonell et al., 2015). It is difficult to quantify organic and inorganic fertilizers use and productivity at the national scale due to other unobserved variables, such as field conditions, input application timing, and inorganic fertilizer use associated with access and affordability (Ragasa & Mazunda, 2018).

Malawi’s agricultural practices dissemination is limited by the limited number of extension educators, with extension to farmer ratio ranging from 1:1600 to 1:3000 per district. In contrast, the nationally recommended ratio is extension to farmer of 1:750–1:850 (C. Masangano & Mthinda, n.d.). Some studies also report that resource-poor farmers have limited capacity to participate in extension activities, particularly women farmers (Kundhlande et al., n.d.; C. Masangano & Mthinda, n.d.).

While our study provides insights regarding the spatial distribution of agricultural intensification in Malawi, there are limitations. We base our analysis on diverse time series satellite data products available for Malawi, including gridded climate datasets with spatial resolutions ranging from 1km to 5km. These were chosen due to high temporal resolution; however, the spatial resolution is coarse, and if a high spatial resolution product existed, this would enable improved detection of local drivers of agricultural variability (Xu et al., 2018). Additionally, sustainability presents an imprecise endpoint and is, as we define it, a trajectory of production resulting from the complex interplay of diverse phenomenon. We acknowledge that we cannot account for all factors nor disentangle all drivers producing particular classes of results measured in pixels. Another challenge is that the two cross-sectional household surveys were not directly comparable since different households were sampled in 2010–2011 versus 2016–2017 surveys. However, the cross-sectional households are considered nationally representative of households.

This study contributes to the literature on agricultural intensification of small scale farming (e.g., (Franke et al., 2014; Garnett et al., 2013; S. Snapp & Pound, 2017) by highlighting patterns of increasing productivity not driven by a changing, mesic climate or land suitability. Market access to inputs and outputs, farmer knowledge, and goals are all expected to influence agricultural intensification.

Few studies have focused on trend analysis in resource-poor regions where intensification of agriculture is occurring despite biophysical impediments to productivity. Overall, there are worrying downward productivity trends on Malawi agricultural lands. At the same time, spatial identification of sites associated with agriculture intensification for maize over a 10-year time series suggests that Malawian farmers are adopting and improving the use of available natural and social resources. Such efforts are likely to improve crop productivity over time despite challenging climate, social, and edaphic factors. This research improves our understanding of agricultural intensification at multiple scales, to better inform decision makers on the use of spatial information for targeted solutions that address sustainable intensification of agriculture[2].

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3. SMALLHOLDER FARMS AND THE POTENTIAL FOR SUSTAINABLE INTENSIFICATION[3]

3.1 Introduction

Agricultural development in sub-Saharan Africa faces challenges from climate change, natural resource degradation, persistent food insecurity, and increasing intensification pressures from the millions of people whose livelihoods are rooted in smallholder farming. Godfray et al. (2010) argue that to address these challenges, more food needs to be produced in sustainable ways as compared to use of unsustainable practices that contribute to continuous loss of biodiversity and land overuse that causes land degradation (Vitousek et al., 1997).

Agricultural intensification practices that increase food productivity are often equivocal in terms of environmentally sustainability (Petersen and Snapp 2015, Pretty, 2008). Sustainable Intensification (SI) of agriculture is an approach of agricultural production whereby desired outputs are increased without adversely affecting the environment or expanding the agricultural footprint (Giller et al. 2015). The important features of such an agricultural system include: producing more output per unit area; accruing natural, social and human capital; and increasing the flow of environmental services (Giller et al. 2015; Pretty et al. 2011; Godfray et al., 2010). Yet, putting SI into practice is complicated by divergent understandings of goals, the sometimes challenging implementation of SI practices for farmers, temporal delays in positive returns or yield

[3] This is an Accepted Manuscript of an article published in Frontiers in Plant Science on 17 November 2016, available online at doi.org/10.3389/fpls.2016.01720. Reference: Mungai, L. M., Snapp, S., Messina, J. P., Chikowo, R., Smith, A., Anders, E., ... & Li, G. (2016). Smallholder farms and the potential for sustainable intensification. *Frontiers in plant science*, *7*, 1720.

increases, and limited supportive policy frameworks for sustainable agriculture (Petersen and Snapp 2015; Pretty, 2008).

Nevertheless, SI approaches have been considered to promote improved management of natural resources with attention to minimizing tradeoffs between productivity and profitability (Pretty and Bharucha, 2014, Kaczan et al., 2013, Garnett et al., 2013). Agricultural technologies that are often promoted as supporting pathways to SI include Conservation Agriculture, Integrated Soil Fertility Management (ISFM), and Climate Smart Agriculture (Place et al., 2003, Giller et al., 2015). Factors that limit the sustainability of agricultural development are not only global climate and market-economics related, but also related to any community's access to education, health care, and infrastructure. Farmers might be unable to reach markets to access fertilizer and seeds or sell produce. Many face labor shortages, limited farm credit access and poor governance (Pretty et al., 2011, Sumberg, 2005). These elements likely lead to constrained farmer decision making processes, as well as a disconnection between farmer knowledge and use of technologies (Sumberg, 2005, Tchale 2009).

Rather than focus on specific practices like many of the above-mentioned approaches to SI, in this paper we focus on principles of SI: resource conservation, promotion of agrobiodiversity, building on local knowledge and assisting farmers to incorporate modern innovations (Petersen and Snapp, 2015). We review the challenges and opportunities for sustainable intensification of maize based cropping systems on smallholder farms in Malawi. A survey of farmers elucidates current practices, and farmer perceptions that are relevant to many southern and east African smallholder maize-based systems.

3.1.1 Background

Sustainability of Africa's natural resources, conserving biodiversity, and enhancing current farming practices has not always been a priority of international agricultural research and development initiatives. Nonetheless, efforts are underway to develop African agriculture by promoting the revitalization of sustainable farming practices in partnership with smallholder farmers, extension advisors, and local communities. These efforts seek to understand current farmer-agroecosystems, identify cultural constraints, and explore options for improving crop production (Giller et al., 2011). Additionally, there is a progressive shift towards agricultural research, technology accessibility and implementation that involves the public and decision makers (Ochieng, 2007).

A practical tool for African agricultural development is through the use of "bottom-up" approaches where agricultural scientists co-learn with farmers and collaborate on developing options that are appropriate to local priorities, livelihoods, and practices (Snapp et al., 2002, Altieri 2002). Most farmers have knowledge of diverse crops such as cassava, millet and sorghum that contribute to the resilience of their farms to climatic variability (Rufino et al., 2013). Other practices that promote sustainable production include combinations of organic amendments with suitable fertilizers and the use of modern seed varieties (Pretty et al., 2011). Soil management techniques that improve water infiltration and storage are very important in rainfed systems for mitigating variable rainfall patterns across space and time (Thierfelder and Wall, 2009; Krull et al., 2004; Turmel et al., 2015). However, the use of organic inputs such as compost and incorporation of legume residues has been shown to vary widely in terms of the intensity of use by farmers (Valbuena et al., 2011).

In this paper we focus on the characterization of Malawian smallholder agriculture as a case study for regional agricultural production challenges and development opportunities. In the last two decades, Malawi maize production has seen wide variability driven by climate and policy related issues with a range of strategies promoted by the government and international debates (Dorward and Chirwa, 2011). Regular droughts threaten farmers' livelihoods and food security thus in the late 1990s, to alleviate drought risk, the Malawi government, with the assistance of international aid, implemented the use of a "starter pack" of affordable inputs of maize seeds and fertilizer to poor farmers (Levy, 2005, p.274). Further, policies formed in the early 2000s focused on inputs subsidies for fertilizers, and modern hybrids to improve production across the Malawi smallholder farmer sector (Dorward and Chirwa, 2011). There is considerable debate regarding implementation of the input subsidy program and also its subsequent impact with regards to improving access to inputs, and overall agricultural productivity. Survey findings suggest farmers are growing more modern maize varieties, although the impact on drought-resilience has been moderate and disappointment among some farmers has led to disadoption (Snapp and Fisher, 2015). Subsidy impact on fertilizer access appears to vary markedly from year to year and with farmer socio-economic status (Whiteside, 2014, Tchale 2009).

Notwithstanding these challenges, Malawian farmers have experience with indigenous systems aimed at improving land and food quality, preserving soil moisture, and preventing soil erosion (Mulwafu, 2011). Farmers historically used shifting cultivation known as 'makusa' that improved soil fertility. Through this process, farmers gathered and burned tree branches and grasses, then mixed the ash with soil, and grew maize, cucumbers and pumpkins. On the sloping hills of Shire highlands, the mound cultivation 'matuto or katuto' technique was used. These were flat mounds used for planting sweet potatoes and cassava, and intercrops of beans and groundnuts.

In the plains, farmers cleared and tilled the ground ‘kulima pansi or chitipula’ before sowing maize, cowpeas, pigeon peas, (mphonda) edible gourds and sorghum (Mulwafu, 2011). Many of these practices have become challenging to practice given very limited use of fallows and diverse rotations given the small size of land holdings (due to rapidly growing population and government policies on land allocation, Jayne et al., 2014). Another traditional practice well suited to high labor availability is the production of compost, which could help meet urgent soil rehabilitation requirements. Some farmers used the compost heaping systems known as ‘Changu’ (turned and watered regularly) and ‘Chimato’ (covered with mud and static) to improve soil fertility (Nalivata 2007).

At the foundation of sustainable practice is the production and management of crop residues. Intensification of crop production can lead to greater residue biomass, but this must be managed properly in order to build soil quality. There is a debate in the agronomic literature on whether crop residues should be incorporated early - directly after crop harvest - as a means to enhance soil nitrogen stocks and biological processes, or left on the soil surface as a mulch to prevent erosion (TerAvest et al., 2015). The quality of the residues matters, as the decision tree developed by Palm and colleagues illustrates: low quality residues are well suited to erosion control, and medium to high quality residues (with a narrow C: N ratio, and biochemical constitutes that support rapid decomposition) are better suited to incorporation (Palm et al., 2001). Long-term benefits are derived from early incorporation of residues, but given that associated labor demands are high (as at harvest time residues tend to be high volume and the soil difficult to turn over), the deferred gains in soil organic matter pose challenges to farmer adoption (Vanlauwe et al., 2002). Mulch management can also have high labor requirements due to livestock control requirements and the transfer of biomass often recommended (Thierfelder et al., 2015); indeed, the soil cover practices associated with conservation agriculture have been critiqued as having limited relevance to smallholder farmer systems in Africa (Giller et al., 2009).

Different regions of Malawi employ specific crop residue management practices. Valbuena et al. (2015) reported that in the Mzimba area of northern Malawi farmers who do not own livestock tend to have more residue biomass available. In Southern Malawi, community norms are employed to control livestock year round (Rogé et al., 2016). Some studies have observed that the usage of crop residue depends on four related elements: farmers' decisions, food production quantities, access to other biomass sources, and biomass requirements (de Leeuw, 1997, Erenstein et al., 2011).

Table 3.1: Environmental and physical farming system characteristics of four sites in Central Malawi based on s spatial data from various sources[1-6] and surveys conducted in July of 2013

	Golomoti	**Kandeu**	**Nsipe**	**Linthipe**
Productivity Potential	Low	Medium	Medium	High
<u>Physical Characteristics</u>				
Latitude/Longitude[4]	14.32°S/34.66°E	14.65°S/34.68°E	14.80°S/34.72°E	14.26°S/34.10°E
Elevation local point (meter above sea level)	555	904	868	1238
Elevation[5] (meters above sea level)	504	877	967	1248

[4] Latitude and Longitude values derived from the EPA polygon (source: GCS 1984, UTM zone 36S). Used ArcGIS to dissolve extra polygons within the same EPA, converted polygon features to points, and created a centroid point, used calculate geometry option to get each centroid point in degree (units).
[5] Digital Elevation Model, Shuttle Radar Topographic Mission (SRTM) 90m: spatially joined with EPA polygons, calculate zonal statistics for each EPA

Table 3.1(cont/d)

TRMM Annual[6] Average rainfall (mm)	895	866	866	953
Local rainfall (mm)	884	-	875	667
Evapotranspiration[7] (mm)	960	619	607	595
EPA Mode Soil[8] Suitability	Moderately Suitable	Marginally Suitable	Marginally Suitable	Moderately Suitable
Primary Income Sources	Crop Sales; Small Business	Crop Sales; Horticulture	Crop Sales; Small Business	Crop Sales; Farmer Laborer (Ganyu)
Distance from small market (km)	1	2	9	5
Distance from large market (town) (km)	40	35	20	40

3.1.2 Africa RISING-Malawi Sites

The Africa Research in Sustainable Intensification for the Next Generation (Africa RISING) program is funded by the United States Agency for International Development (USAID) as a part of the United States Government's Feed the Future initiative. The program aims to improve food security, farmer livelihoods, and agroecological indicators of system health through the sustainable intensification of key African farming systems, notably maize-based, rainfed production by use of action research. Africa RISING sites in Central Malawi were selected as representative of the widespread maize-mixed systems that encompass over 250 million hectares in sub-Saharan Africa (Blackie and Dixon, 2016).

[6] TRMM Annual Average Rainfall: spatially joined TRMM and EPA polygons, calculated EPA average rainfall (mm)
[7] Global long-term (1983-2006) daily Evapotranspiration (1degree): spatially joined with EPA polygons, calculate zonal statistics for each EPA
[8] Source: Africa Soil Information Service (AfSIS) soil dataset, calculated mode-zonal statistics per EPA using spatial analyst in ArcGIS

The Africa RISING project identified entry points for sustainable intensification of maize-based farming based on integrated nutrient management, judicious fertilizer use combined with enhanced legume presence, and improving utilization of legume products and residue management practices. In particular, pigeon pea was identified as a nitrogen-fixing leguminous crop producing protein-rich grain and substantial biomass that can be used for soil improvement as well as for multiple benefits, including forage and compost (Snapp et al., 2010). During the first year of the project, farmer practice was surveyed to assess current practice. Action research was initiated in the beginning of the growing season (November 2012), to introduce modern varieties of legumes and doubled-up legume technologies, including mixtures of pigeonpea and soybean as well as improved varieties of groundnut and cowpea. This key SI farming technique involves growing a two-legume intercrop in the first season, followed by intercropped pigeonpea and maize or sole maize in the second season (Snapp and Silim, 2002). Residue management of the doubled-up legume system is crucial to obtaining benefits for soil fertility as well as enhanced harvests (two crops) per land area (Bezner Kerr et al., 2007).

Simulation studies suggest that climatically risky sites may benefit from this doubled up legume technology, although this requires extensive testing on-farm (Smith et al., 2016). Further, simulation research in Mozambique highlights the role that crop residues and management practices play as key regulators of nutrient retention and organic matter inputs to build soil carbon and nutrient pools (Rusinamhodzi et al., 2015). Thus, understanding how farmers practice integrated management, and in particular residue management, is essential information for assessing performance and SI potential across marginal and mesic sites.

3.2 Materials and Methods

3.2.1 Description of Sites

The study sites were chosen using a stratified random approach, where four sites were chosen along a gradient of agroecological zones from low to high production potential across central Malawi (Dedza and Ntcheu districts). The locations were randomly chosen extension sections (with several villages located within each section), within Golomoti and Linthipe Extension Planning Areas (EPA) in Dedza, and Kandeu and Nsipe EPAs in Ntcheu. The four EPAs vary in geophysical features as Malawi's land surface straddles the North West-to-South East, low-to-high elevation parts of the African rift valley[9] (Brown and Young, 1965). The varying geographical gradient, and climatic conditions play a role in influencing productivity. As shown in Table 3.1, Golomoti is a low agricultural potential site located at low elevation, with high evapotranspiration and variable rainfall, Kandeu and Nsipe are medium agricultural potential, located on medium elevation, with medium rainfall and Linthipe is a high agricultural potential, high elevation site, and well-distributed rainfall (Tamene et al., 2015, Smith et al., 2016). Malawi has a unimodal rainy season occurring from November to April, and a dry season from May to October (Jury and Mwafulirwa, 2002). Figure 3.1 shows the long-term annual average rainfall for Malawi from 2001 to 2014 using Tropical Rainfall Measuring Mission (TRMM) dataset, and monthly weather station data graphs from August 2014-July 2015 for the three selected EPAs. The rainfall pattern shown here illustrates the regional spatial and temporal variability (Kumbuyo et al., 2014, Ngongondo et al., 2011).

[9] The Malawi Project link http://www.malawiproject.org/about-malawi/geography/ accessed 11 June 2016

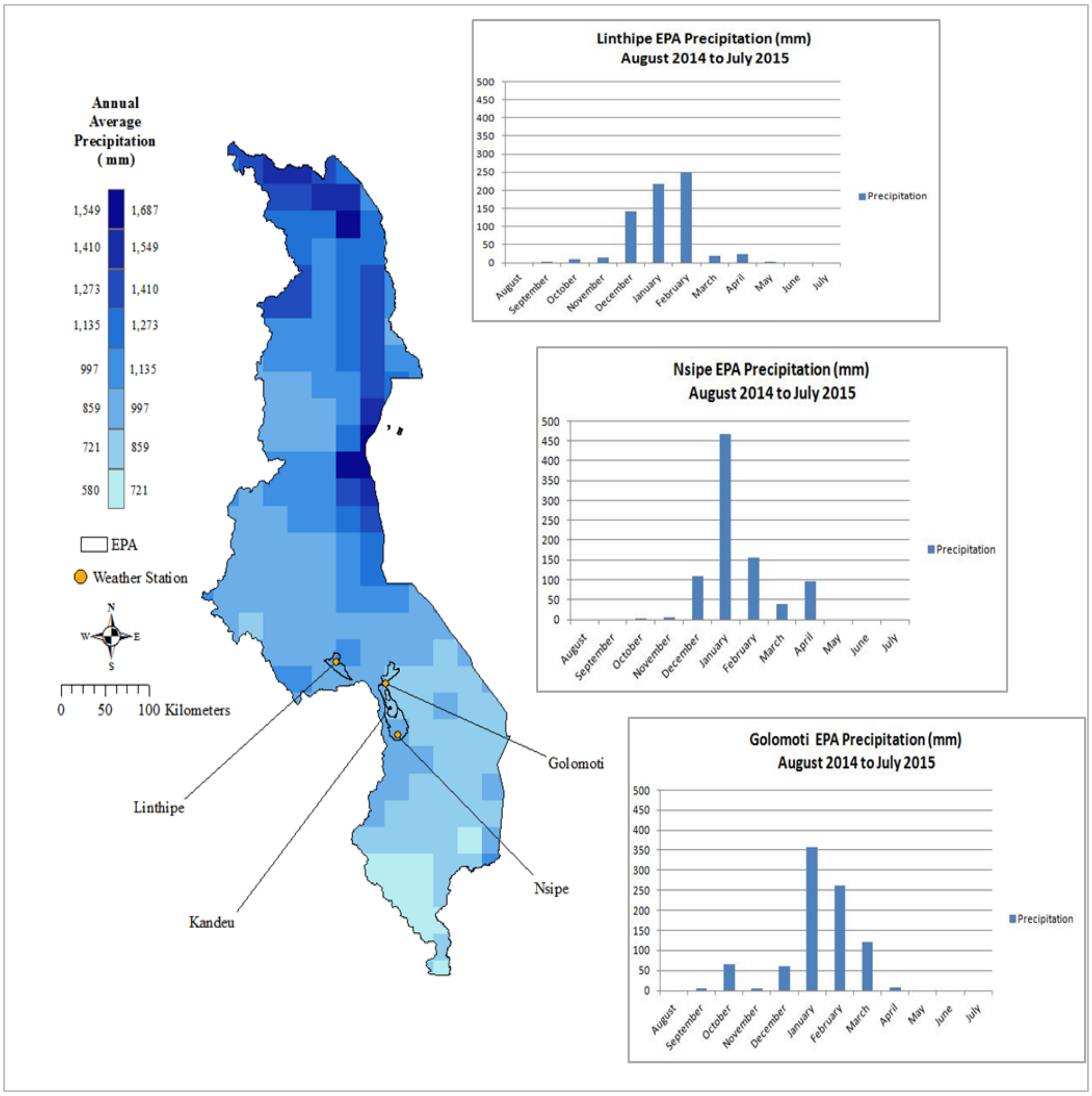

Figure 3.1: Malawi Annual Average Precipitation (mm) based on TRMM rainfall data for 2001 to 2015; and monthly rainfall amounts of selected EPAs from Weather Station datasets for August 2014 to July 2015 (Linthipe 677mm, Golomoti 884mm, and Nsipe 874mm).

Soils at Golomoti tend to be coarse and a mix of eutric cambisols and eutric fluvisols, the Kandeu and Nsipe sites are dominated by mixed chromic luvisols and orthic ferralsols, while Linthipe are primarily ferric luvisols (Lowole, 1983). Soils in these locations were characterized further as seen in (Figure 3.2). The Malawi agricultural land suitability was assessed based on eight terrain and soil factors including soil erosion risk, soil organic carbon, soil texture, soil depth, soil exchange capacity, soil drainage, and soil pH derived from the Africa Soil Information Service (AFSIS) soil dataset, and terrain slope from SRTM DEM (Shuttle Radar Topographic Mission 90m). We combine several empirical models such Square Root, Storie, Rabia, Weighted average, Geometric Mean. All variables were quantitatively rated, and grouped into eight soil suitability classes (Storie, 1978, Rabia and Terribile 2013, Li et al., 2017, Pourkhabbaz et al., 2014).

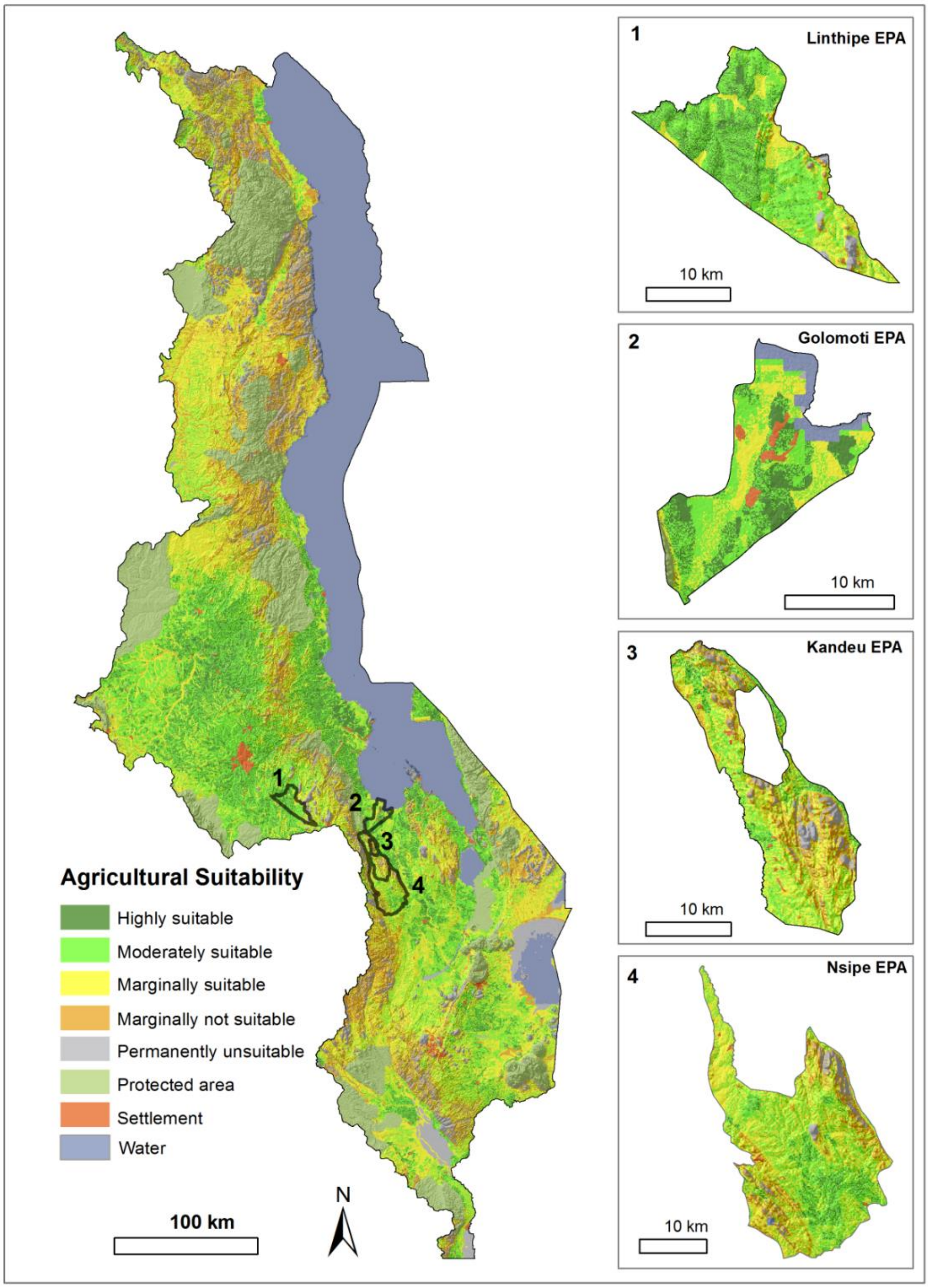

Figure 3.2: Malawi agricultural land suitability Map that highlights the four EPA regions (data source Li et al., 2017)

3.2.2 Survey Method

A semi-quantitative interview instrument was used to survey 324 farm families over a 10-week period from late-May to late-July, 2013. This survey dataset included intervention, local control, and distant control households from 22 village clusters in two districts including Dedza (Linthipe and Golomoti) and in Ntcheu (Kandeu and Nsipe). Note that Mtakataka is adjacent and highly similar to Golomoti and was combined with Golomoti for this study. Preliminary statistical analyses showed no difference in farming practices between intervention farmers and control farmers, which is not surprising as this was a survey conducted as part of a baseline characterization exercise.

The sample consisted farmers who participate in an Africa RISING research project that was started in 2012, and near control and distant control farmers chosen using a "Y-sampling frame". The survey instrument was approved through the MSU IRB human subjects protocol, and translated into local languages with information provided as to the voluntary nature of the survey, and every effort was carried out to maintain confidentiality. Enumerators were trained over a one-week period, and supervised in the field by graduate students, and the data collection process included close attention to data entry and data quality control, as described in an earlier report on the gendered-aspects of farmer experimentation reported in this survey and in a complementary qualitative research project (Hockett and Richardson, 2016).

The total participants comprised 97 males and 227 females. Participants from Dedza district were a total of 163 (about 2.61% of the population of Dedza) and 161 participants were from Ntcheu district (3.41% of the population of Ntcheu). The survey involved 71% male-headed households and 29% female-headed households, which is a typical distribution of household characteristics in Central Malawi (World Bank 2016).

The survey topic addressed socioeconomic characteristics such as household size, dependency ratio (calculated as the number of individuals who are either younger than 15, or older than 65, relative to adult members of the family who contribute fully to agricultural labor * 100, Hockett and Richardson, 2016). The survey also asked questions about farm management, including detailed information on practices in the 2012/2013 season on a field by field basis, e.g., crops grown, intercrops with maize systems and other cropping systems, soil fertility practices, and types of animals owned. This allowed characterization of baseline farming activities and social situation. Note that we do not report here on the small experimentation plots some of the Africa RISING intervention farmers started carrying out in 2012, as information on these plots was excluded from the analyses.

We were interested in the common farm practices across the entire Central Malawi area where this work is being carried out including among farmers not interacting with the Africa RISING projects (indicated here as control farmers). All crops grown per plot were documented in the survey. We report here on the most important cropping systems as characterized by the first two reported species. For example, the maize + pigeonpea intercrop included a few instances of maize + pigeonpea + cowpea, and maize + groundnut included a few instances of maize + groundnut + common bean.

Soil fertility measures including compost and manure application, residue management and fertilizer use were asked about on a field by field basis, which allowed evaluation of use by cropping system as well as by farm household. Field size was reported for a subset of fields, 70% of the 657 fields reported in the survey, and those fields were used to calculate application rate of fertilizer. Compost and manure use was asked about separately in the survey, but in general animal manure was a small proportion of amendments applied and included aged manure dug out of confined livestock areas which is similar to compost. Based on the literature, both compost and manure are very low in nutrient status on smallholder farms (about 1% or less N; Vanlauwe et al., 2002); thus, we combined manure and reported it within the compost category.

3.2.3 Natural Resource Management Context

To explore the sustainability in relationship to a variable natural resource management context and farmer practices we present data from the survey and predict crop yield and soil organic matter trends over time at the three sites where we have conducted crop and soil modeling simulations Golomoti, Kandeu and Linthipe (Smith et al., 2016). The simulations are based on the analysis by Smith et al., (2016) that used the Agricultural Production Systems Simulator (APSIM) crop and soil simulation model. APSIM has been used widely over a decade in the sub-Sahara Africa region and has been validated using crop yield data from sole, intercrop, and rotational systems of maize –legume crops (Keating et al., 2003, Whitbread et al., 2010).

Here the simulation analysis was carried out using a subset of this survey dataset collected in 2012-2013 season and 2013-2014 growing seasons for maize-legume rotation low potential-Golomoti, medium potential-Kandeu and high potential-Linthipe. Also, the APSIM model used ancillary datasets including soils and weather data, and parameters such as plant spacing, crop varieties and crop residue removal practices for 26 growing seasons of a maize /legume rotation scenario nominally run from November 1, 1979 through June 30, 2005 (Smith et al. 2016).

3.3 Results

Table 3.2: Social characteristics for farmers in the four sites in Central Malawi based on surveys (n=324 except where otherwise noted) conducted in July of 2013.

	Golomoti	Kandeu	Nsipe	Linthipe
Extension Contact %				
None	46	53	39	41
Received advice on one agricultural topic	14	11	20	12
Received advice on two agricultural topics	15	12	7	13
Received advice on three agricultural topics	25	24	34	34
Household (HH)				
Male HH head: n (%)	60 (75%)	56 (69%)	58 (73%)	57 (69%)
Female HH head: n (%)	20 (25%)	25 (31%)	22 (27%)	26 (31%)
Average HH size (persons)	5.1	5.2	5.1	5.2
Dependency Ratio[7]	108	104	108	112
Avg. farm size (ha) (n=600)	0.83	0.89	0.97	0.71
Avg. # of fields	1.89	2.38	2.4	2.24
Avg. # laborers available (from within HH)	2.61	2.81	3	2.76
Avg. # months food supply	7.16	7.83	9.65	8.24
Major crops	Maize, cotton, groundnut	Maize, tobacco	Maize, tobacco, groundnut	Maize, tobacco, groundnut
Unique crops	Cowpea	Groundnut, soybean	Soybean, sweet potato	Soybean, common beans
Livestock ownership (%)				
Cattle %	3.8	13.6	2.5	8.4
Goats %	46.3	37	50	45.8
Pigs %	17.5	14.8	30	19.3
Poultry %	62.5	80.2	81.3	72.3
Average population per sq. km [8]	75	150	75	150

[7] Dependency Ratio as the number of age population not in the labor force divided by working age population (World Bank 2016).

[8] Source: Benson, Todd. (2002). Malawi Atlas of Social Statistics. Used population area averages for the traditional authorities' map based on our EPA centroid

3.3.1 Socioeconomic characteristics

Generally, smallholder farmers at the four sites have very limited resources. This is typical of the smallholder sector in Southern Africa. Household size comprised 5.1 persons with a dependency ratio of 104-112. An average of 2.8 persons from each household contributed labor to agricultural production (Table 3.2). The majority of farm households (88.9%) held two fields or fewer and cultivated an average of 0.85 hectares; food produced by the average household was reported to last 8.22 months. Farmers generally reported the sales of their agricultural produce from their rainfed fields as their key income source, with no secondary source of income. At Linthipe there was greater reliance on other income sources, compared to the other sites (Table 3.2).

Several farmers own small animals, but only a few own cattle, and there was no reported use of animal traction. The low levels of livestock limit the use of animal manure in the fields. Farmland cultivation is labor intensive as hoes are used to break up the soil in preparation for sowing and to build planting ridges, as well as for manual weeding.

Overall, 45% of farmers reported having had no contact with extension agents during the previous seasons for agricultural information on topics such as crop/variety guidance, land preparation techniques, and fertility measures (Table 3.2). Of the 55% that received extension advice, about 20% received advice on one or two agricultural topics and the remainder reported contact with extension agents that addressed three or more agricultural areas. Contact with the extension educators was a higher percentage for Africa RISING participants than for control farmers, which was not surprising as this was a baseline study.

Table 3.3: Soil organic C status measured in 2014 and simulated change over 25 years using APSIM, calibrated for three EPA sites in Central Malawi, and range of simulated maize nitrogen efficiency for continuous maize, maize-groundnut rotation and maize-pigeonpea intercrop over 25 years at low and high potential sites (Adapted from Smith et al., 2016)

Measures	Cropping systems	Golomoti	Kandeu	Linthipe
Soil Organic C change*	Initial SOC	0.85	1.05	2.33
	Maize	-0.136	-0.1	-0.88
	Maize & groundnut	-0.036	0.076	0.72
	Maize & pigeonpea	0.112	0.456	0.088
Maize nitrogen efficiency (kg maize grain / kg N fertilizer per ha)	Maize	30.1-68.9	43.0-80.0	18.7-69.8
	Maize & groundnut	32.4-105.0	29.0-110.0	34.8-116
	Maize & pigeonpea	20.9-70.6	13.7-66.2	39.1-73.6

*% soil organic C (SOC) change over 25 years

3.3.2 Agricultural Potential

The agricultural land potential was categorized based on soil and environmental factors, with land being classified as follows: highly suitable (8.2%), moderately suitable (24.1%), marginally suitable (28.0%), and unsuitable (39.7%) of the total land area (Figure 3.2). The four EPA sites in our study were ranked based on the majority of pixels' classification in each site: on this basis, Golomoti and Linthipe land was generally classified as moderately suitable, while Kandeu and Nsipe was classified as marginally suitable (Figure 3.2). The soil organic matter change over 25 years based on APSIM simulation of the most common cropping systems (continuous maize, maize- groundnut rotation and maize –pigeon pea intercrop), and range of maize response to N fertilizer for three low= to high potential sites, Golomoti, Kandeu and Linthipe (Table 3.3). This exercise highlights that soil organic matter has the potential to decline the most in Linthipe, the high potential site, particularly relative to Kandeu, a medium potential site. The model simulated response of maize to N fertilizer varied markedly over the three sites (13 to 116 kg grain/kg N/ha), but was much higher in maize response to fertilizer was also influenced by the cropping system, as maize systems with legumes present compared to continuous maize (Table 3.3), with implications of agricultural sustainability.

Table 3.4: Crop species grown in 2012-2013 growing season by farmers at four sites in Central Malawi, number of farmers reporting each crop shown, and percentage of farmers per site presented in parentheses. Based on survey (n=324) conducted July of 2013 in Central Malawi.

Crops	**Golomoti** (n=80)	**Kandeu** (n=81)	**Nsipe** (n=80)	**Linthipe** (n=83)	**Total** (n=324)
Local maize*	55 (69%)	66 (81%)	69 (86%)	53 (64%)	243 (75%)
Hybrid maize	49 (61%)	37 (46%)	56 (70%)	49 (59%)	191 (59%)
Tobacco	1 (1%)	10 (12%)	9 (11%)	6 (7%)	26 (8%)
Cotton	24 (30%)	2 (2%)	0	1 (1%)	27 (8%)
Pigeonpea	11 (14%)	4 (5%)	17 (21%)	7 (8%)	39 (12%)
Groundnut	20 (25%)	46 (57%)	46 (58%)	42 (51%)	154 (48%)
Soybean	12 (15%)	24 (30%)	17 (21%)	31 (37%)	84 (26%)
Common bean	0	25 (31%)	22 (28%)	69 (83%)	116 (36%)
Cowpea	50 (63%)	12 (15%)	16 (20%)	6 (7%)	84 (26%)
Bambara nut	0	0	4 (5%)	0	4 (1%)
Sorghum	0	0	4 (5%)	0	4 (1%)
Cassava	0	2 (2%)	7 (9%)	0	9 (3%)
Sweet potato	2 (3%)	2 (2%)	4 (5%)	5 (6%)	13 (4%)
Irish potato	0	0	0	1 (1%)	1 (0.3%)
Cocoyam	0	1 (1%)	0	0	1 (0.3%)
Millet	0	33 (41%)	25 (31%)	0	58 (18%)
Rice	2 (3%)	0	0	0	2 (0.6%)
Pumpkin	3 (4%)	10 (12%)	28 (35%)	3 (4%)	44 (14%)
Tomato	0	0	1 (1%)	0	1 (0.3%)
Cucumber	1 (1%)	0	2 (3%)	0	3 (0.9%)

*Total maize grown exceeds sample size as some farmers grew both local and hybrid maize

Table 3.5: Farming system combinations grown at four sites in Central Malawi, percentage of farmers using the combination per site. Based on survey (n=324) conducted July of 2013 in Central Malawi.

Crops	**Golomoti (%)**	**Kandeu (%)**	**Nsipe (%)**	**Linthipe (%)**
Maize (sole)	53.8	67.9	65	18.1
Maize + pigeonpea	12.6	2.4	11.3	3.6
Maize + groundnut	6.3	18.5	12.5	3.6
Maize + soybean	7.6	24.7	12.6	8.4
Maize + common bean	1.3	23.5	26.3	82.3
Maize + cowpea*	50	11.1	15	2.4
Groundnut + soybean	0	1.2	0	8.4
Groundnut + common bean	0	0	5	3.6
Groundnut + cowpea	1.3	0	1.3	2.4
Pigeonpea (sole)	1.3	1.2	7.5	0
Groundnut (sole)	12.5	35.8	33.8	34.9
Tobacco (sole)	1.3	11.1	11.3	7.2
Cotton (sole)	25	2.5	0	1.2
Sweet potato (sole)	2.5	2.5	2.5	6
Soybean (sole)	1.3	6.2	7.5	20.5

*Cowpea grown as a relay crop with maize

3.3.3 Cropping systems

For the 2012-2013 season, farmers reported growing a variety of crops seen in (Table 3.4); 59% of farmers reported growing a maize hybrid variety and 75% reported growing a local variety, as might be expected as maize is the staple food of the region and grown for household consumption as well as sale. For maize hybrid varieties, Golomoti and Linthipe farmers grew about 60%, compared to Nsipe farmers who grew 70% and Nsipe was lower at 46%. More local maize varieties were grown in medium potential areas of Kandeu and Nsipe (81% and 86%), and relatively fewer in Golomoti (69%) and Linthipe (64%). Farmers grew legumes primarily for consumption and were either grown as a sole crop or intercropped with maize. Groundnut was grown by more than 50% of the farmers Nsipe, Kandeu and Linthipe and grown significantly less frequently in

Golomoti (25%). Common bean was grown by a majority of farmers (83%) in Linthipe in contrast with nearly 30% of farmers in Kandeu and Nsipe.

Golomoti farmers did not grow common bean but rather 63% of farmers in Golomoti reported growing cowpea while farmers in the other three EPAs reported growing it infrequently (20% and less). Soybean was grown less commonly as reported by 26% of all farmers in all locations. Pigeon pea crop was infrequently grown in Nsipe (21%), Golomoti (14%), Linthipe (8%) and Kandeu (5%). Tobacco was grown by a few farmers in Kandeu (12%), Nsipe (11%), Linthipe (7%) and Golomoti (1%). Cotton was grown mainly in Golomoti as a cash crop, but infrequently (5%) in both Linthipe and Kandeu, and Nsipe farmers did not report growing it at all.

There were a number of farmers that reported growing other crops, such as millet (41%) in Kandeu, (31%) in Nsipe. Sweet potato was grown by only 3% of farmers in Golomoti, (2%) in Kandeu, (5%) in Nsipe and 6% of farmers in Linthipe. One household in Nsipe grew tomatoes. Cocoyam was grown by one household in Kandeu, cucumber was grown by three households, Nsipe (2), and Golomoti (1). Rice was grown by two households in Golomoti. These alternative crops were locally important as intercrops with maize in specific communities, such as finger millet grown as an intercrop with maize by 41% of households in Kandeu and 26% of households in Nsipe; presumably for local use in beer brewing. Pumpkin and cucumber were grown as intercrops in 4% of fields in Linthipe, 5% in Golomoti, 12% Kandeu and in 34% in Nsipe, but were not included as separate cropping systems.

The low potential site, Golomoti, exhibited a few unique farming characteristics, as about 50% of farmers reported growing cowpea with maize as a relay intercrop, where cowpea is planted before the maize crop is harvested, as compared to about 10% of farmers at Kandeu and Nsipe, and fewer farmers in Linthipe (2%). The cash crop cotton was also grown as a sole crop by a substantial number of Golomoti farmers, 25%, and grown by fewer farmers in Kandeu (2%) and Linthipe (1%). Pigeon pea was grown as part of a maize intercrop by about 13% of farmers in Golomoti, and 11% in Nsipe, and at lower levels in Linthipe and Kandeu (2 and 4% respectively). A surprising result was that some farmers reported growing groundnut as an intercrop with another grain legume, particularly in Linthipe where farmers reported sowing groundnut and soybean (8%), and 1% in Nsipe, farmers reported growing groundnut and common bean (5%) in Nsipe, and 4% in Linthipe. Groundnut and cowpea was grown at about 2% in Linthipe, and 1% of farmers in Nsipe, and Golomoti respectively. Overall, legume crop area was markedly higher in Linthipe relative to the other sites (Table 3.5). This was due primarily to the popularity of a maize-bean intercrop at this mesic agricultural site present in about 80% of the maize area (Table 3.4).

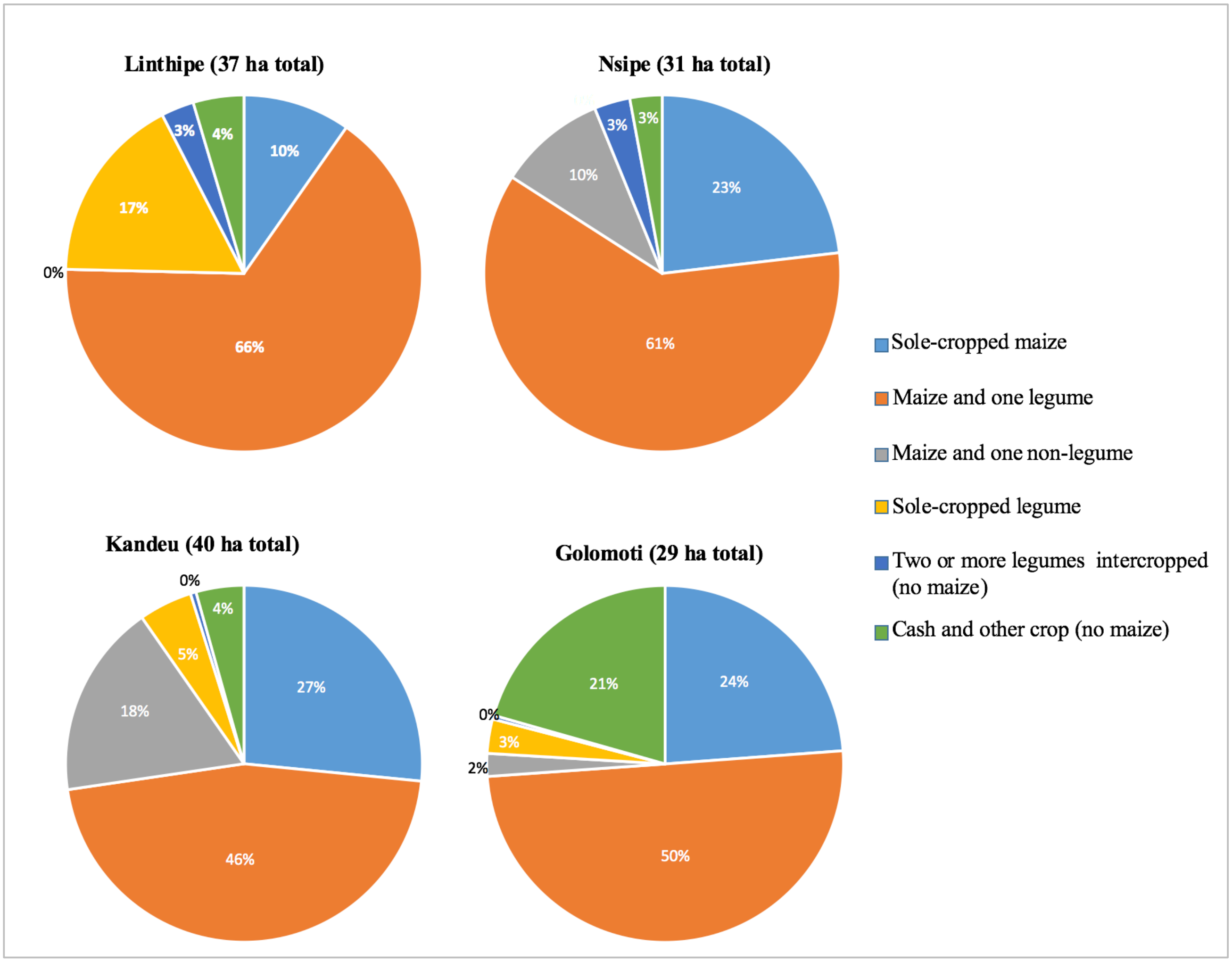

Figure 3.3: Proportion of area devoted to each crop is shown in this figure for low (Golomoti), medium (Nsipe and Kandeu) and high (Linthipe) potential sites in Central Malawi based on project survey conducted July of 2013, fields n=600.

Overall, we see that the patterns of cultivation are more pronounced when presented on an area basis rather than a field basis (Figure 3.3). The area devoted to maize is substantially larger compared to the other crops grown. EPAs have diverse cultivation by area of cereals and legumes and also the arable land varies across the EPAs. Linthipe farmers reported 37 ha total area, and grew a maize-legume crop on over 60% of their fields, a sole legume also occupied 17% of the fields followed by other crops. Nsipe had 31 hectares reported, where farmers cultivated 61% of their fields with a maize-legume, followed by 23% of sole maize crop. Kandeu reported 40 hectares of land, with sole maize (46%) while 27% of land with at least two legumes, and 18% land had a maize and other cereal crop. Golomoti reported on 29% hectares, of which 50% was in a maize-legume intercrop, 24% sole maize, and a high allocation to cash and other crops, namely cotton (21%). The other three EPAs had less than 5% in cash and other crops.

Table 3.6: Inorganic fertilizer use, compost and residue management practices at four sites in Central Malawi, percentage of farmers using the combination per site. This is based on survey subset of farmers with detailed fertility management and area questions (n=220) conducted July of 2013 in Central Malawi.

	Golomoti (n = 54)	**Kandeu** (n = 58)	**Nsipe** (n = 55)	**Linthipe** (n=53)	**Total** (N = 220)
Fertilizer Management					
% applying mineral fertilizer	75.9	82.8	92.7	79.2	82.7
N rate where applied (kg/ha)*	52	65	70	70	65
N rate standard deviation	43	48	46	38	45
N rate range	0.07 - 21.6	1.42 - 37.2	1.06 - 42.6	2.27 - 21.3	
P rate where applied (kg/ha)*	14	24	20	22	21
P rate standard deviation	10	21	14	12	15
P rate range	0.06 - 6.4	0.32 - 12.9	0.32 - 7.8	0.86 - 6.5	
% applying manure/compost	25.9	22.4	30.9	43.4	30.5
Residue Management					
% incorporated residues early	29.6	58.6	18.2	39.6	36.8
% incorporated residues late	29.6	34.5	72.7	28.3	41.4
% burned residues	37	13.8	16.4	37.7	25.9
% removed residues	5.6	15.5	0	22.6	10.9

*Fertilizer rate is in relationship to fertilized fields

3.3.4 Fertilizer and compost manure practices

Farmers were asked to report amendments applied in 2012-2013 on a field-by-field basis, the amounts and type of inorganic fertilizers, as well as compost and manure. Over 80% of surveyed farmers reported applying mineral fertilizer (average nutrient rate applied to fertilized fields was 65 kg N/ha; 21 Phosphate-P kg/ha) in one or more of their fields. The standard deviations for the fertilizer N and P applied suggests high variability in application dose, as does the range of fertilizer use shown across the four EPAs (Table 3.6). The average rate applied is close to the Malawi government recommended rate for N applied to hybrid maize, which is 69 kg N/ha. Surprisingly, the rate applied to fertilized fields of P fertilizer was higher than the recommended rate of 9 kg Phosphate-P kg/ha. However, we note that a recent convening of Malawi agricultural experts report indicated that maize fertilizer recommendations are shifting, towards the recommendation from the early 1990s which was a country-wide blanket recommendation of 92 kg N/ha and 45 kg Phosphate-P kg/ha, plus 4 kg S/ha (Mutegi et al., 2015). The proportion of farmers who applied fertilizer was consistently high across all sites, from 76% at the marginal Golomoti site to 93% at the Nsipe site. This likely reflects the apparent effectiveness of Malawi government policies that have emphasized subsidization of fertilizer to improve farmer access (Dorward and Chirwa, 2011). The lowest amounts of nutrients were applied in Golomoti, at 52 kg N/ha and 14 Phosphate-P kg/ha. This is to be expected, as rainfall variability and marginal soils are often associated with moderate doses of fertilizer as a risk mitigation strategy (Kurwakumire et al., 2014). The APSIM simulated response of maize to N fertilizer varied markedly over the three sites (13 to 116 kg grain/kg N/ha), but was much higher in maize systems with legumes present compared to continuous maize (Table 3.3).

Thirty percent of all farmers reported applying organic amendments (compost or animal manure). Linthipe farmers reported the highest rate of organic amendment use (43%). At the other locations 31% or fewer farmers reported applying an organic amendment to one or more of their fields (Table 3.6).

Mineral fertilizers were overwhelmingly applied to systems that included maize or a cash crops; 88 to 89% to sole-maize and maize-intercrop systems, and 48% to a cash crop (Table 3.7). There were zero instances of mineral fertilizer application in sole legume crops. Likewise, organic soil amendments were not applied to sole legumes. Sole-maize and maize-non-legume intercrops were amended with compost or manure by about 21% of farmers, whereas maize-legume intercrops were amended by 35% of farmers (Table 3.7). In terms of use of SI practices, few farmers are using all organic nutrient sources (10-12%), but many farmers are combining residue incorporation, or compost application, with fertilizer use, about 40 to 50% of fields (Figure 3.4). Fertilizer use alone was common, with about 42-47% of farmer fields using no residue incorporation or compost to ensure sustainable management of fertilizer. There was no clear pattern of environmental context influencing SI practice, as practices were approximately evenly distributed across sites (Figure 3.4) and no significant differences between the control and participant farmers on farm practices, and thus the outputs were based on EPA sites.

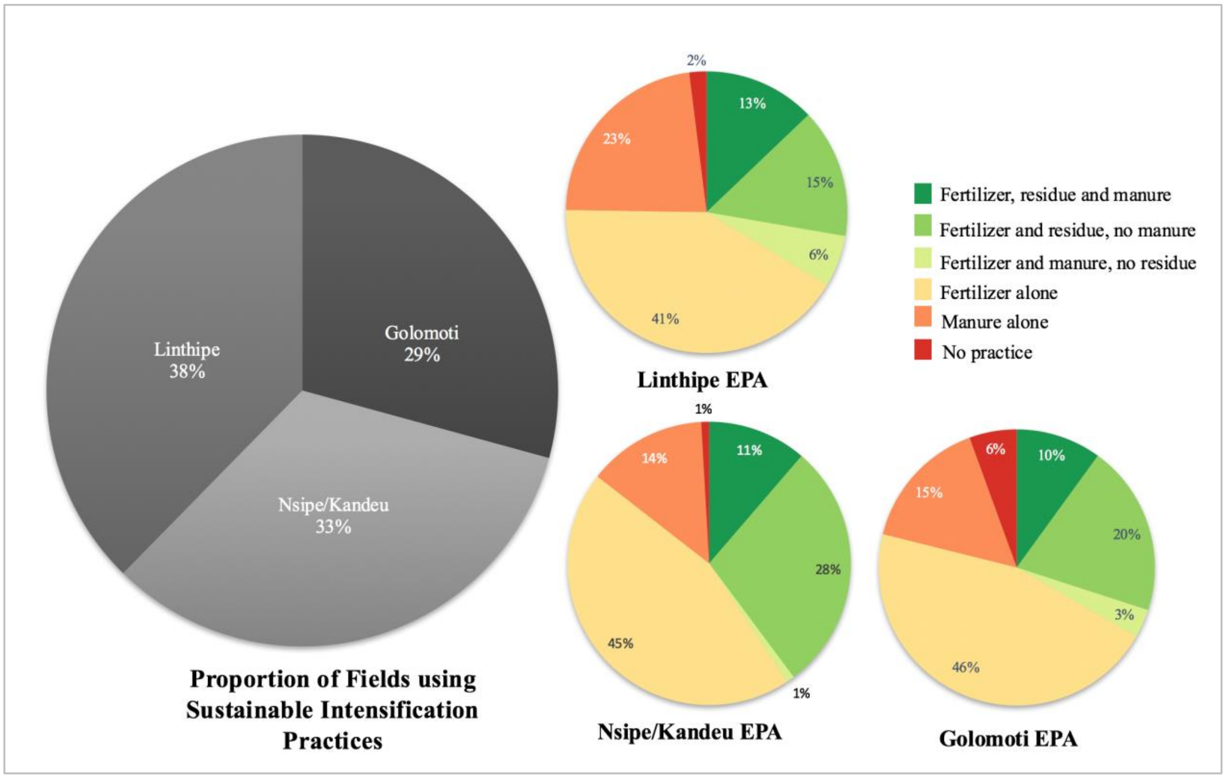

Figure 3.4: Proportion of area devoted to field management practices is shown in this figure for low (Golomoti), medium (Nsipe and Kandeu) and high (Linthipe) potential sites in Central Malawi based on project survey conducted July of 2013, fields n=600. The overall pie chart shows the proportion of area devoted to combined practices that represent sustainable intensification, those in shades of green (fertilizer combined with an organic amendment such as residue incorporation or manure).

Table 3.7: Inorganic fertilizer use, compost and residue management practices by cropping systems, percentage by cropping system. Based on survey subset of farmers with detailed fertility management and area questions (n=220) conducted July of 2013 in Central Malawi.

	MzSol (*n* = 67)	**MzLeg (*n* = 137)**	**MzOth (*n* = 25)**	**LegSol (*n* = 28)**	**LegLeg (*n* = 7)**	**Cash and Other (*n* = 33)**
applying mineral fertilizer	88.1	86.9	88.0	0.0	0.0	48.0
N rate where applied (kg / ha)	62	62	76	N/A	N/A	75
N rate Standard Deviation	53	40	59	N/A	N/A	57
N Rate Range	11- 341	6 - 227	17 - 227	N/A	N/A	0.60-170.5
P rate where applied (kg / ha)	20	19	21	N/A	N/A	28
P rate Standard Deviation	17	14	16	N/A	N/A	19
P Rate Range	1.3-103.1	1.3-69.1	5.1-51.9	N/A	N/A	0.51-51.9
% applying manure / compost	22.4	35.0	20.0	0.0	0.0	9
Residue Management by Cropping System						
% incorp. residues early	43.3	32.8	28.0	25.0	16.7	6
% incorp. residues late	35.8	36.5	60.0	39.3	33.3	21
% burned residues	10.4	19.0	4.0	21.4	16.7	57.6
% removed residues	4.5	7.3	4.0	17.9	33.3	12.1

MzSol = sole-cropped maize; MzLeg = maize intercropped with at least one legume;
MzOth = maize intercropped with at least one non-legume; LegSol = sole-cropped legume; LegLeg = two or more legumes intercropped (no maize); includes one legume intercropped with a non-legume (no maize);
Cash and Other = cotton or tobacco (no maize); includes any cropping system not falling into the above categories

3.3.5 Residue Management

Farmers reported using diverse practices for residue management. For example, some farmers incorporated residues early (i.e. soon after harvesting the crop); others incorporated residues late (i.e. in the following season, during land preparation); and still others burned residues on the field; or removed the residue to use for fodder, building materials, etc. A large majority of farmers reported incorporating residues on at least some fields (78%), while 11% removed the residues for other purposes and 26% of farmers reported residue burning (Table 3.5). We note that farmers commented that residue burning was sometimes beyond their control, carried out by other members of the community as a rodent hunting or pest control activity, where fire is not always confined to the intended field.

No clear relationship was observed for residue management across the sites in terms of an environmental gradient, as the largest number of farmers who practiced residue incorporation were in the medium potential sites, however these farmers practiced contrasting patterns of incorporation. That is, the majority of farmers based in Kandeu reported practicing early residue incorporation (59%) whereas a modest number of farmers based in Nsipe (18%) practiced this, and a large majority (73%) in Nsipe opted for late residue incorporation during land preparation. Over one-third of farmers (38%) reported residue burning at both the marginal Golomoti site and the high potential Linthipe site, whereas burning was minimal at the medium potential sites (14-16%). Nearly 16% of farmers in Kandeu and 23% of farmers in Linthipe reported crop residue removal, for various purposes. The patterns of residue management are shown in (Figure 3.5).

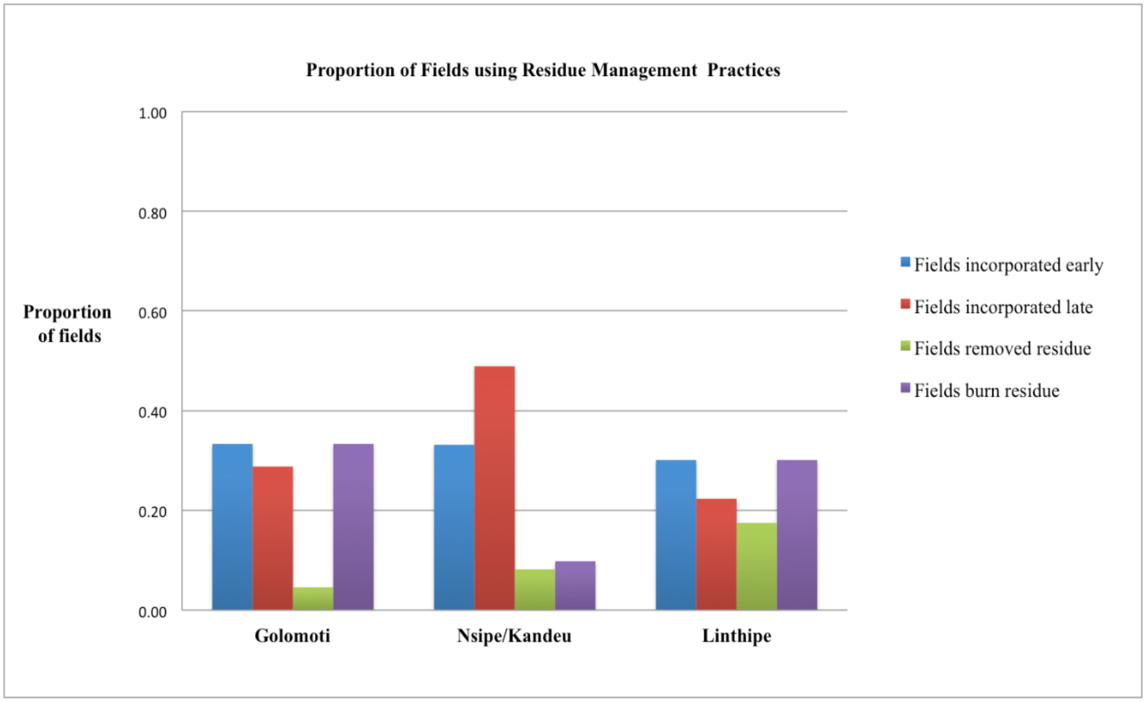

Figure 3.5: The proportion of fields using a specific residue management practice presented in terms of low, medium and high potential sites in Central Malawi. Based on survey conducted July of 2013, field n=600.

Here we see that the proportion of fields with residue incorporation practices is common, compared to removal or burning of residues, which is practiced at all sites but particularly in the medium potential areas. Of those farmers who reported residue removal, some farmers used legume residues for fodder and soil improvement, while a surprisingly number of farmers reported burning legume residues (21%). This compared to maize residues that were rarely removed (5%) or burned (10%). Residues from legume fields were incorporated early about 20% of the time; whereas in maize-based fields (including sole maize and maize-legume intercrops) residues were incorporated early about one-third of the time (Table 3.7).

3.4 Discussion

The household socio-economic characteristics from the 2013 survey suggests scarcity of resources for smallholder farmers across the four EPAs, and relatively large family sizes. The average dependency ratio of 108 observed in the study is higher than the overall average in Malawi which was reported in 2015 as 95 (World Bank, 2016). Farmers are cultivating small size land holdings averaging 0.85 hectares, which includes 1 to 2.4 fields. A modest diversity of crops were grown overall, that included a few dominant crops, notably maize, groundnut, tobacco that were grown regardless of the varied climatic factors (Table 3.2). Farmers also own few livestock relative to the region, but typical of Malawi thus suggesting that there is modest farm diversity in Malawi. This may be a result of the very high poverty, and limited market access.

The rural population in Malawi is increasingly existing on small land parcels, which could be attributed to historical, cultural and political socio-economic disparities. In 2010 GINI coefficient measure of 0.34 for Malawi suggests significant inequalities across the rural population (National Statistical Office of Malawi 2013). This finding is also consistent with neighboring countries such as in Mozambique where rural farmer resource endowment is attributed to land ownership, livestock ownership and historical events that impact the rural populations (Rusinamhodzi et al., 2016). We found significant challenges to promote increased agriculture production relying on intensification alone, as the resource base is, in many cases simply too degraded requiring multiple investments in input resources to support maintenance of production potential.

The characterization of maize-based systems from the Central Malawi action research sites of Africa RISING and nearby villages highlight farmer cropping system choices and investments being made in soil fertility. Generally, agricultural land was characterized as moderately to marginally suitable for production. Soil limits to productivity were compounded by a highly variable climate and topographically driven evapotranspiration that can limit yield potential of crop species not suited to high temperatures and poor water availability (Table 3.1). These biophysical limits to production interact, often unpredictably, with socio-economic elements to affect agricultural production. Classification of agricultural sites based on soil and environmental factors (Figure 3.2) such as soil properties, terrain and precipitation analysis of these external influences to land suitability and gives us a general trend across scales for agricultural productivity in Malawi. Such agricultural land suitability maps could be used to inform agricultural extension workers and researchers across different land classification systems for particular regions and to assist the formulation of different approaches to address different sites and farmer needs.

Overall soil fertility status was marginal, particularly in the climatically risky lakeshore area of Golomoti. This is consistent with earlier findings regarding low soil organic matter and nitrogen availability countrywide on smallholder farms in Malawi (Snapp, 1998) and more broadly in the region (Tully et al., 2015). We found evidence of agricultural intensification practices, in terms of widespread fertilizer use across all sites, with 80% or more of farmers applying fertilizer to one or more fields. Golomoti had the lowest rate of fertilizer use, which may be related to high evapotranspiration and marginal soils at this site, which could increase the risk of unprofitable fertilizer application. Fertilizer use across the sites was in range of the Malawi government recommended N rate for maize (Chirwa et al., 2011).

Our findings suggest significant challenges to agriculture that relies on intensification alone, as the resource base is poor, with degraded soils and farmers have limited labor or land. Access to fertilizers has been enhanced in Malawi through subsidies, but in addition, investments in education and organic resources are required to support production potential being maintained in an increasingly marginal environment. Farmers across the sites were constrained in terms of resources to support use of organic amendments, including limited to nil livestock, and labor limitations (Table 3.2). Animal manure and compost applications was modest on most fields, presumably related to the limited manure resource availability but may have also been due to poor extension contact and labor constraints. Research has shown that Malawian farmers with livestock in the northern region use farmyard manure, and have benefited from incorporating manure into their systems. There appears to be less access to manure for soil fertility improvement in Central Malawi, due to a smaller animal population and greater density of farmers (Kabuli 2006). Additionally, burning of residues is practiced; especially in the Dedza district a third of farmers burn residues according to our findings. Past studies for Malawi show that farmers have a range of reasons for burning residues, including reduced labor requirements relative to land preparation without burning, and in some cases extension messages recommend burning to eradicate pests and weeds (Snapp et al., 2002b). Burning and removal of crop residues reduces organic inputs, which can lead to loss of soil organic matter, an insufficient nitrogen (N) supply, ultimately decreasing soil water holding capacity and crop productivity. There is a considerable evidence base that complementary use of inorganic and organic fertilizer is essential for sustainable management of crop production in Southern Africa (Vanlauwe et al., 2011).

3.4.1 Maize-legume technologies

Over 85% of farmers grew maize intercrops in the 2012-2013 growing season, with about three-quarters of those growing some combination of maize-legume intercrop (Table 3.5). This level of intercropping has been reported previously for the highly populated southern region of Malawi, but not for the central region (Shaxson and Tauer, 1992). Not all maize-legume intercrops have beneficial effects on resource sustainability, as some early maturing and poor nitrogen-fixing cultivars support high removal of nutrients in the form of harvested grain (Giller and Cadisch, 1995). However, the presence of highly vegetative, nitrogen fixing legumes is an important sustainable practice, including many locally grown varieties of pigeonpea, cowpea, soybean and mucuna such as reported here.

A previous Central Malawi survey conducted in the late 1990s found a low proportion of land in legume crops (9% to 28%) and many barriers to legume production (Snapp et al., 2002). Another study in Northern Malawi also found very low proportion of land is allocated to legume crops on smallholder farms (Mhango et al. 2013). Our results indicate a much larger proportion of land in legume crops than that reported in previous studies, notably due to a large area devoted to maize-legume intercrops (Table 3.5). It may be that in the intervening decade that input and output markets have improved, and provided support for legume production. For example, since 2011 the Malawi government has provided smallholder agricultural subsidies that included vouchers for seeds of modern varieties of groundnuts and common bean. However other input factors may have acted as barriers, including a prioritization of maize seed and fertilizer vouchers, and the logistical challenges of government procurement of legume seed that is not available through formal seed markets and biologically is not conducive to rapid multiplication. This led to modest numbers of legume seed vouchers being distributed in most years (Dorward and Chirwa, 2011). The effectiveness of the fertilizer subsidy is reflected in the high levels of fertilizer use observed in this study, with 76 to 93% of farmers applying fertilizer. Farmer access to modest varieties of legumes crops doesn't appear to have been effectively promoted in Central Malawi, and indeed there is evidence of declining legume crop area overall (Chibwana et al. 2012).

A surprising finding was that some farmers were growing combinations of two or more legumes in an intercrop system. This is an uncommon cropping system practice, in contrast to the combination of legume-cereal that is biologically complementary and a widespread practice on smallholder farms in Malawi and elsewhere (Shaxson and Tauer, 1992). Complementarity of legume crops can be achieved through the deliberate combination of early and late growth habits, with shallow versus deep rooting systems, to reduce competition for resources (Snapp and Silim, 2002). However, this doesn't seem to be achieved by the farmer mixtures reported, which involved legumes with similar growth characteristics such as soybean and groundnut.

Maize and legume mixed production systems have the potential of increasing total soil C and N over time (Smith et al. 2016). Results from model simulations of soil C change over time are reported here for three of our sites, where continuous, unfertilized maize was associated with declines over time and maize in rotation with grain legumes maintained or saw modest accrual of soil organic C. For example, Table 3.3 shows that Linthipe's soil organic matter status is initially high, but is vulnerable to decline with removal of large amounts of grain compared to the other sites with lower yield potential. This is a somewhat surprising result indicating the value of crop and soil simulation models (Keating et al., 2003).

Also, legume presence in a maize intercrop has been shown to decrease soil surface exposure, for reduced soil moisture loss, and protection against soil erosion (Locke and Bryson, 1997). There have been reported productivity improvements through incorporating legume residues in other regions (Mureithi et al. 2005), although on-farm studies in Malawi have shown variable results (Snapp et al., 2010). Legume residue practices may be particularly beneficial for sites such as Golomoti that experience high evapotranspiration and Kandeu with intermittent dry conditions. The use of early residue incorporation in this study was highly variable within sites, by field and by crop. It was notably lacking for legume fields (Table 3.5). Further, almost a quarter of farmers burned legume residues, whereas only 10% of farmers burned maize residues. This is surprising given that legume residues have high nutrient content and are of value for livestock feed as well as soil building. This phenomena of legume residue burning has been observed previously in Malawi (Snapp et al., 2002).

Sustainable intensification requires integrated management that combines not only greater production of legumes, but also appropriate residue management and investment of complementary inputs such as fertilizer. As noted in a recent study, there is a paradox in that the poorest farmers may benefit the most from legume production, yet are rarely able to invest in inputs such as rhizobium and phosphorus, that support good legume agronomy (Franke, et al., 2014).

Where extension support and other services are available to Malawi farmers (Table 3.2), as seen in the Linthipe and Nsipe areas, farmers may be able to access information on cropping techniques such as growing 'best bet' legume crops. These have been promoted in Malawi to contribute towards improving sustainability of intensive farming practices, by use of legume crops that combine highly vegetative growth habits with production of grain (Gilbert, 2004; Giller and Cadisch, 1995). However, there appears to have been almost no extension attention to residue management practices, and there is little knowledge of tradeoffs associated with early versus late season residue incorporation (Bezner Kerr et al., 2007).

3.4.2 Policy and Community Partnership

In recent years, Malawi's agricultural input subsidy program has increased access of improved inputs for many smallholder farmers by providing vouchers that enable access to agricultural inputs, primarily modern maize varieties and fertilizer (Dorward and Chirwa, 2011). However, Chirwa et al. (2011) found that farmers of the most marginal agricultural lands received few benefits. Further, there have been no complementary investments in extension education to support sustainable use of inputs, and farmer access to extension services in Malawi remains poor. Increasing returns to rural agricultural investments in Malawi for resource poor farmers is a core goal of the Africa RISING program and related agricultural development initiatives.

Analysis that explores agricultural land suitability across scales, and modeling scenarios on using available agroecological and environmental datasets is advantageous to assist researchers and decision makers to monitor current agricultural practices and to identify knowledge gaps and complementary investments to support sustainable use of resources. We found evidence in this study of an increase in farmers applying fertilizer at recommended doses to maize production fields; compared to earlier studies. However complementary investments in sustainable practices such as applying manure or investing in legume production remains widely neglected. Overall, farmer practices vary widely in terms of manure and crop residue management, and would benefit from extension advice.

3.5 Conclusions

The results from this characterization paper highlight Malawi's smallholder farmer's current practices as constraints and opportunities for developing sustainable intensification of agriculture. Marginalized farmers are at the center of most adoption strategies, working together with scientists and local extension agencies. Sustainable intensification progress for Malawi is challenged by many preconditions, for example; lack of local infrastructure, poor extension and access to inputs, which is financially out of reach for most farmers (Sumberg, 2005). The study illustrates for a range of environmental conditions and local practice the implications for sustainable intensification of agriculture. Crops grown and how soils and crops are managed, particularly crop residues, were found to vary markedly within and across districts. Fertilizer use was fairly widespread, yet variable, which may reflect the effect of not only the Malawi government's investment in subsidies but the disconnect between access and knowledge with only a little over half of farmers receiving contact with extension services.

Sustainable intensification practices such as fertilizer application appear to be widespread, along with legume intercropping and growing maize, both hybrid and local varieties. However, management of organic inputs was inconsistent. Only 20 to 40% of farmers applied organic manure or compost to a field, and residue management of legumes includes some highly unsustainable practices such as burning and removal of residues from the field. Early residue incorporation is important for maximizing soil benefits from residues, and recycling of nutrients, however it was primarily practiced on sole maize plots. This study can serve as a guide for a sustainable trajectory that emphasizes strengthening holistic agricultural development with decision makers and scientists working alongside marginalized farmers. Finally, SI practices for Southern Africa have great potential, yet further work is needed to support improved extension messages and consideration of the wide range of practices needed for sustainable, integrated crop management[10].

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4. QUANTIFYING LAND USE AND LAND COVER CHANGE, AND LANDSCAPE PATTERNS FOR CENTRAL MALAWI

4.1 Introduction

According to the FAO (2016), Africa is second, after Southeast Asia in land cover conversion rates. In Africa forest land cover has been reduced from occupying 23 percent of land to 10 percent. Between 1990 and 2010, approximately 75 million hectares of forest land were converted to subsistence and commercial agricultural (Lambin, Geist and Lepers 2003). In Malawi, land conversation is mainly for agricultural production both subsistence and commercial. The majority of Malawians have smallholder farming systems that are characterized by diverse land tenure systems. Studies show that Malawi's land conversions impacted by processes such as population increased tenure systems, social-economic, environmental and political factors exacerbate land degradation (Frank and Otsuka 2001, Kalipeni 1996).

Land degradation is a historical and ongoing trend in Central Malawi, as in most countries in Sub Saharan Africa. During the colonial period, land management approaches were mainly concerned with protecting Malawi's natural forests and wildlife, not to mention that the land ordinances promoted a land classification system (Kanyongolo 2005). This classification system involved dividing lands into public /state land, private or leased lands that are mostly used for commercial purposes and trust lands where most of the Malawian population would have to practice agriculture (Mulwafu 2011).

Malawian farmers cultivate crops in small land holdings divided between family/village members, where low input resources and the poor farming practice of over cultivation have led to soil degraded and marginal lands (Kishido 2004). Malawi's customary land tenure systems that includes communally and privately owned lands, enables further land cover sub divisions on farm properties to non-contiguous parcels, thus landscape fragmentation increases (Kishindo 2004).

Intensification of agriculture is a well-known solution widely associated with use of resource inputs as fertilizer, improved seed varieties and use of innovative interventions focused on increasing crop yields (Ruiz-Martinez et al., 2015, Morris et al., 2007, Vanlauwe et al., 2014). Malawian smallholder farmers are agents of intensification as they embrace strategies such as new seed cultivars, use of inorganic fertilizers and other improved farming practices for food production (Mungai et al., 2016).

Evaluating intensification processes in complex agricultural system is limited due to few studies, lack of a common framework on how to assess smallholder systems, and also data constraints. Most existing datasets are from field experiments collected at a specific time and thus the longitudinal data necessary for this intrinsically temporal process are lacking. To address these complexities, indicators of anthropogenic changes are quantifiable through Land Use and Land Cover (LULC) change trajectories to derive spatial and temporal patterns from these agricultural landscapes (Lambin, Geist and Lepers 2003). Turner et al., 2007 study gives an overview assessment on Land change science that seeks to understand the dynamics of human-environment systems and LULC. Additionally, Lambin's (2001) synthesis recognizes LULC change causes in different contexts, and the underlying specific human-environment conditions under which socio-economic and biophysical drivers of land change operate.

Landscape spatial structure is the spatial organization of elements with different sizes and shapes and their connections as influenced by human-environment processes (Wang et al., 1999, Risser 1987). Spatial structures found in agricultural landscapes may suggest differences in underlying processes and functions overtime (Crews-Meyer 2004). For example, increase or loss of spatial structure through the landscape transitions can be linked to farming activities due to land conversion and/or restoration through use of good farming practices (Yesuph and Dagnew 2019). This phenomenon is seen in smallholder farming for its heterogeneous patterns suggest ongoing interactions of multifunctional processes that are a result of landscape conversion or restoration (Turner 1990).

4.1.1 The knowledge gap

There is a research gap in understanding patterns of intensification of agriculture in heterogeneous smallholder farming systems as found in Sub Saharan Africa for resilience to short- or long-term shocks. The primary gap is the lack of spatial-temporal indicators that link intensification of agriculture patterns and processes across scales. Knowledge of spatial-temporal patterns of the agricultural intensification can improve scientists understanding of the farmers' environment and what processes are impacting sustainable food production.

Several studies show that long term assessment of land use and land cover is best captured using satellite datasets, such as a regional scale mapping of cropland area across Africa (e.g., Vancutsem et al., 2013), and that land use and land cover repository information of regional forest cover, agriculture, and urban settlements is invaluable for understanding inter-connected issues such as deforestation and climate change (Haack 2015). Other specific studies used scenario analysis to assess impacts of human activities, such as on a forest reserve in Lilongwe, Malawi (Munthali and Murayama 2011), quantified agricultural land conversion to settlement areas (Munthali et al., 2020), and land cover change temporal analysis in Upper Shire river catchment areas in Malawi (Palamuleni et al., 2011). The study objectives are (a)Test the scalability of the land use patterns as scale dependent phenomenon, (b) Identify land use patterns that are indicators of intensifying agriculture. And (c) Link the patterns to social process.

4.1.2 Theoretical Framework

Two frameworks used to address the research questions, scale-pattern-process and human-environment. Scale-pattern-process framework aids our understanding of landscape as a spatial organization of elements with complex interactions, and of spatio-temporal nature (Walsh et al., 1998, Crews and Walsh 2009). The interaction is based on complex processes and functions seen at different scales in the landscape, and the patterns of potential agriculture intensification are seen by analyzing the landscape over time and scale (Huang et al., 2017). The Human-Environment framework is used to assess the relationship between environmental, physical, social-cultural structures that have a feedback mechanism, that emerges in the scale, pattern and process analysis. These frameworks guide our understanding of Central Malawian farming systems in a changing landscape (Turner 1989, Messina and Walsh 2005, Irvine 2013).

This study addresses the following questions:

Question 1a. What are the land use patterns of Malawi?

Question 1b. Where and at what scales do patterns that are indicators of intensifying agriculture emerge across Central Malawi?

> **Hypothesis**: Different scales determine where proxies of indicators of intensifying agriculture patterns are found.
>
> **Hypothesis**: Patterns of indicators of intensifying agriculture vary across scales

Question 2: How does spatial structure of intensifying agriculture vary across space and time?

Assumption: Process is a combination of pattern and function across time and space.

Assumption: Spatial structure is driven by indicators reflected as processes/functions and thus patterns are scale dependent

Hypothesis: Farm scale spatial structure is a significant driver of productivity

4.2 Study Area

This study takes place in two districts – Dedza and Ntcheu - in Central Malawi (Figure 4.1). These two districts have four study sites (Linthipe, Golomoti, Kandeu and Nsipe) under the Africa Research in Sustainable Intensification for the Next Generation (Africa RISING) project, which aimed to improve food productivity potential and farmer livelihoods in maize-mixed farming systems.

Dedza district is located approximately 50 miles, south-east of Lilongwe, the capital city of Malawi (malawiproject.org). According to Malawi National Statistics Office (NSO), in 2018 the population of Dedza is approximately 840,000, with 221.2 persons per Square Kilometer (Km^2) and mostly comprises smallholder farmers. Crops grown include maize, cassava, sorghum, millet, rice and sweet potatoes, and also some farmers maintain small herds of goats, pigs, cattle and poultry. The elevation of Dedza ranges from 500m to 1600m. The mean annual temperature is 18 Celsius; mean annual precipitation is 896 mm (NSO 2008).

Ntcheu district, population 660,000, with 202.9 persons per Square Kilometer (Km^2), and is similar to Dedza but has greater variety of farming activities. Crops grown include maize, common beans, soy bean, cow peas, groundnuts, sorghum, tobacco, millet, cow pigeon pea, sweet potato and cassava. Many families also depend on the land for livestock, firewood collection and charcoal production. Ntcheu elevation range is similar to Dedza's 550m to 1,500, with few areas that have steep slopes, unlike Dedza. The mean temperature and precipitation is similar to Dedza.

Dedza and Ntcheu districts both have trading centers with weekly farmers' markets. Additionally, the districts have some paved roads connecting each district to Lilongwe. Villages have developed along the major and minor roads (M1, M5, M10), the majority of farming communities are located in rural areas. Locally, farmers can have one or multiple fields that average range approximately 0.84 to 2.50 hectares; however, across the two districts, farm sizes in Ntcheu are larger, with heterogeneous landscapes comprising natural vegetation, grasslands and forests.

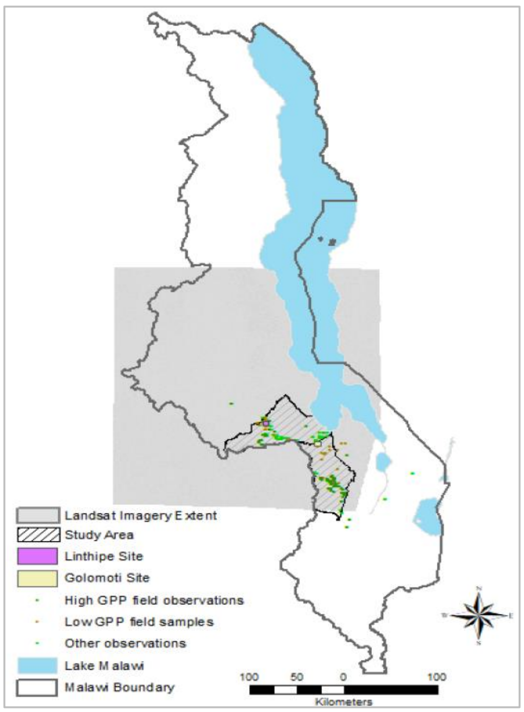


Figure 4.1: Landsat imageries 2014, 2017, 2019 (imagery covers Central and Northern parts of Malawi), Image clipped to study area

4.3 Data

In this study, remote sensing imagery and field observation datasets are used. Given that the geographic location of Malawi is predisposed to excessive cloud cover, especially during growing season period (November to April), cloud-cover free satellite imagery sufficient to cover the entire study site is selected. Four sets of Landsat 8 Operational Land Imager (OLI) and the Thermal

Infrared Sensor (TIRS) sensor Surface Reflectance Tier 1 from United States Geological Survey (USGS) were selected.

Landsat imagery collection from November to May (growing season) were stacked, and thus each stack represented growing seasons for 2014, 2017 and 2019. The 2015/2016 imagery years were omitted from our dataset due to the anomalous drought effects of the El Nino rains experienced across Malawi. Secondly, fine spatial resolution imagery sourced from Digital Globe Foundation; from GeoEye-1, 5-meter (2014) for Golomoti site, a Worldview 2 imagery 2-meter resolution (2017) for Linthipe site, and a coarse 250-meter Moderate Resolution Imaging Spectroradiometer (MODIS) NDVI imagery were acquired for spatial scalability tests. NDVI is Normalized Difference Vegetation Index that is calculated as (NIR-Red/NIR+Red) function. The satellite imageries were atmospherically corrected and radiometrically calibrated from the source.

4.3.1 Ground Truthing Data

To prepare the ground truthing field work to obtain data that will be used to validate the LULC, sample points are extrapolated from 500m by 500m MODIS mean Gross Primary Productivity (GPP) time series dataset (2000-2017) for maize crop growing season in our study area. There were a total of 200 random samples within Dedza and Ntcheu districts and a set of 100 outside the study area.

We used the Jenks natural breaks classification to classify the GPP values into five classes, then further reclassified into two classes; high and low GPP pixel values as the agricultural land classes found within our study area. Our initial analysis showed less GPP variability within the EPA sites which were mainly low GPP values. Due to this, we adjusted the sample size by including samples outside the EPA sites but within the study area to ensure that the GPP pixel values were balanced between the low and the high GPP points. Additionally, geographic latitude and longitude locations of these random pixels were extracted in ArcGIS.

Field ground truthing was carried out over Summer 2018 across the four Extension Planning Areas (EPAs) sites- Linthipe, Golomoti, Kandeu and Nsipe and surrounding areas of Dedza and Ntcheu district covering a 200km (124.3mi), (Figure 4.2). The field observed points were collected within the 500m by 500m GPP grid, where accessible. Approximate locations points were recorded as close as possible where land was inaccessible. Over ninety field samples with high GPP and fifty field samples with low GPP were recorded using Geographic Positioning System (GPS) and geotagged field photographs captured the existing land use-cover taken in this dry season, were all recorded in a field logbook. Field samples are used in the analysis stage to aid in identifying features /land classes in land use and land classification section below.

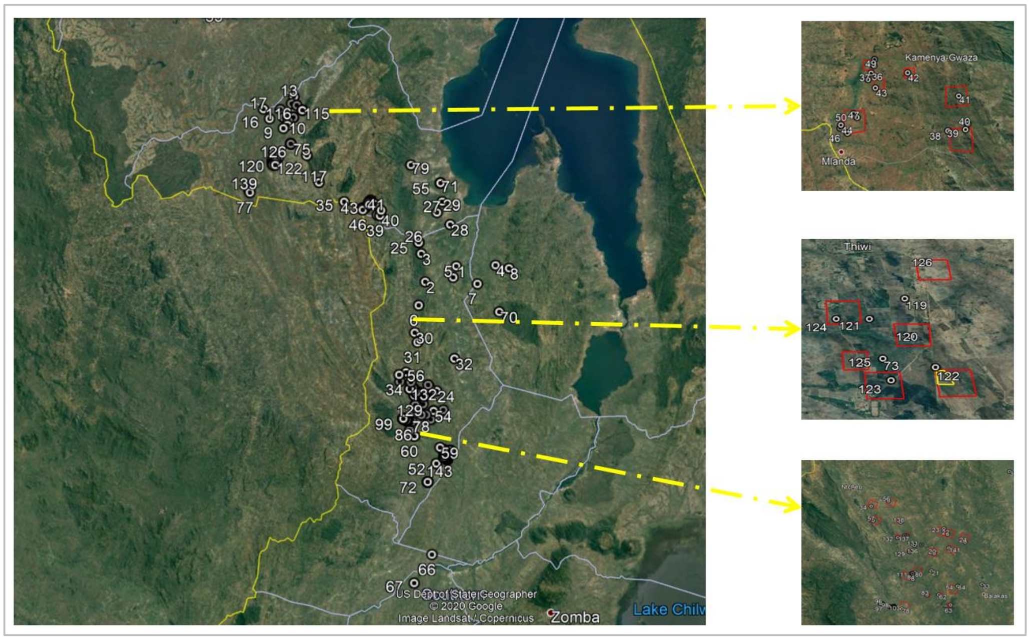


Figure 4.2: Ground truthing samples collected in June 2018 in Dedza and Ntcheu Districts.

4.4 Method

Below Figure 4.3 shows the logical flow processes of the methodology to address the three objectives that we mentioned above.

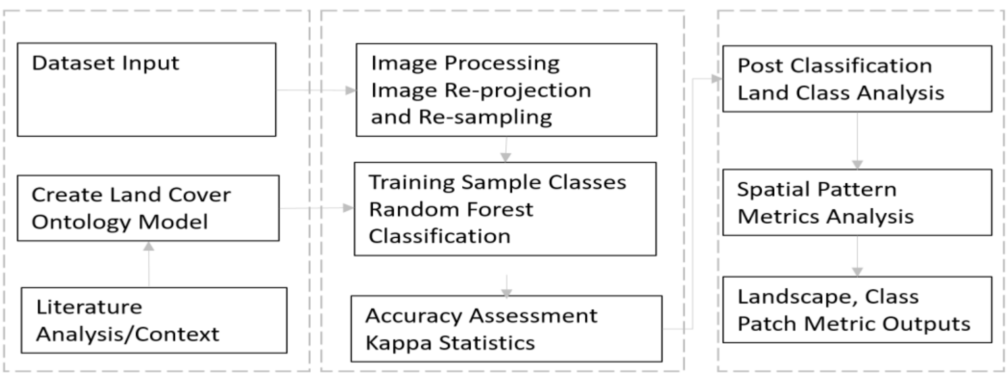


Figure 4.3: Logical Flow of Methodology (adapted from Gu et al., 2017)

4.4.1 Test the Scalability of patterns

To test for spatial scalability, we hypothesize that pixel aggregation can be used to scale patterns observed by fine spatial resolution satellite imagery to coarse spatial resolution imagery. First, we set a boundary of the imagery to 6 Km^2 for our two study sites - Linthipe and Golomoti. Secondly, each image is rescaled using the nearest neighbor resampling algorithm; (a)Linthipe's 2-meter resolution is rescaled to 30 meter), while Golomoti site's 5-meter resolution to 30meters (Figure 4.4 and 4.5), (Goodin and Henebry 2002). Thirdly, on both the original and rescaled imagery, we select 150 training samples from each imagery on google earth engine, and run Random Forest algorithm for supervised classification (Breiman 1999).

Random Forest (RF) machine learning classifier algorithm uses a dynamic ensemble of decision trees to define a class based two techniques; bagging – used to generate the training dataset randomly and random selection with replacement that classifies pixels by voting the popular class from all the tree predictors in the forest (Breiman 1999, 2001). RF was selected as it is straight forward where the user is able to modify (a) the number of trees to grow, and (b) number of randomly selected attributes at each node (Ghimire, Rogan and Miller (2010). RF is beneficial as it handles categorical and unbalanced datasets and is fast and stable (Pal 2005). For this study, we acquired 500 training samples on the land cover in the study area selected from high spatial resolution imagery on google earth with a minimum of 50 training samples for each land cover (Congalton 1991).

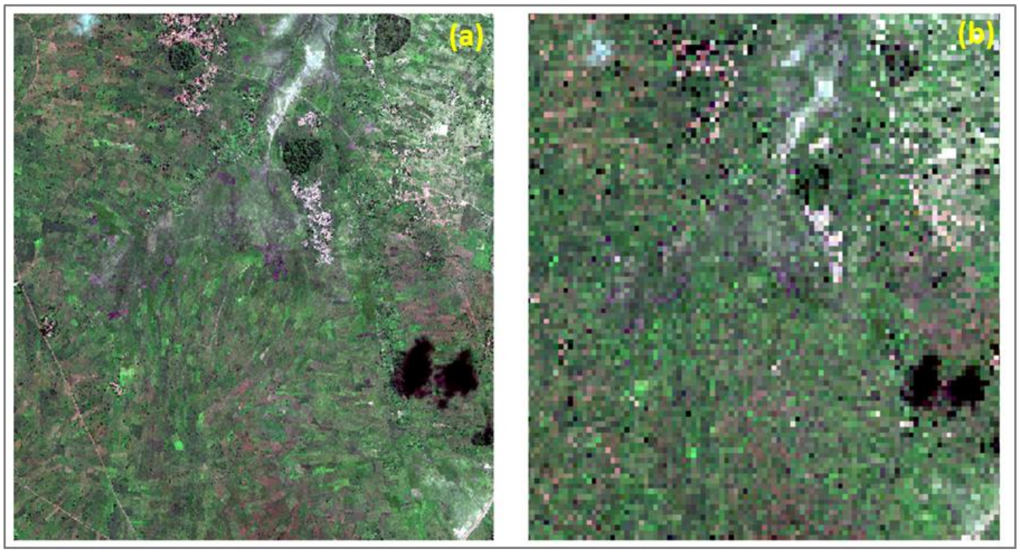


Figure 4.4: Linthipe site – (a) Original imagery, 2m resolution, and (b) rescaled 30m imagery.

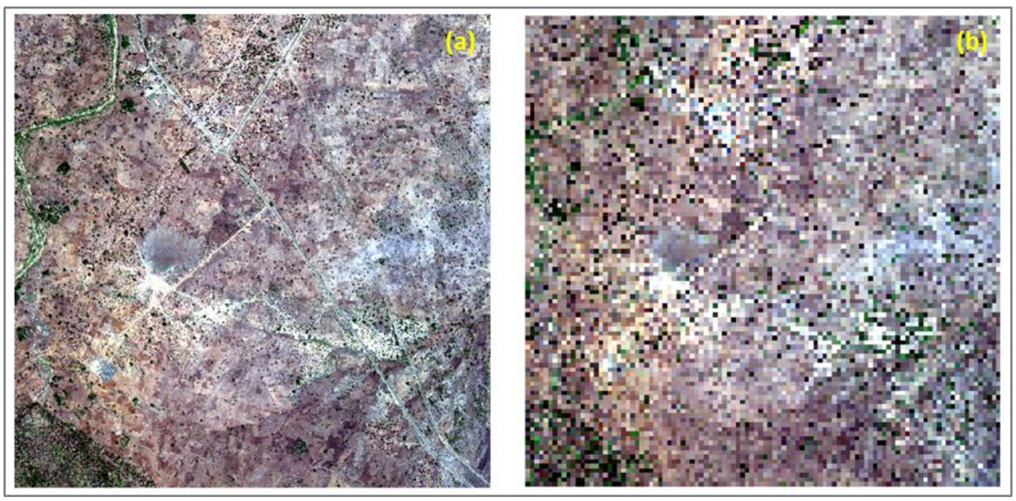


Figure 4.5: Golomoti site (a) Original imagery, 5m resolution, and (b) rescaled 30m imagery.

Also, we test the spatial dependency using NDVI values extracted from Landsat 8, 30 meter and MODIS NDVI, 250-meter image data. Landsat NDVI/MODIS NDVI common site area was selected from the least cloudy location for both images (Figure 4.6), (Chen and Henebry 2009). The Landsat 8 original image of 30m resolution was resampled to 250m. This Landsat 250-meter image was to be compared with the re-projected MODIS NDVI 250m (i.e., UTM projection) (Feng et al, 2012, Chen and Henebry 2009).

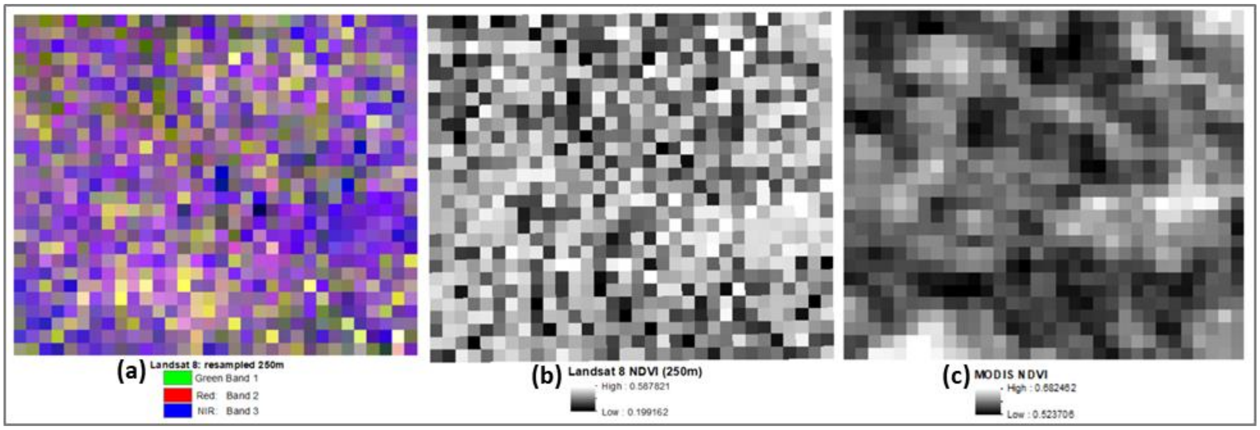


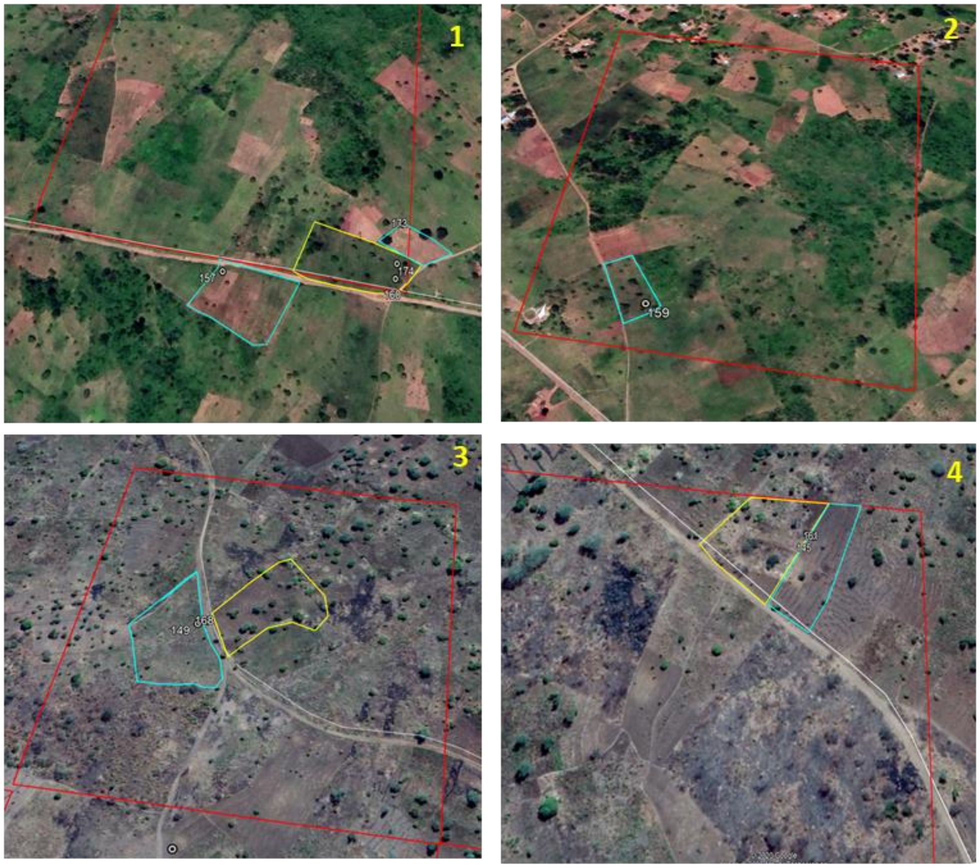
Figure 4.6: (a). Modis –Landsat 8 overlay (Modis in grey in the background, Landsat in yellow-pink-blue color), (b): Landsat NDVI, (c.). MODIS NDVI

To examine the spatial structure of the resampled imagery above, we use kriging and semi-variograms to estimate the resampled imagery and examine the variance in the spatial structure. A spherical model is fitted on the dataset to describe the semi-variance (Oliver and Webster 1990, Goodin and Henebry 2002). Simple kriging assumes stationarity; expecting the mean and distribution to remain constant across a region; the semi-variograms characterize the spatial structure of the original imagery and the rescaled imagery using spatial structure metrics (sill, nugget and range) (Oliver and Webster 1990, Goodin and Henebry 2002). Overall changes in scale affects the spatial autocorrelation between observations in the landscape, therefore relevant scales should be considered for measuring landscape patterns (Karl and Maurer 2010).

4.4.2 Land Use Land Cover Classification

Smallholder farming landscape in Central Malawi was observed to have diverse agricultural landscapes based on the: ground truth” field data collection. The sample points based on the low-high GPP values described in the data section show real features unique to Malawian landscapes. For example, in the field observations we are able to have a clear distinction that high GPP values were diversity areas such as agroforestry fields, and fields with diverse vegetation cover, while low GPP areas were mostly cleared, actively cultivated fields with less vegetation cover.

To determine agroforestry, and mixed /cultivated/bare fields, methods using remote sensing, photo interpretation and Google Earth Explorer. GPS reference points collected for each field during June 2018 are overlaid in Google Earth Explorer – June 2018 Landsat Imagery. Using 1km x1km grids the GPS points represent sites that show field composition, with trees presence, absence, or hedge row trees. Fields that have several trees or trees as hedge rows (boundaries) are observed and trees inside the fields counted (Chiocchine 2018, Coulibaly et al., 2017). Agroforestry fields have tree count from 5 and more, compared with the adjacent fields that are cultivated or mixed fields with no trees in sight or shrubs or less than 5 trees (Figure 4.7).



1.Mixed /cultivated field no.157 and no.173, Agroforestry >5 trees: no.174.
2.Agroforestry > 5 trees: no.159
3.Agroforestry >5 trees: no.168, Mixed /cultivated fields: no.149
4. Mixed /cultivated fields: no.145, Agroforestry>5trees:no.161

Figure 4.7: Examples of land use classes derived from field observations.

We developed a database to record these field observations and used photographs to document off season types of agricultural landscapes. We then used the field observation to improve land classification types for Dedza and Ntcheu districts (Figure 4.8), and this information was used to aid in identifying land class in the remote sensing analysis.

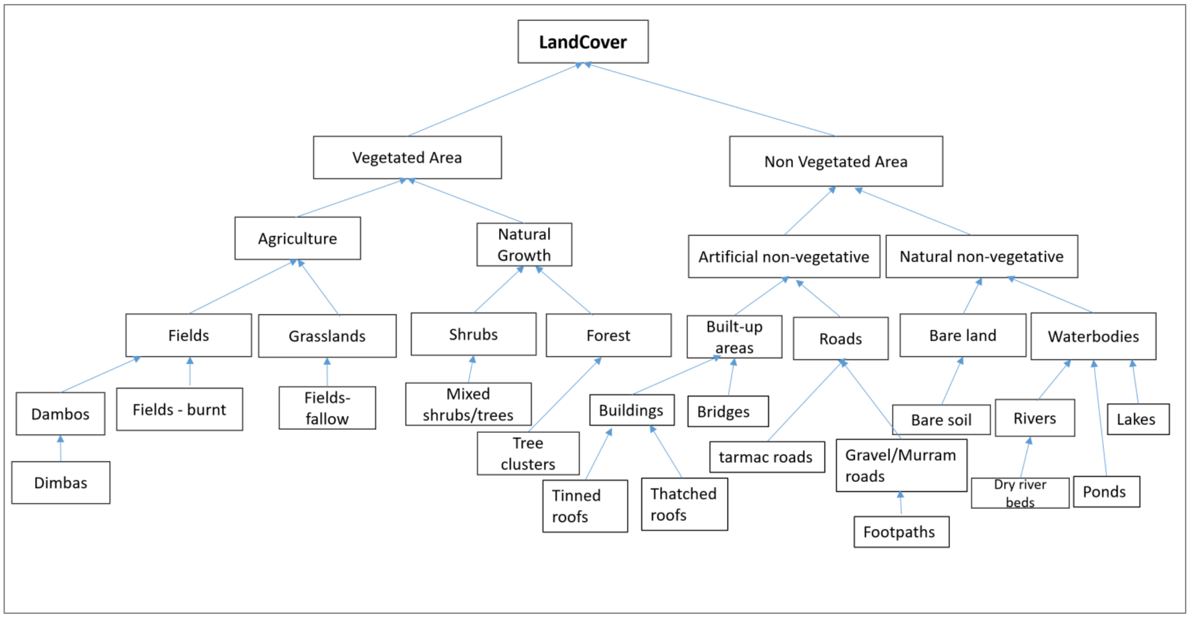


Figure 4.8: Land Cover ontology (adapted from Gu et al., 2017).

For the LULC analysis, the Landsat 8 dataset was used to derive the 500 samples on the land cover from each imagery stack; 2014, 2017, 2019. A minimum of 50 training samples for each land cover was extracted as the recommended rule (Congalton 1991). The training samples were fed to the RF algorithm for a supervised classification in Google Earth Engine, we set 80% as training data and 20% of the training samples for the accuracy assessment. The same RF algorithm settings were used to for the 2014, 2017 and 2019 imagery.

Seven LULC classes were identified from the land classification; mixed fields, water, agroforestry fields, bare fields, settlement, shrubs/forest and suspended sediments/shallow water (Table 4.1). Lastly, a simple image analysis approach was used on the post classification imagery to detect land use transitions between 2014 and 2019 in Dedza and Ntcheu districts (Zewdie and Csaplovics 2016). Statistical summary tables were generated and the classified area (in hectares) was measured by multiplying the number of pixels from the post classification and by the pixel's area in hectares (30m x 30m = 0.09ha).

Table 4.1: Land class definitions adopted from Zewdie and Csaplovics 2016.

Land Cover Class	Description
Mixed fields*	Cultivated land, crop fields
Water	Lakes, rivers, streams, reservoirs
Agroforestry fields*	Fields that have more tree cover based on trees counted per field grid
Bare fields*	Recently cultivated fields
Settlement	Villages, all weather roads, town centers
Shrubs/forest	Shrubs, woodland, dense trees
Suspended sediments/shallow water	Ponds, surface water on marshy swamps
Shrubs	Scattered or thick woodland
Field edges/shrubs	Boundary vegetation on the fields
Other	bare rock, unmanageable areas, not covered any defined categories
Cultivated dambo	Low-lying cultivated areas where the water table is high
Shadows	Shadows or clouds captured in the imagery
Impervious/built up	Built-up areas as villages, all weather roads, town centers
Tree clusters	Scared groves used for cultural purposes.

*See example of land classes from photos taken from field observations in Figure A4.1–in Appendix section

4.4.3 Extract and Measure Landscape Patterns

Spatial pattern is evaluated using a set of pattern metrics that is a combination of patch, class and landscape metrics to quantify landscape patterns from the categorical LULC classes derived above (Table 4.1), (Frohn 1997, Linh Erasmi, Kappas 2012). Categorical LULC classes characterize the composition and spatial configuration of landscape mosaics, assist to identify patches that are generally homogeneous and have relatively abrupt transition to adjacent areas (Gustafson 1998, McGarigal 2014). We used FRAGSTATS version 4.2 software to compute the pattern metrics at a patch, class and landscape levels (McGarigal, Cushman & Ene 2012).

In this section, our interpretations of scale-pattern-process will be constrained by landscape definition. We use the Crews-Meyer (2004) study definition of landscape as a spatial scale using 30m x 30m pixel grain that is the smallest unit of study/observation, similar to a quadrat. Thus we use the 30m by 30m pixel as our unit of observation, and the extent is the district administrative boundary for Dedza and Ntcheu districts. We assume that a landscape is a hierarchical representation that contains smaller units such as patches, and can be aggregated based on the scale of inquiry (Crews-Meyer 2004). Table 4.2 lists the descriptions of the landscape patterns metrics that will be used in the section below.

Table 4.2: Landscape patterns metrics description (adapted from McGarigal 2002,Linh Erasmi, Kappas 2012)

Index (unit)	**Description**
PLAND	Percentage of Landscape
CA	Class Area (ha)
NP	Number of patches in the class
LPI%	The percentage of the landscape comprised by the largest patch
AREA_MN	Average size of patches
SHAPE_MN(ha)	Mean patch shape complexity weighted by patch area, based on shortest edge to edge distance
PROX_MN (m)	Mean proximity index for all patches in a class
ENN_MN(m)	Mean Euclidean nearest neighbor distance
IJI (%)	Interspersion and juxtaposition index measures the juxtaposition of a focal patch class with all other classes (the extent to which patch types are interspersed).
SHDI	Shannon's diversity index is amount of patch per individual. Used for comparing different landscapes or same landscape to different times
SHEI	Shannon's evenness index is the observed level of diversity divided by the maximum possible diversity for a given patch richness

4.5 Results

4.5.1 Scalability Test Results

The summary statistics on the rescaling of original imagery and rescaled imagery are displayed on the Tables 4.3 to 4.5 below. From the summaries below, there are not significant differences in spatial variance between the observed and rescaled imagery here, however we note that rescaled imagery in all outputs have slightly smaller means and variance.

Table 4.3: Summary of overall training accuracy for both original and rescaled Linthipe and Golomoti Sites.

Overall Training overall accuracy and Kappa Coefficient			
Linthipe 2017	**Resolution (m)**	**Training Accuracy**	**Kappa Coefficient**
Original	2	0.897959	0.861057
Rescaled	30	0.848802	0.793318
Golomoti 2019	**Resolution (m)**	**Training Accuracy**	**Kappa Coefficient**
Original image	**5**	0.855263	0.807530
Rescaled	30	0.693140	0.623044

Table 4.4: Summary statistics for Land classification for both Linthipe and Golomoti sites - original Image and rescaled images.

Summary Statistics for measure and rescaled image sets - classifications						
Linthipe 2017	**Resolution (m)**	**Min (classes)**	**Max**	**Mean**	**SD**	**CV(%)**
Original image	2	1.0000	8.0000	4.2934	2.0503	4.16415
Rescaled	30	1.0000	7.0000	3.7854	1.5140	2.27046
Golomoti 2019	**Resolution (m)**	**Min (classes)**	**Max**	**Mean**	**SD**	**CV(%)**
Original image	5	1.0000	7.0000	4.9514	10.1087	100.66022
Rescaled	30	1.0000	7.0000	4.6049	9.0094	79.95784

Table 4.5: Summary statistics for Landsat 8 original 30m, and Rescaled Landsat to 250m NDVI compared with MODIS NDVI 250 meters.

Summary Statistics: MODIS NDVI, Landsat NDVI 30m, and rescaled 250m						
Landsat 8	**Resolution (m)**	**Min**	**Max**	**Mean**	**SD**	**CV(%)**
Landsat 8	30	0.1421	0.5946	0.4126	0.0827	0.00670
Landsat 8	250	0.1992	0.5878	0.4131	0.0787	-0.12609
MODIS NDVI*	250	0.5237	0.6825	0.5899	0.0260	-0.25109
*calculated with the sensor's narrow bands, and thus NDVI values appear higher than calculated Landsat NDVI values						

Figure 4.9 and 4.10 below, show the LULC classifications of the landscape. In Linthipe site, we note that rescaled imagery drops the cultivated dambo class (described in Table 4.1) that

suggests that scale increases, observations in the landscape become more homogenous and are not easily differentiated. Golomoti site's LULC classifications remains unchanged despite rescaling of the imagery.

4.5.2 Supervised classification

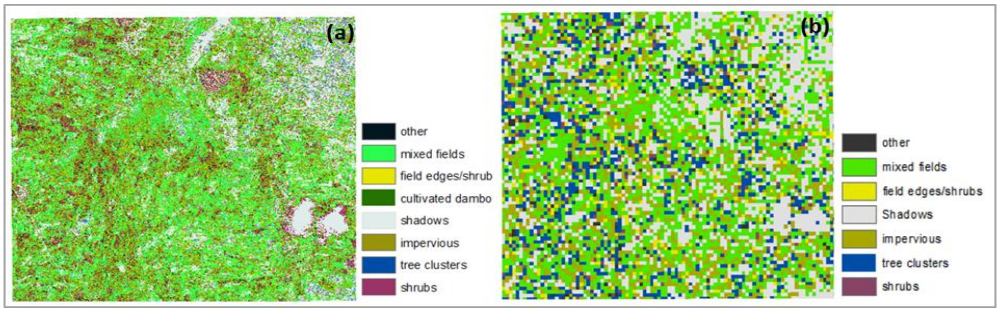


Figure 4.9: Land classification: Linthipe- (a) Original 2m resolution and (b) Rescaled to 30m

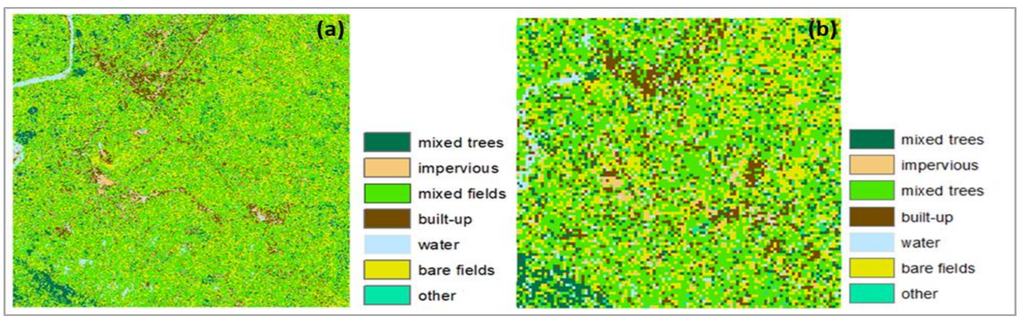


Figure 4.10: Land classification for (a) Golomoti 5m resolution (b) Golomoti – 30 m rescale

Observed and rescaled imagery differences in spatial structure seen in Figures 4.11 to 4.16 using semi-variograms. The semi-variograms display the distance between points in the x-axis, and y-axis is the variance between two sample locations, while prediction maps show the predictions of our model for original and rescaled imagery. The rescaling test affirms the Tobler law of geography (spatial autocorrelation) that closer things are more alike than things farther apart (Tobler 2004), thus complexity exists in determining landscape spatial structure as it is scale dependent. We identify that original observations are not preserved as spatial structure is observed in the rescaled imagery, thus slight differences in spatial aggregation may influence the outcome and thus our interpretations should be taken with this caveat in mind.

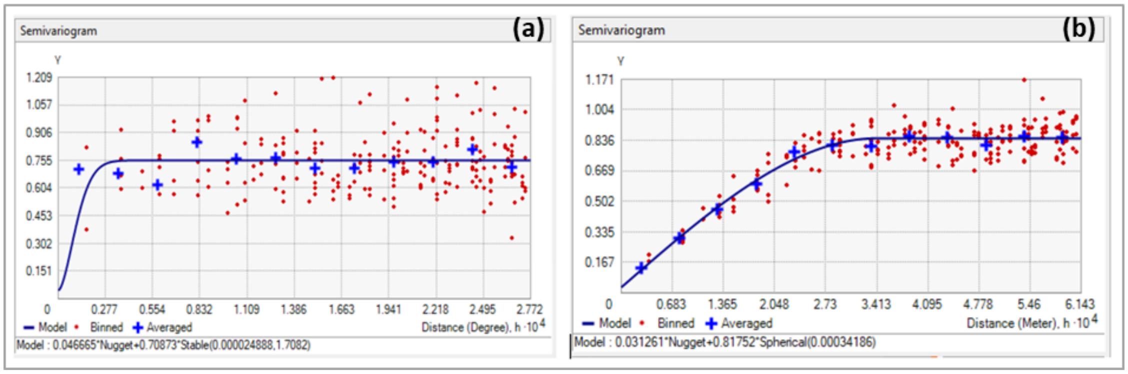


Figure 4.11: (a) Linthipe 2 meters – original, (b) Linthipe 30m rescaled.

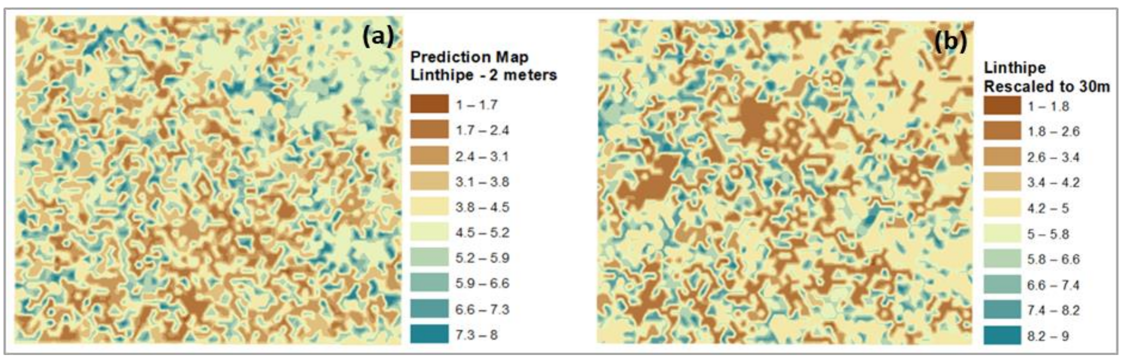


Figure 4.12: Linthipe- (a) Original 2m resolution and (b) Rescaled to 30m.

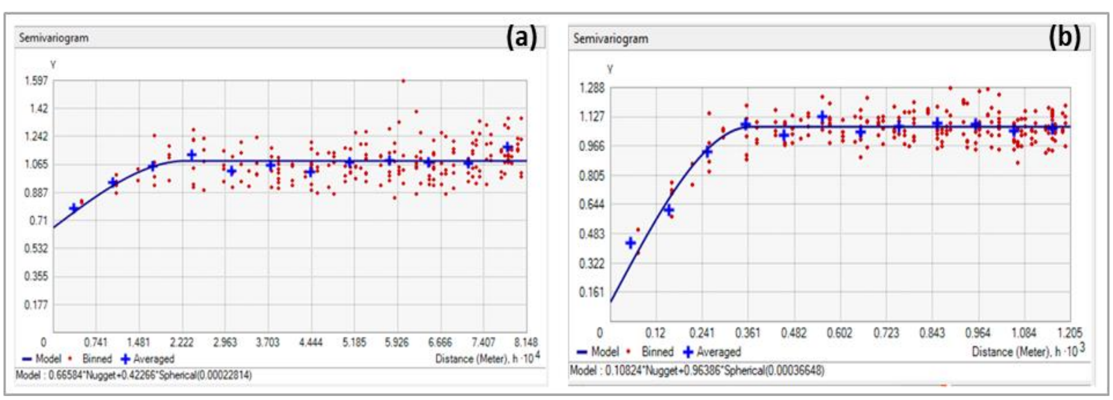


Figure 4.13: (a) Golomoti original 5 meters’ resolution, (b) Golomoti 30m rescaled to 30meter.

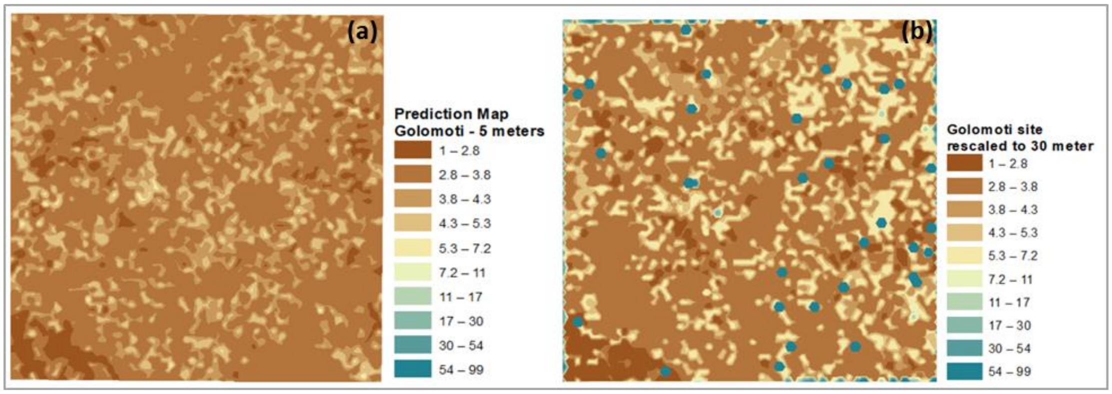


Figure 4.14: Golomoti (a) Original 5m resolution and (b) Rescaled to 30m.

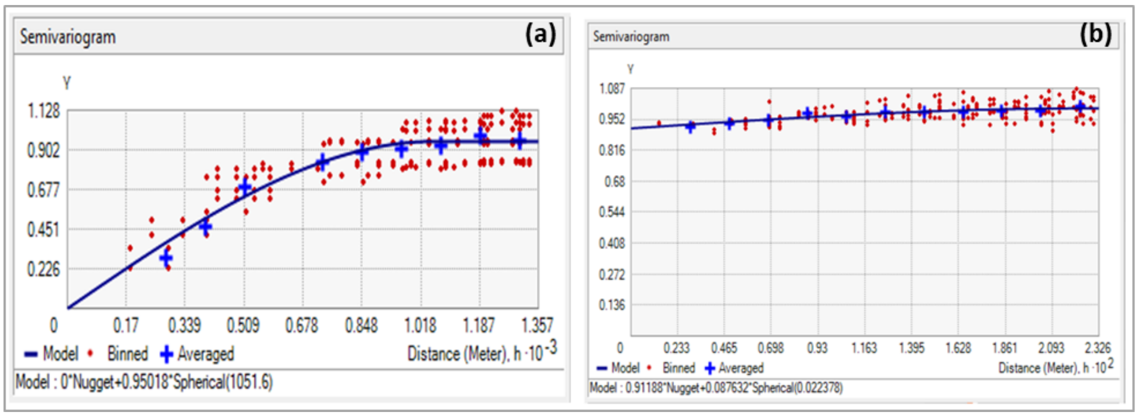


Figure 4.15: (a) MODIS NDVI (250m) original (b) Landsat rescaled to 250m.

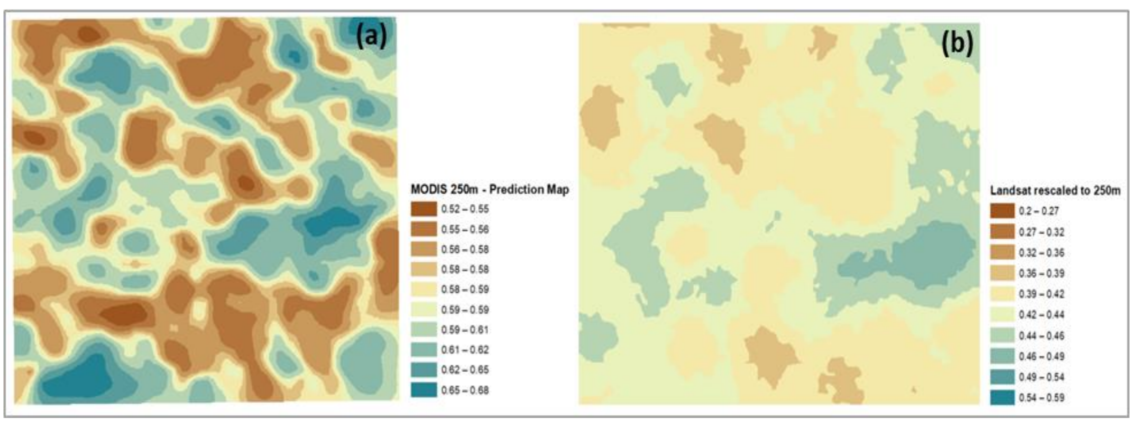


Figure 4.16: MODIS NDVI (a) Original 250m resolution and (b) Rescaled Landsat NDVI from 30m to 250m.

4.5.3. Accuracy Assessment for Random Forest Classification

The random forest performance was evaluated from the resulting accuracy assessments, confusion matrix, and kappa coefficient for 2014, 2017 and 2019 Landsat imagery classifications (Stehman 1997, Lewis and Brown 2001).

Table 4.6 – 4.8 show the overall accuracy assessment for Landsat 2014, 2017, and 2019 was 90%, 90%, and 92% respectively. Kappa coefficient was 83%, 86% and 87% respectively. The producer's accuracy shows the percentage of pixels that were correctly classified in each class (column), while the user's accuracy shows the percentage of correctly classified pixels that each class (rows). In 2014, the producer's and User's accuracy showed great accuracy, while in 2017 producer's and user's accuracy were moderately acceptable within the 80 – 95% range, however unlike 2014, the settlement and water classes had a greater omission error were 64%, and 62%, this could be due to pixels mixing especially due to settlement areas also include hatched houses (using dry vegetation as rooftops), while water class may also include shadows.

In 2019 the producer's and user accuracy are within the overall acceptable range, and show a higher percentage of pixels correctly classified. Several issues that may have contributed to the relatively high errors of omission seasonal variations in the imagery that contribute to errors in pixel mismatches in the confusion matrix and our choice of using Random sampling strategy may also contribute to the varying inclusion (error of commission) of pixel classifications), but more likely to reduce the effects (Campbell 1981). Overall, the accuracy assessment and the Kappa coefficient has a strong level of agreement and is in line with assessment of classification at 85 percent accuracy for satellite-derived LULC imagery (Anderson, et al., 1976, Congalton 1991).

Table 4.6: Confusion matrix for 2014 classification.

	Landsat 2014 - Reference Data								
	Mixed fields	Water	Agroforestry fields	Bare fields	Settlement	Shrubs/forest	Shallow water	Row Total	User's Accuracy (%)
Mixed fields	148039	582	2213	3316	463	4470	10	**159093**	93
Water	565	7497	340	20	8	357	8	**8795**	85
Agroforestry fields	2067	358	20951	52	227	1799	17	**25471**	82
Bare fields	3147	32	23	10349	23	72	0	**13646**	75
Settlement	520	9	181	17	4528	927	2	**6184**	73
Shrubs/forest	4546	296	1829	69	927	56585	7	**64259**	88
Shallow water	26	22	8	0	0	4	5343	**5403**	99
Total column	**158910**	**8796**	**25545**	**13823**	**6176**	**64214**	**5387**	**282851**	
Producer's Accuracy (%)	93	85	82	75	73	88	99		
Overall accuracy (%)	90								
Kappa	83								

Table 4.7: Confusion matrix for 2017 classification.

	Landsat 2017 - Reference Data								
	Mixed fields	Water	Agroforestry fields	Bare fields	Settlement	Shrubs/forest	Shallow water	Row Total	User's Accuracy (%)
Mixed fields	73137	38	223	1491	177	2987	181	**78234**	93
Water	20	192	4	69	3	10	4	**302**	60
Agroforestry fields	230	1	1983	14	2	226	0	**2456**	79
Bare fields	1300	71	3	9500	40	204	50	**11168**	83
Settlement	142	8	0	35	462	96	2	**745**	60
Shrubs/forest	3019	9	286	265	87	43674	35	**47375**	92
Shallow water	184	1	2	25	4	23	4693	**4932**	94
Total column	**78032**	**320**	**2501**	**11399**	**775**	**47220**	**4965**	**145212**	
Producer's Accuracy (%)	93	64	81	85	62	92	95		
Overall accuracy (%)	92								
Kappa	86								

Table 4.8: Confusion matrix for 2019 classification.

	Landsat 2019 - Reference Data								
	Mixed fields	Water	Agroforestry fields	Bare fields	Settlement	Shrubs/forest	Shallow water	Row Total	User's Accuracy (%)
Mixed fields	73234	35	214	1626	128	2970	27	**78234**	94
Water	15	233	5	47	0	2	0	**302**	64
Agroforestry fields	281	4	2919	2	16	206	2	**3430**	86
Bare fields	1530	77	7	9362	24	166	2	**11168**	83
Settlement	115	2	10	37	495	86	0	**745**	65
Shrubs/forest	2974	12	252	187	89	43861	0	**47375**	92
Shallow water	31	2	6	13	6	7	4871	**4936**	99
Total column	**78180**	**365**	**3413**	**11274**	**758**	**47298**	**4902**	**146190**	
Producer's Accuracy (%)	94	77	85	83	66	92	98		
Overall accuracy (%)	92								
Kappa	87								

4.5.4 Spatial patterns of land use land cover

Figure 4.17 shows the land classification results from Landsat 2014, 2017 and 2019, for Dedza and Ntcheu, while Figure 4.18, shows the land classification of each administrative boundary. There are seven land classes displayed as mixed fields, water, agroforestry fields, bare fields, settlement, Shrubs/forests and suspended sediments/shallow water. These land classes are further elaborated in the Figure 4.19-4. 20, Tables 4.9 to 4.11.

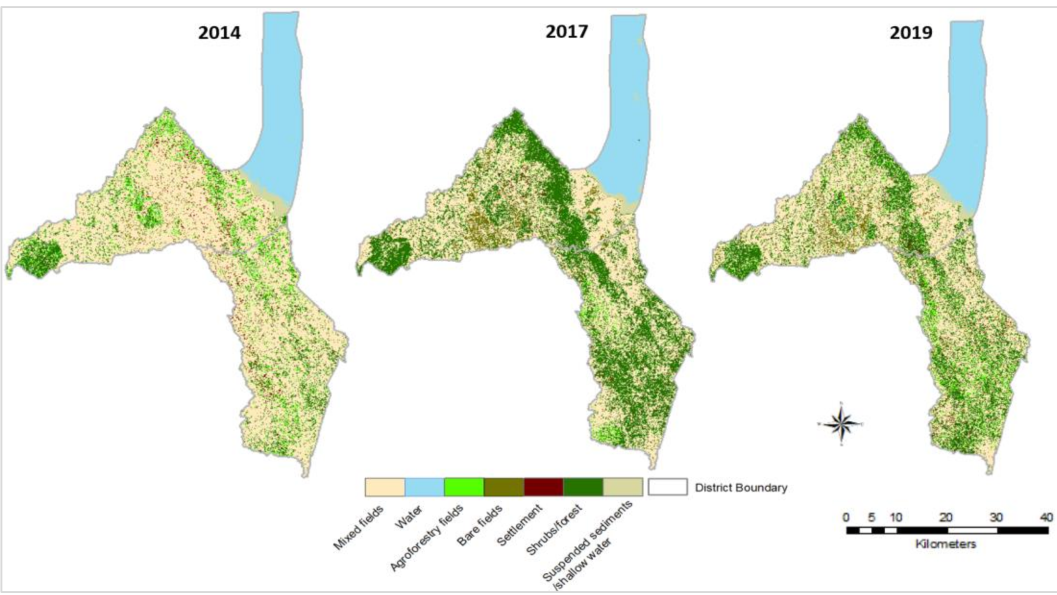


Figure 4.17: Land Use / Cover for Two Districts 2014 – 2019.

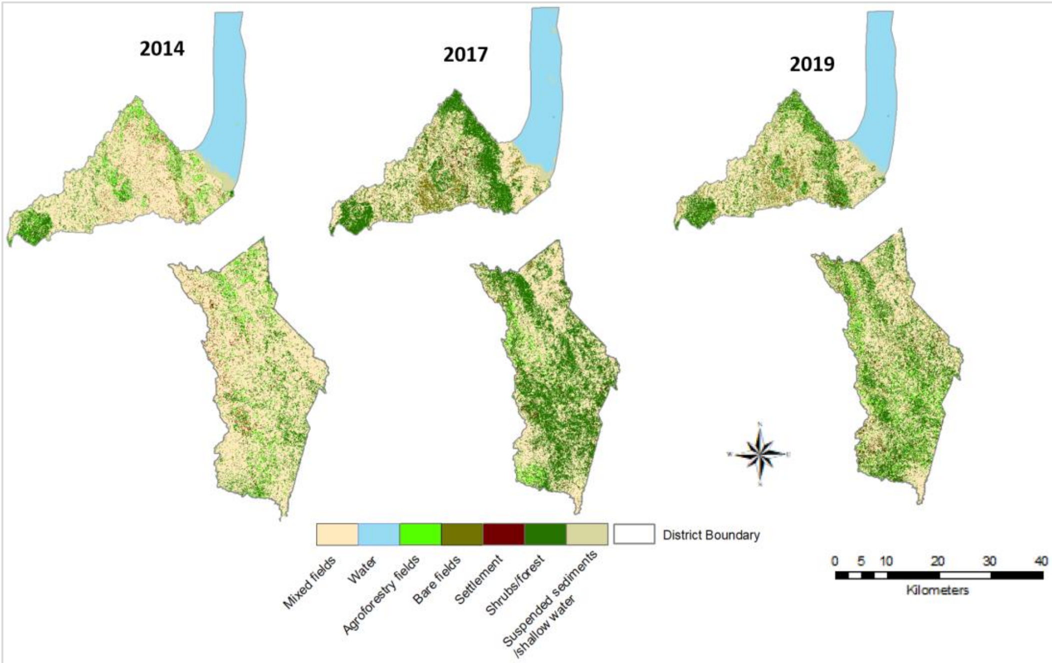


Figure 4.18: Land Use /Cover for Dedza and Ntcheu Districts 2014 – 2019.

Figure 4.19 below shows the changes in land use between 2014 to 2019 for Dedza and Ntcheu districts. The output is image overlay analysis in Arcgis used to show difference in land use changes between the 2019 image from 2014. The low changes (light grey) shows areas that potentially had minimal land use changes/transitions, and high changes (black) show areas with potential land use changes /transition.

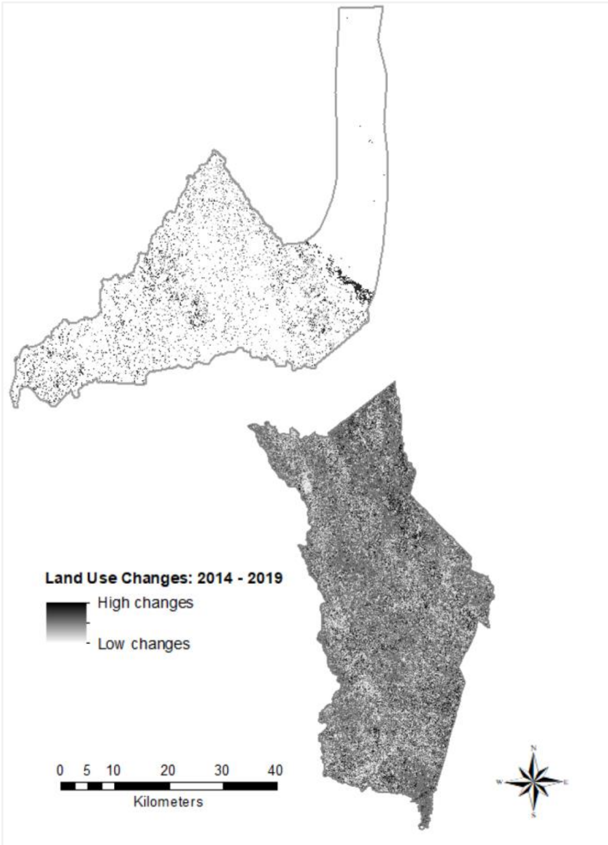


Figure 4.19: Land use/change showing areas of high and low changes for between 2014 – 2019 using image overlay analysis.

Based on Figure 4.20 below, mixed fields are the dominant class, and have 60%, 43% and 48% total area for 2014, 2017 and 2019. Agroforestry fields show low changes under 10% over time periods 2014, 2017 and 2019. While bare fields show a slight increase from 2014 to 2019 but remain under 10% total area. Shrubs and forests has significant temporal changes with 10% in 2014, 32% in 2017 and around 23% in 2019. The temporal changes on the vegetation changes that increased or decreased between 2014, 2017 and 2019, that may be driven by precipitation. However, in 2017, Landsat 8 reported a sensor calibration in April 2017 that may have caused the greening on the imagery (Micijevic et., 2016).

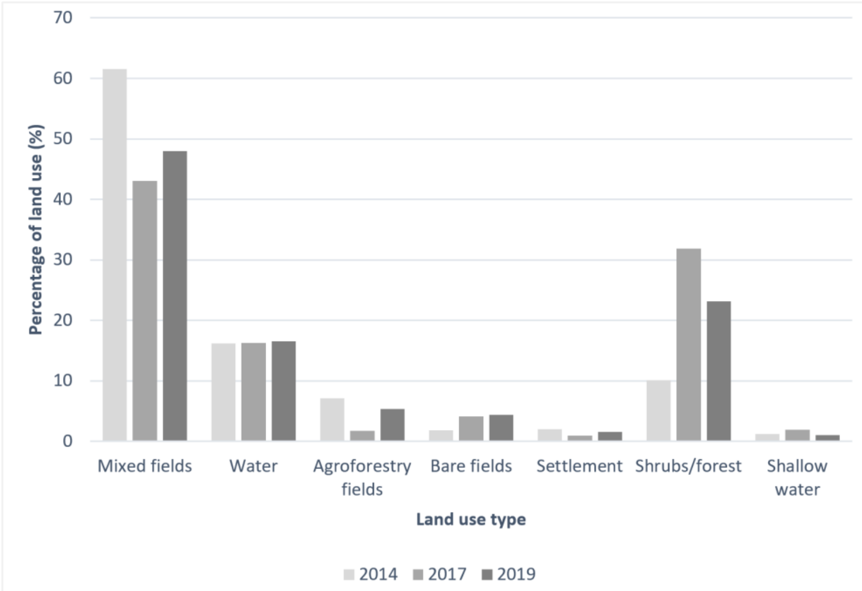


Figure 4.20: Land use/cover classes for Dedza and Ntcheu districts (note: sediments/shallow water).

Summary statistics for Dedza and Ntcheu districts are shown in Table 4.9-4.11. A combined summary of the two districts, land classifications is shown in Table 4.9 below. In this Table 4.9, the following classes: mixed fields, agroforestry, settlement classes decreased by 18.4%, 5.3% and 1% respectively across the three years. While bare fields, and shrubs and forests increased by 2.3% and 21.8 respectively. Between 2017 and 2019, we found significant increases in mixed fields, agroforestry 4.9% and 3.6% respectively, while a decrease was seen in shrubs and forests. Overall from 2014 to 2019, mixed fields, agroforestry has decreased 13.5%, 1.7% respectively. Settlement, water and suspended sediments/shallow water classes has insignificant changes or less than 1% across the years.

Table 4.9: Classification area statistics summary for two districts (Dedza and Ntcheu).

	Two Districts						Percent %	Percent %	Percent %
	2014		2017		2019		area change	area change	area change
LULC Class	Area(ha)	%	Area(ha)	%	Area(ha)	%	(2017-2014)	(2017-2019)	(2019 -2014)
Mixed fields	514467.7	61.5	360351.4	43.1	401504.0	48.0	-18.4	4.9	-13.5
Water	135629.5	16.2	136187.2	16.3	138209.1	16.5	0.1	0.2	0.3
Agroforestry fields	59195.8	7.1	14971.9	1.8	44775.5	5.4	-5.3	3.6	-1.7
Bare fields	15413.5	1.8	34320.9	4.1	36961.8	4.4	2.3	0.3	2.6
Settlement	16906.1	2.0	7915.9	0.9	12941.6	1.5	-1.1	0.6	-0.5
Shrubs/forest	84528.5	10.1	266656.1	31.9	193586.8	23.1	21.8	-8.7	13.0
Suspended sediments/Shallow water	10251.4	1.2	16087.0	1.9	8511.2	1.0	0.7	-0.9	-0.2
Total	836392.3	100	836490.2	100	836489.9	100	0.0	0.0	0.0

Table 4.10: Dedza district land classes percentage

Dedza District							Percent %	Percent %	Percent %
	2014		**2017**		**2019**		**area change**	**area change**	**area change**
LULC Class	**Area (Ha)**	**%**	**Area (Ha)**	**%**	**Area (Ha)**	**%**	**2017-2014**	**2019-2017**	**2019-2014**
Mixed fields	269308.98	52.7	196269.66	38.4	220855.59	43.2	-14.3	4.8	-9.5
Water	134883.18	26.4	135558.45	26.5	137537.73	26.9	0.1	0.4	0.5
Agroforestry fields	34124.4	6.7	5077.62	1.0	17982.63	3.5	-5.7	2.5	-3.2
Bare fields	11106.63	2.2	27009.81	5.3	25568.91	5.0	3.1	-0.3	2.8
Settlement	8858.61	1.7	4157.28	0.8	4848.21	0.9	-0.9	0.1	-0.8
Shrubs/forest	42890.13	8.4	131761.53	25.8	96873.39	18.9	17.4	-6.8	10.6
Suspended sediments/shallow water	10189.89	2.0	11608.2	2.3	7776	1.5	0.3	-0.7	-0.5
Total	511361.82	100	511442.55	100	511442.46	100	0.0	0.0	0.0

Table 4.11: Ntcheu district land classes percentage

Ntcheu District							Percent %	Percent %	Percent %
	2014		**2017**		**2019**		**area change**	**area change**	**area change**
LULC Class	**Area (Ha)**	**%**	**Area (Ha)**	**%**	**Area (Ha)**	**%**	**2017-2014**	**2019-2017**	**2019-2014**
Mixed fields	244960.7	75.4	164007.4	50.5	180559.2	55.6	-25.0	5.1	-19.9
Water	699.1	0.2	588.4	0.2	629.7	0.2	0.0	0.0	0.0
Agroforestry fields	25047.7	7.7	9886.1	3.0	26783.5	8.2	-4.7	5.2	0.5
Bare fields	4297.3	1.3	7301.3	2.2	11381.9	3.5	0.9	1.3	2.2
Settlement	8043.5	2.5	3757.5	1.2	8090.6	2.5	-1.3	1.3	0.0
Shrubs/forest	41604.0	12.8	134846.9	41.5	96683.7	29.8	28.7	-11.7	16.9
Suspended sediments/Shallow water	58.7	0.0	4473.7	1.4	733.3	0.2	1.4	-1.2	0.2
Total	324711.0	100	324861.3	100	324861.9	100	0.0	0.0	0.0

Table 4.10 seen above, provides LULC change results for Dedza district. From 2014 to 2017, mixed fields, agroforestry, settlement classes decreased by 14.3%, 5.7% and 0.9% respectively. While bare fields, and shrubs and forests increased by 3.1% and 17.4 respectively. From 2017 to 2019, increases were found in mixed fields, agroforestry and bare fields classes; 4.8% and 2.5% respectively, while settlement and water, suspended sediments/shallow water classes had insignificant increases of less than 1%. Overall from 2014 to 2019, bare fields, and shrubs and forest increased 2.8% 10.6% respectively, while mixed, agroforestry fields decreased 9.5%, and 3.2% respectively. Settlement, water and suspended sediments/shallow water classes has insignificant changes or less than 1% across the years.

Table 4.11, displays the Ntcheu district post classification. From 2017 to 2014 the mixed fields, agroforestry, settlement classes decreased by 25%, 4.7% and 1.3% respectively. While bare fields, and shrubs/forests each increased by 0.9% and 28.7 %. From 2017 to 2019, increases were found in mixed fields, agroforestry, bare fields and settlement classes; 5.1%, 5.2%, 1.3% and 1.3% respectively, while shrubs and forests decreased by 11.7 %. Water and suspended sediments/shallow water classes had no changes, and 1% change respectively. Overall from 2014 to 2019, agroforestry fields, bare fields and shrubs and forests increased by 0.5%, 2.2% and 3.2%. While mixed fields decreased significantly by 19.9%, Settlement, water and suspended sediments/shallow water classes has insignificant changes or less than 1% across the years.

We used the change matrix as another approach to understand the nature of the LULC that occurred during the years 2014-2019. The from –to- change matrix in three intervals; 2014-2017, 2017-2019, 2014-2019 was used to analyze these temporal transitions of our seven land use land cover classes.

Judicious interpretations of the above results as best as possible, we acknowledge that some apparent changes may be produced by spectral overlap, registration or boundary problems (Howarth and Wickare 1981). Thus interpretation is based on the study area context and was aided by field observations ground truthing and photographs as well as the use of google earth explorer for references for landscape features identification.

Table 4.12: Ntcheu district from-to change matrix summary 2014 – 2017.

2017	2014 (Ha) Mixed fields	Water	Agroforestry fields	Bare fields	Settlement	Shrub/forest	Shallow water	2017 Total
Mixed fields	133411.1	179.5	9605.8	2214.6	3245.1	15215.9	5.8	163877.7
Water	473.9	6.5	41.2	12.2	8.6	44.2	1.4	588.0
Agroforestry fields	7460.6	29.9	706.5	125.6	406.1	1149.1	2.5	9880.4
Bare fields	6080.2	13.8	410.5	339.6	100.1	346.4	0.4	7290.9
Settlement	3038.0	4.1	199.0	49.6	99.2	365.1	0.0	3755.0
Shrubs/forest	91347.4	436.4	13702.3	1474.8	4009.3	23808.8	14.1	134793.2
Shallow water	3110.2	29.1	377.4	79.7	173.4	666.2	34.6	4470.5
2014 Total	**244921.5**	**699.1**	**25042.7**	**4296.2**	**8041.8**	**41595.7**	**58.7**	
Change 2014-2017	-81043.83	-111.15	-15162.3	+2994.75	-4286.79	+93197.52	+4411.8	

Table 4.12, highlights Ntcheu's 2014 and 2017 LULC results. Between 2014 and 2017, land area decreases were found in mixed fields, agroforestry, settlement, and water classes, while bare fields, shrubs/forest and suspended sediments/shallow water increased. Shrubs and forests have the highest increase during this time.

Table 4.13: Ntcheu district from-to change matrix summary 2017 - 2019

2019	2017 (Ha) Mixed fields	Water	Agroforestry fields	Bare fields	Settlement	Shrub/forest	Shallow water	2019 Total
Mixed fields	105903.3	382.4	4728.2	4749.8	2150.3	60521.1	2123.7	180558.8
Water	279.5	12.2	28.6	45.4	9.4	215.2	39.5	629.7
Agroforestry fields	10213.8	23.7	1502.6	261.0	380.3	14010.4	391.7	26783.4
Bare fields	7452.1	40.7	180.8	1040.0	159.6	2408.6	100.2	11381.9
Settlement	4115.2	13.0	388.3	113.5	128.6	3239.3	92.9	8090.6
Shrubs/forest	35752.7	108.1	3030.3	1078.7	920.7	54121.0	1672.0	96683.4
Shallow water	290.9	8.4	27.4	13.0	8.7	331.3	53.7	733.3
2017 Total	**164007.4**	**588.4**	**9886.1**	**7301.3**	**3757.5**	**134846.8**	**4473.7**	
Change 2017-2019	+16551.45	+41.31	+16897.32	+4080.6	+4333.14	-38163.42	-3740.4	

In table 4.13, above is Ntcheu's LULC change results from 2017 to 2019. Overall majority of classes showed increases, except shrub/forest and suspended sediments/shallow water classes that showed decreases.

Table 4.14: Ntcheu district from-to change matrix summary 2014 - 2019

	2014 (Ha)							
2019	**Mixed fields**	**Water**	**Agroforestry fields**	**Bare fields**	**Settlement**	**Shrub/forest**	**Shallow water**	**2019 Total**
Mixed fields	147512.3	203.9	11228.8	2354.4	3517.3	15601.0	11.9	180429.5
Water	436.1	18.6	59.5	30.0	26.6	52.4	6.2	629.4
Agroforestry fields	18462.1	58.6	2497.4	298.4	1019.1	4433.0	2.3	26770.8
Bare fields	10010.4	8.1	339.9	502.7	142.6	361.2	3.5	11368.4
Settlement	6236.5	9.7	551.3	91.4	243.8	952.4	0.9	8086.0
Shrubs/forest	61818.6	383.6	10248.1	1014.4	3070.4	20074.5	29.6	96639.2
Shallow water	446.0	16.7	117.6	5.0	22.0	121.4	4.3	732.9
2014 Total	**244921.9**	**699.1**	**25042.7**	**4296.2**	**8041.8**	**41595.8**	**58.7**	
Change 2014-2019	-64492.38	-69.75	+1728.09	+7072.2	+44.19	+55043.46	+674.19	

In table 4.14, Ntcheu's LULC changes from 2014 -2019 show an overall decrease in mixed fields, water, however, agroforestry fields, bare fields, settlement, and suspended/shallow water classes in Ntcheu district.

Table 4.15: Dedza district from-to change matrix summary 2014-2017

	2014 (Ha)							
2017	**Mixed fields**	**Water**	**Agroforestry fields**	**Bare fields**	**Settlement**	**Shrub/forest**	**Shallow water**	**Total 2017**
Mixed fields	159432.8	651.3	12758.4	4649.0	3197.3	15261.2	257.7	196207.7
Water	794.2	131204.3	58.2	96.6	20.3	35.5	3272.5	135481.4
Agroforestry fields	3310.7	58.0	648.5	100.8	200.3	744.0	12.3	5074.7
Bare fields	22154.0	106.5	603.3	3447.7	254.1	435.6	4.6	27005.8
Settlement	3524.0	8.1	165.6	188.1	115.5	155.7	0.0	4157.0
Shrubs/forest	77589.4	1163.7	19452.3	2517.7	4937.9	25868.3	180.7	131709.9
Shallow water	2424.5	1685.3	429.7	103.3	133.0	368.2	6460.1	11604.2
Total 2014	**269229.7**	**134877.2**	**34115.9**	**11103.2**	**8858.3**	**42868.4**	**10187.9**	**511240.6**
Change 2014-2017	-73021.95	+604.26	-29041.29	+15902.55	-4701.24	+88841.43	+1416.24	

In table 4.15 shows Dedza district LULC changes results from 2014 -2017. There is an overall decrease in mixed fields, agroforestry fields, and settlements from 2014 to 2017, while classes such as bare fields, water, and suspended sediments/shallow water show increase.

Table 4.16: Dedza district from-to change matrix summary 2017-2019

	2017 (Ha)							
2019	**Mixed fields**	**Water**	**Agroforestry fields**	**Bare fields**	**Settlement**	**Shrub/forest**	**Shallow water**	**Total 2019**
Mixed fields	145453.5	590.6	2432.3	15056.0	2526.1	52930.7	1866.3	220855.5
Water	765.9	132633.8	57.9	416.7	18.9	720.9	2923.7	137537.7
Agroforestry fields	6133.3	23.0	555.5	278.1	225.4	10543.8	223.6	17982.5
Bare fields	12929.3	248.3	74.3	9343.4	450.5	2387.5	135.6	25568.9
Settlement	1919.9	5.9	100.8	216.5	129.1	2414.2	61.9	4848.2
Shrubs/forest	28835.9	122.2	1830.1	1691.0	794.3	62393.5	1206.4	96873.3
Shallow water	231.8	1934.6	26.9	8.2	13.1	370.7	5190.8	7776.0
Total 2017	**196269.6**	**135558.5**	**5077.6**	**27009.8**	**4157.3**	**131761.3**	**11608.2**	**511442.2**
Change 2017-2019	+24585.93	+1979.28	+12904.92	-1440.90	+690.92	-34887.96	-3832.2	

In table 4.16 shows changes from 2017 – 2019 LULC changes in Dedza district with increases in mixed fields, agroforestry fields, bare fields, settlements and water, decreases were reported in bare fields, shrubs/forests and suspended sediments/shallow water.

Table 4.17: Dedza district from-to change matrix summary 2014-2019

	2014 (Ha)							
2019	**Mixed fields**	**Water**	**Agroforestry fields**	**Bare fields**	**Settlement**	**Shrub/forest**	**Shallow water**	**Total 2019**
Mixed fields	178017.5	807.8	15619.1	5793.5	4006.4	16324.7	214.7	220783.7
Water	1328.7	132065.6	255.2	162.8	46.8	147.0	3452.7	137458.7
Agroforestry fields	11043.7	168.0	2710.6	361.1	738.7	2895.8	57.2	17975.3
Bare fields	21441.4	70.9	498.3	2950.7	217.6	380.3	3.1	25562.3
Settlement	3434.8	29.0	470.6	144.0	179.5	543.7	45.2	4846.7
Shrubs/forest	53640.8	871.6	14433.1	1676.9	3633.5	22475.3	108.5	96839.6
Shallow water	322.6	864.2	129.2	14.2	35.7	101.8	6306.6	7774.2
Total 2014	**269229.4**	**134877.2**	**34116.0**	**11103.2**	**8858.3**	**42868.4**	**10187.9**	**511240.4**
Change 2014-2019	-48445.74	+2581.56	-16140.78	+14459.13	-4011.57	+53971.11	-2413.71	

Table 4.17, shows Dedza's overall LULC changes results, from 2014 -2019, where there is a decrease in mixed fields, agroforestry fields, settlement and suspended sediments/shallow water, while an increase in bare fields, shrubs/forests and water classes.

4.5.5 Landscape Pattern Metrics Results

Table 4.18, below displays the landscape metrics for Dedza district from 2014 to 2019. Here, statistics of mixed fields showed that the percentage of landscape (PLAND) index decreased from

52.7% to 43.2%, while the number of patches (NP) increased from 17,657 to 32,133. This combination suggests fragmentation of agricultural fields into smaller parcels. This is also supported by the largest patch index (LPI) that decreased from 50.4% to 30.6% and the mean patch area *AREA_MN – decreased from 15.3% to 6.9%, suggesting a net increase in the perimeter area and the patches may be subject to intensified edge effects. This is anticipated from the land use transitions that might have been taking place.

The Agroforestry class area decreased from 34,124 to 17,982 from 2014 to 2019, the percentage landscape (PLAND) also decreased from 6.7% to 3.5% while the number of patches (NP) increased. These changes are consistent with a reduction of tree biomass in 2019, and or a change in farming practice. Shrubs/forest, and bare fields increased from 42,890.1 to 96,873.4, and from 11,106.6 to 25,568.9 respectively. Settlement class decreased from 8,856.6 to 4,848.2.

Between 2014 to 2019, the mean nearest-neighbor distance (ENN_MN) across the classes had slight changes whereas the mean proximity index (PROX_MN) revealed that the patches are less isolated mainly the mixed field class. The observed interspersion (IJI) - distribution of adjacencies among unique patch types did not change much, but shows that the patch types are already uneven as IJI approached 0.

Table 4.18: Summary landscape structure index metrics for Dedza district, 2014 and 2019

Dedza 2014 LULC Class	CA (ha)	PLAND %	NP (#)	LPI (%)	AREA_MN (ha)	SHAPE_MN (ha)	PROX_MN (m)	ENN_MN (m)	IJI (%)
Mixed fields	269309.0	52.7	17657	50.4	15.3	1.3	305368.8	69.1	76.9
Agroforestry fields	34124.4	6.7	68131	0.1	0.5	1.2	15.3	85.0	59.6
Shrubs/forest	42890.1	8.4	51970	2.4	0.8	1.2	631.1	89.9	50.8
Bare fields	11106.6	2.2	31019	0.0	0.4	1.2	1.9	129.7	43.0
Settlement	8858.6	1.7	36640	0.0	0.2	1.1	1.6	117.1	60.4
Water	134883.2	26.4	10807	25.9	12.5	1.1	371.2	190.8	82.7
Suspended sediments/shallow water	10189.9	2.0	974	1.8	10.5	1.1	446.0	522.1	52.7
Dedza 2019									
Mixed fields	220855.6	43.2	32133	30.6	6.9	1.3	97894.2	70.5	65.2
Agroforestry fields	17982.6	3.5	74571	0.0	0.2	1.1	2.0	92.3	55.7
Shrubs/forest	96873.4	18.9	56339	6.3	1.7	1.3	5511.1	85.5	52.9
Bare fields	25568.9	5.0	36437	0.3	0.7	1.2	26.4	117.0	39.9
Settlement	4848.2	0.9	30792	0.0	0.2	1.1	0.5	140.7	67.9
Water	137537.7	26.9	10457	26.4	13.2	1.1	1372.8	197.7	89.1
Suspended sediments/shallow water	7776.0	1.5	3419	1.3	2.3	1.1	425.6	287.5	73.4

Dedza Year	SHDI	SHEI	NP (#)	LPI (%)	AREA_MN (ha)	SHAPE_MN (ha)	PROX_MN (m)	ENN_MN (m)	IJI (%)
2014	1.3092	0.6728	217198	50.3602	2.3544	1.2027	25001.614	103.8757	65.1508
2019	1.4062	0.7227	244148	30.5835	2.0948	1.1876	14225.232	104.9063	59.7719

Table 4.19: Summary landscape structure index metrics for Ncheu District, 2014 and 2019

Ntcheu 2014 LULC Class	**CA (ha)**	**PLAND %**	**NP (#)**	**LPI (%)**	**AREA_MN (ha)**	**SHAPE_MN (ha)**	**PROX_MN (m)**	**ENN_MN (m)**	**IJI (%)**
Mixed fields	244960.7	75.4	9123	74.1	26.9	1.2	495373.9	63.6	68.0
Agroforestry fields	25047.7	7.7	75039	0.1	0.3	1.2	4.9	85.1	53.3
Shrubs/forest	41604.0	12.8	57436	0.3	0.7	1.3	29.1	83.9	45.6
Bare fields	4297.3	1.3	23616	0.0	0.2	1.1	0.5	152.8	53.0
Settlement	8043.5	2.5	34324	0.0	0.2	1.1	1.4	120.9	58.2
Water	699.1	0.2	3931	0.0	0.2	1.1	0.6	292.7	69.2
Suspended sediments/shallow water	58.7	0.0	212	0.0	0.3	1.0	0.1	955.7	80.6
Ntcheu 2019									
Mixed fields	180559.2	55.6	31696	45.9	5.7	1.3	161582.2	66.9	63.2
Agroforestry fields	26783.5	8.2	83160	0.1	0.3	1.2	5.2	83.9	53.3
Shrubs/forest	96683.7	29.8	62549	2.6	1.5	1.3	1057.6	74.6	53.9
Bare fields	11381.9	3.5	39048	0.0	0.3	1.1	2.3	119.5	49.2
Settlement	8090.6	2.5	45695	0.0	0.2	1.1	0.8	116.5	64.8
Water	629.7	0.2	4082	0.0	0.2	1.0	0.3	310.5	76.9
Suspended sediments/shallow water	733.3	0.2	2929	0.0	0.3	1.1	1.2	237.1	58.9

Ntcheu Year	**SHDI**	**SHEI**	**NP (#)**	**LPI (%)**	**AREA_MN (ha)**	**SHAPE_MN (ha)**	**PROX_MN (m)**	**ENN_MN (m)**	**IJI (%)**
2014	0.8371	0.4302	203681	74.1247	1.5942	1.1892	22198.44	102.5925	57.7317
2019	1.1281	0.5798	269159	45.9119	1.207	1.2012	19275.7	95.5575	57.9192

Overall, the number of patches (NP) increased slightly from 217,198 in 2014 to 244,148 in 2019, suggesting high fragmentation across the landscape (Table 4.18). The SHDI and SHEI were both greater in 2019, suggesting a slight increase in landscape heterogeneity (Table 4.18).

In Table 4.19, Ntcheu's mixed fields class decreased in class area, from 244,960 to 180,559 as well as a decrease in the percentage of landscape (PLAND) index from 75.4% to 55.6%, however the number of patches (NP) increased from 9123 to 31696 from 2014 to 2019. This suggests further fragmentation of mixed fields into smaller parcels. Mixed and bare fields increase/decrease are temporal as from season to season based on farmer decision to sow plants or leave fields cultivated without sowing crop in the growing season, thus caution should be taken while interpreting the bare fields.

Class Area (CA) and percentage of landscape (PLAND) for agroforestry fields and shrubs/forest classes increased slightly from 2014 to 2019. - both in class area (CA). Only the mixed fields have a significant decrease in largest patch index (LPI) from 74.1% to 45.9% than any other classes, and also its mean patch area -AREA_MN was slightly significant – 26.9% to 5.7% from 2014 to 2019. In summary, the SHDI and SHDI show a slight increase in landscape heterogeneity. Also, there is an overall increase of number of patches from 2014 to 2019 across Ntcheu district.

4.6 Discussion

In this research study, LULC change for three growing seasons (2014, 2017, 2019) was analyzed to understand scale and quantified land use patterns in Dedza and Ntcheu district by (a) identifying and testing scalability of patterns using fine to course imagery spatial structure (b) quantifying LULC and land cover post classification change analysis and (c) landscape structure analysis of the land cover classes to determine spatial-temporal patterns and whether the nature of these patterns can be linked to occurring function and processes.

There is evidence of differences in spatial structure for rescaled fine to course imagery. In Linthipe site, a rescaled imagery from 2m to 30m where both images were in a classification analysis showed that land classes declined from 8 classes on the original image to 7 land classes on the rescaled imagery. The cultivated dambo class (small cultivated areas located in low lying water table areas) is lost in the rescaled imagery although dambos represent intensifying agriculture patterns where farmers grow variety of crops and vegetables. Linthipe site is interesting as the landscape has unique features as cultivated dambos where low slope (elevation) plays part in the spatial structure of the landscape. Golomoti site land classes before and after rescaling remained at 7 classes, however, the spatial structure changes are captured in the semi variogram model of the rescaled imagery.

Scaling findings for original Landsat NDVI 30m to rescaled 250m Landsat NDVI imagery, show the mean and variance statistics have significant decrease between the original and the rescaled imagery. Also, a comparison between a rescaled Landsat NDVI 250m imagery to a MODIS NDVI 250m original imagery have differences in spatial structure based on the semi variogram. In all cases, the rescaled imagery has higher values than original imagery due to the spatial structure changes due to resampling effect. In small holder farming context, its complex heterogeneous landscape such as cultivated dambos may not be captured as differences in spatial resolution causes particular observations to be overstated while others are missed as they are sensitive to scale. This caveat should be noted in the scale variation of remote sensing data, as it is important to show intensification of agriculture patterns as captured in dambos areas at fine scale.

The LULC change analysis and post classification findings show that we have seven land classes for found in Dedza and Ntcheu districts from 2014, 2017 and 2019. The kappa coefficient of land classification and overall accuracy achieved from the classification results are higher than 80% that fits the standard requirement for land cover classification. All land classes had consistently high accuracies, especially the suspended sediments/shallow water, mixed fields, agroforestry and shrubs/forest classes.

The Agroforestry, mixed, and bare fields accuracies suggest similar spectral values, where pixels were also into different land classes; for example, some pixels in mixed fields and bare fields were also classified under agroforestry, shrubs and forest, while in some cases agroforestry fields pixels were classified under mixed fields and shrubs/forest classes. This is expected as the heterogeneous landscape of smallholder farming in Malawi may not be fully captured using Landsat imagery. Caution was taken while interpreting mixed and bare fields as they are temporal and are expected to switch from season to season depending on farmer decision to sow new crop or leave the field cultivated.

In the LULC change post classification, our findings show that land cover changes occur across all the 7 land classes. From the agricultural landscape, mixed fields are the dominant class with the highest percentages over 60%, 43% and 48% total area for 2014, 2017 and 2019 across both districts, this is followed by the Agroforestry fields that show slight temporal changes over time. These findings highlight likely conversions between the diverse agricultural fields with an overall increase in fragmented classes across Dedza and Ntcheu. Mixed fields is the predominant class, however, Ntcheu has more fragmented patches that may suggest land cover conversion and possible higher rates of change.

Over time, agroforestry fields class showed a slight increase in Ntcheu, unlike Dedza district whose decrease could be attributed community practices such as use of fuelwood-charcoal, green biomass, and as livestock food. Increase in agroforestry was mainly where farmers have a variety of nitrogen-fixing trees such as *Gliridicia sepium* and *Faidherbia albiba* and fruit trees as palm, bamboo, and mango trees, such agroforestry practices details can be found in (Coulibaly et al., 2017).

Temporal changes in the landscape noted between the years; 2017 and 2019 suggest patterns influenced by environmental factor in 2017 and 2018 where severe flooding was reported in Central Malawi that may influence increase in biomass in shrubs and forestry class prior to this event was at (1.4%) in 2017, and 2019 (5%). From field observations in Malawi, flooding also affects the low lying areas, such as dambo fields during the rainfall seasons between January and March. Fields located close to rivers and streams are also high risk of flooding during the growing season, thus temporal and seasonal flooding could cause increases or decreases of suspended sediments/shallow water that may suggest temporal flooding seasons in some cases. Overall decrease percentage changes were also noted in mixed fields class; 61.5% (2014 prior to climate shock), 43% (2017) and 48% (2019), while shrubs/forest class shows percentage changes of 7%(2014), 1.4%(2017) and 5% (2019). Haack (2015) study showed that certain land cover and land use change can be a consequence of climate change, especially in forested/natural land cover.

Spatial structure metrics used to quantify the nature of agricultural landscape patterns in each district. We use a pixel level 30m by 30m scale and also took into account the hierarchical levels found in a landscape, class and patch levels (Table 4.2 above). Our overall results show that between 2014 to 2019, percentage of landscape index decreased in both districts, while there is an overall increase in the number of patches in both districts; simultaneously, there is a decrease in the largest path index (LPI) and the mean patch area (AREA_NM) decreases that suggest edge effects. These combined metrics outcomes are indicative of underlying processes that cause fragmentation of agricultural fields into smaller parcels. This is due to agricultural activities seen in agroforestry and mixed fields suggest constant changes, also human activities found at shrub/forest edges, and increased fragmentation across the years studied.

The SHDI and SHEI were both greater in 2019 in both districts, suggesting a slight increase in landscape heterogeneity and overall changes in the spatial structure of the landscape as seen in the decrease of the interspersion and juxtaposition index (IJI)that indicates that the landscape configuration is not uniform.

At the class level findings for Dedza district bare fields class area in hectares has a significant rise from 11,106.6 in 2014 to 25,568.9, while the other agricultural classes showed moderate decreases; as mixed fields class area was over 260,000 ha in 2014, but decreased in 2019 to approximately 220,000 ha, agroforestry class had over 30,000 to less than 20,000 ha, while shrubs/forest have over 40,000 ha in 2014, and increased to over 90,000 ha in 2019. The increases in bare fields in Dedza district may be driven by the fact that mixed or agroforestry fields areas, may have less vegetation during the time of imagery acquisition suggest that farming practices or external shocks may contribute to these shift in changes. This pattern is also noted in Ntcheu district where bare fields class area had a significant rise from 4,297.3 in 2014 to 11,381.9, while the other agricultural classes showed very slight increase such as; mixed fields class have majority of class area in 2014 over 240,000 ha that decreased in 2019 to 180,000 ha, agroforestry class 25,000 to 26,000 ha, while shrubs/forest class has around 40,000 ha in 2014, and over 90,000 ha in 2019.

The use of multiple spatial metrics shows that the agricultural landscape during 2014 to 2019 experienced temporal changes, that are noticed at a class and patch level, were fragmentation patterns. The differences in indexes outputs in both districts suggest that heterogeneous landscapes are complex and are not predictable. From these temporal LULC changes and fragmentation, farming activities that lead to intensification of agriculture patterns are seen at a field class level.

A main limitation in this study is that social interactions over time and space are complex to measure especially capturing past events through remote sensing thus our patterns are attributed to a sum of events that have occurred in the area (Walker and Peters 2007).

Additionally, spatial metrics are sensitive to spatial resolutions at sensor level when observations are collected, thus spatial structure transitions that can create artificial edges are arrived at sooner in finer than in course resolution (Goodin and Henebry 2002), as in our scalability tests. Thus caution is applied while interpreting the results in this study as it is based on short-term satellite datasets. Future studies would use long term datasets for landscape pattern analysis and also test sensitivity to different sensor systems.

4.7 Conclusion

From this study, use of land classification and landscape pattern analysis assisted in examining and quantifying land use change for Dedza and Ntcheu districts. Given the heterogeneous nature of smallholder farming systems, 7 land classes were derived across the two districts. Two land classes (mixed, and bare fields) are interpreted with caution, as they as seen interchangeable season by season based on which fields farmers cultivate or /and sow crops. This study makes advances in knowledge in understanding smallholder farming landscape fragmentation and processes. This information is important for land planning and management for stakeholders, extension and also farming communities that lack spatial-temporal inventory of land use and management that can assist in prioritizing sustainable agriculture.

5. THE ROLE OF AGRICULTURAL EXTENSION DELIVERY ON THE MALAWIAN LANDSCAPE

5.1 Introduction

In the last two decades, there has been more pressure on land in Africa than elsewhere, as the majority of its population is dependent on the land for subsistence farming and raw materials for industry, fuel wood, and human settlement expansion (Kendie 2002). Increased food demand has led smallholder farmers to practice agricultural intensification. This intensification occurs predominantly under rain fed conditions and is impacted by climate change, social-economic challenges along with shifting global and regional food production policies (Tittonell and Giller 2013).

Poor land management and mis-managed intensification practices such as over cultivation and insufficient input resources have depleted the soils (Snapp 1998). Also farmers continue to seek new fertile soils by extensification through the use of slash and burn and deforestation (Tittonell and Giller 2013, Kendie 2002). In many cases, areas occupied by most smallholder farmers have shrunk in size as families rely upon traditional land inheritance models to further divide the land for younger generations (Holden and Otsuka 2014).

Sustainable Intensification (SI) of Agriculture has been promoted to assist African farmers to improve food production using available resources while protecting their environment (Giller et al. 2015). These involve natural solutions through crop diversification, improving soil organic matter and integrated crop management. The Malawi government promotes the use of SI technologies to improve sustainable agriculture; farm practices as intercropping with legumes, multipurpose legume systems, and integrated soil management practices (Messina et al., 2017). New SI technologies are carried out through farmer experimentation and has been on the rise over the years. Hockett and Richardson (2018) describes experimentation as the “introduction of a new element/technique into a smallholder’s farming system – and is iterative and constantly evolving from season to season”. SI technology performance of maize-legume diversification has demonstrated multipurpose benefits and tradeoffs of this SI technology across environmental, social and human dimensions (Snapp et al., 2018). Malawian farmers have shown that doubled-up legume intercrops such as groundnut/pigeon pea is advantageous as the legumes complement each other with their different temporal nature and plant architecture resulting in intercrop optimization (Chikowo et al., 2020, Chimonyo et al., 2019).

The Malawi government has also promoted Fertilizer Inputs Subsidies Programme (FISP) that assisted to improve maize-mixed systems with increases in yields, however, FISP benefits have been contentious as they contribute to unsustainable agricultural practices forming fertilizer application dependency that causes soil degradation, also there is no evidence of long term improvement in yields gains especially in rural smallholder farmers in Malawi (Messina et al., 2017).

A common approach for agricultural knowledge dissemination is through agricultural extension. This has often been promoted as one of the main vehicles to sustainable food production for smallholder farming systems. Over the past two decades, Malawian farmers have received farming strategies to assist in food production that promise to improve crop yields through enhanced resource inputs use, mixed maize intercrop systems, and integrated soil management practices, and incorporating residues into the farm fields. A recent study reported that 45% farmers in study sites in Central Malawi had contact with agriculture extension services (Mungai et. al., 2016). In this study, we examine Malawian agricultural extension delivery as an agent of change, as they bring in knowledge and resources that can lead to land restoration and soil improvement.

5.1.1 Malawi's Agricultural Extension Education

Agricultural extension in Malawi has been in existence since the 1950s, with the introduction of a demand-driven extension services system (Masangano and Mthinda 2012). Like other African countries, the 2000s saw the decentralization of agricultural services by the national Governments. For example, Uganda developed the National Agricultural Advisory Services (NAADS) program objective to increase agricultural productivity through improved extension delivery at a sub-county and village level (AfranaaKwapong, N. and Nkonya 2015). In Ethiopia, improved extension delivery through partnerships and empowering of farmer groups (Dejene 1989).

Over the years, the Malawian government has worked to decentralize its government and made efforts towards public and private partnerships, as seen in education, health and agricultural institutions (Msewa 2005). In 2017, the Government of Malawi revised its vision and strategies for agricultural development as described in Malawi Development Goals III (MDGs III) report (GOM 2017). Amongst agriculture production and productivity, the national government highlighted improving agricultural extension and rural advisory services by regulating service delivery through stakeholders and state and local actors as well as through the Ministry of Agriculture, Irrigation and Water Development (MoAIWD) (GOM 2017).

Agricultural extension's crucial role is to disseminate agricultural information to farmers and to bring awareness to farmers on ways of improving farming practices (Ragasa Mazunda 2018, Trotsky and Mureithi). The Malawi Ministry of Agriculture, decentralized the agricultural system under the National Rural Development Programme (NRDP), and created eight Agricultural Development Division (ADDs) with individual Programme Managers (PM). Lilongwe ADD has five rural development projects (RDP) located in Lilongwe, Dedza and Ntcheu districts. Each district has several Extension Planning Areas (EPAs) where the Department of Agriculture

Extension Services (DAES) is administered and led by the Agricultural Extension Development Coordinator (AEDC) (Msewa 2005). The Agricultural Extension District Officers (AEDO) are based in rural locations working directly with farmers at the Section levels (each EPA has many Sections), where several hundred thousand farming families are typically found (Figure 5.1).

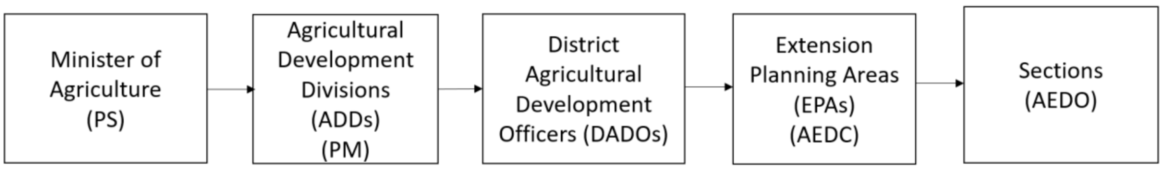


Figure 5.1:(The Structure of Ministry of Agriculture and Food Security in Malawi -adapted from Chinsinga 2008, Malawi: Desk Study of Extension and Advisory Services (Developing Local Extension Capacity (DLEC) Project June 2017).

Additionally, embedded in the above agricultural structure is the local government structure; the Traditional Authority, that is a unit of cluster sections including village groups under the Group Village Heads, and at the village level, the Village Development Committees (VDC) that helps to improve local village participation and extension delivery through the Agricultural Extension District Officers (AEDO) (Masangano et al., 2016). Malawi's land management policies can be traced back to the colonial era, where land management approaches and land classification systems were promoted (Kanyongolo 2005). This classification system involved dividing lands into public lands, and private or leased lands which were mostly used for commercial purposes and trust lands where most of the Malawian population would have to practice agriculture (Mulwafu 2011).

Land tenure reforms and context-specific strategies from agricultural extension have combined to promote the adoption of land restoration practices and improve food production (Holden and Otsuka 2014). Studies show that policies that allow community participation to manage land resources, are mutually beneficial to the farmers and livestock holder's livelihood in forested and agricultural landscapes (Zulu 2008). Mauambeta et al., 2010 study illustrates the successful reforestation of Malawian forests across districts though Improved Forestry for Sustainable Programme (IFMSLP) that assist communities become stewards of their forests for mutual benefits. Additionally, studies shows a continued effort to improve agroforestry in farming communities for soil fertility improvement and biomass for use in residue management and livestock fodder (Thangata and Alavalapati 2002, Beedy et al., 2013).

5.1.2 Landscape Patterns

Mungai et al., 2020 study notes that farming resource inputs and biophysical conditions are among the main influencers of intensification. The agricultural landscape is part of a complex system and thus assessment of SI of Agriculture based on extension advice delivery of SI Technologies requires using approaches that consider spatial-temporal perspectives (Tscharnktke et al., 2005). Linking activities of agricultural extension to SI of agriculture requires the integration of spatial land use inventory information and qualitative non-spatial information. Remote sensing imagery and modeling techniques can be used to explore the impact of agricultural extension delivery of SI technologies to see if these extensions advise can be observed in the smallholder farming systems landscape. By classifying the landscape into classes /elements such as agriculture, forests, and settlements and by development and modeling of landscape pattern metrics, landscape elements representing plots, farms, and villages form patterns that can be measured, and adjacent elements identified and associated with to reveal the trajectory and manifestation of SI of agriculture (Wang et al., 2014).

Examples of successful studies that have linked extension delivery progress as captured on satellite imagery are rare, nonetheless, the recent availability of free satellite imagery across most countries in Africa provides an opportunity to use these datasets to capture land use transitions across time and space. In this study, the primary question is “does agricultural extension delivery improve SI of agriculture”. Our null hypothesis is there is no significant difference on SI of agriculture based on agricultural extension delivery. Our assumption is that SI of agriculture shapes the landscape through farmer practices and that these resulting landscapes can be empirically demonstrated via remotely sensed imagery through landscape metrics. To answer this question, this study used responses from a qualitative semi-structured survey from extension workers in four EPAs sites in Dedza and Ntcheu districts, to add context to the landscape patterns and metrics results presented in Chapter 4.

5.2 Study Area

This study takes place in two districts – Dedza and Ntcheu in Central Malawi and four study sites (Linthipe, Golomoti, Kandeu and Nsipe) (Figure 5.2). Dedza and Ntcheu are similar in many respects including weather, elevation, and farming systems. Both districts have elevation ranging from 550m to 1,500m; however, Ntcheu has steep slopes in some locations. Both districts receive an average rainfall of 986mm and have a mean temperature of 18 Celsius (NSO 2008). The main crops include maize, common beans, groundnut, soya beans, and less frequently, tobacco, sorghum, pigeon pea, cowpea, millet, rice, and cassava. The majority of the farmers cultivate one or multiple fields with an average area of approximately 0.84 hectares. Some farmers keep livestock (rarely cattle, some chicken, and pigs) and the families depend on the land for livestock grazing, firewood collection and charcoal production.

Apart from crop fields, the study area has heterogeneous landscapes comprising natural vegetation, shrubs/grasslands and forests. For the four EPA sites, Linthipe and Golomoti are located in Dedza, while Kandeu and Nsipe are located in Ntcheu district. The general site and farming characteristics are summarized in Table 5.1. below. The sites are characterized as low to high potential sites. Golomoti is located at low elevation, close to Lake Malawi, high temperature with high evapotranspiration potential, it also has lower rainfall. The medium potential sites in Kandeu and Nsipe have moderate climate, are higher in elevation as compared to Golomoti, while Linthipe is highest in elevation and has the coolest climate and high potential for productivity (Table 5.1).

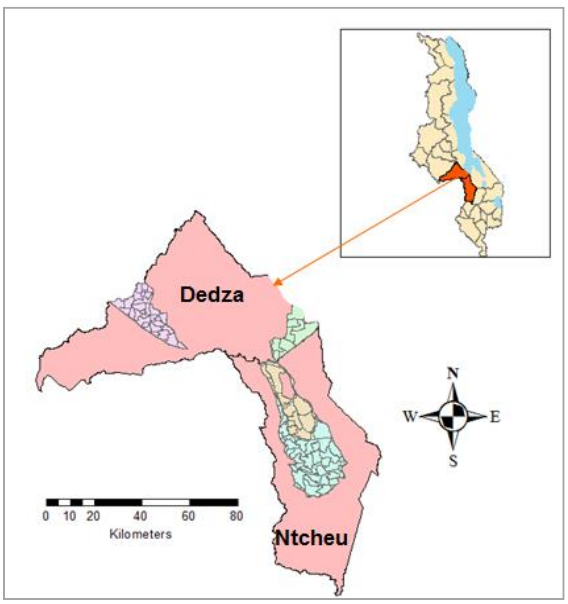


Figure 5.2: Study area districts with sites showing four EPAs Linthipe (purple), Golomoti (green), Nsipe (orange) and Kandeu (cyan).

Table 5.1: Environmental and physical farming system characteristics of four sites in Central Malawi (content source from Mungai et al., 2016) and (^Snapp et al., 2018) , *Nsipe 2014-2016 min-max Temperature from local weather station dataset

	Golomoti	Kandeu	Nsipe	Linthipe
Productivity Potential	Low	Medium	Medium	High
Elevation local point (meters above sea level)	555	904	868	1238
TRMM annual Rainfall(mm)	895	866	866	953
Evapotranspiration (mm)	960	619	607	595
Mean Temperature (min)^	13.3	10.8	*8.0	7.8
Mean Temperature (max)^	32.4	29.9	*32.0	27.7
EPA Soil Suitability	Moderately Suitable	Marginally Suitable	Marginally Suitable	Moderately Suitable

5.3 Data

Survey data was collected as part of the Africa RISING (Research In Sustainable Intensification for the Next Generation), program funded by the United States Agency for International Development (USAID) that is part of the United States Government's Feed the Future initiative. Through action research and development partnerships, the goal is to support Sustainable Intensification (SI) of agriculture and farmer livelihoods for key African maize-based systems, with collaborations with International Institute of Tropical Agriculture (IITA), Michigan State University (MSU), Lilongwe University of Agriculture and Natural Resources (LUANAR), and other partners including Malawi agricultural extension services.

Initial test interviews were carried out at Mpingu EPA in Lilongwe district. The semi-structured interviews were revised to 35 questions that would assist the conversation with the agricultural extension staff regarding their work and advisory delivery on the respective EPA sites.

This survey was conducted in June 2018 with 19 extension staff comprising of 6 females and 13 males and all four sites were sampled. Interview responses were transcribed into MS Excel spreadsheets.

5.4 Method

5.4.1 Agriculture Extension Analysis

A simple thematic analysis is used to organize the responses into similar themes. Thematic analysis is flexible and allows the user to use a theoretical context. The interview responses were parsed per question into separate worksheets. Each question response was trimmed to a short description and then all similar descriptions were grouped into a theme. The themes are a description of agricultural topics /services offered by extension workers across the four EPAs and the two districts (Dedza and Ntcheu), Table 5.2 below.

Table 5.2: Summary of Themes from the extension workers semi-structured interviews

Theme	Items
Intensification practices	Intercropping
	Ridge spacing
	Early maturing varieties
	Fertilizer use
	Manure management
	Weed management
Land Management	Catchment conservation
	Soil-water conservation
Climate Change	Improved cooking stoves
	Improved varieties
	Gullies reclamation
	Rainwater harvesting
	Irrigation uses
	Rainfall pattern updates
	Tree nurseries

Table 5.2 (cont'd)

Livestock Management	Livestock production
	Parasite-disease management
Training Approaches	Lead Farmer
	Farmer Cooperatives
	Farmer Field School
	Farmer Business School
	Village Authority Committee (VAC)
Communication	Mobiles phones/WhatsApp
	Physical visits
	Lead farmers
	Chiefs
	Village Development Committees
Challenges	Mobility
	Staff shortage
	Poor staff housing
	Low technology uptake
	Poor resources

5.4.2 Landscape Pattern Metrics

A subset of landscape classes (mixed fields, agro-forestry fields, bare fields and Shrubs/forest) from previous chapter 4 further examined in the content of agricultural extension delivery themes. Pattern metrics were used to analyze the landscape patterns found in each these classes (mixed fields, agro-forestry fields, bare fields and Shrubs/forest), these metrics provides insight into the changing organization and configuration of the landscape (Wang et al., 2014). Details on the methods can be found in previous chapter four. In this study, eleven pattern metrics listed here were used.

Class area (CA) represents the land class extent, Number of Patches (NP) represents smallest units of class area, percentage of landscape (PLAND), largest patch percentage of landscape index(LPI%), average size of patches (AREA_MN), Mean patch shape (SHAPE_MN(ha)), average proximity for all patches index (PROX_MN (m)), Mean Euclidean nearest Neighbor distance (ENN_MN(m)), Juxtaposition of a focal patch class with all other classes - Interspersion and Juxtaposition index (IJI %), amount of patch per individual -Shannon's diversity index (SHDI), Shannon Evenness index (SHEI) (McGarigal 2014, Linh et al, 2012).

5.5 Results

Table 5.3 below shows common intensification practices that extension staff reported to promote across the EPAs. The widely used farm practices are ridge spacing, plant spacing, use of improved varieties, fertilizer and manure management, and weed management. Most advice given by extension was for main crops such as maize, common beans, groundnut and soya bean, grown widely across the four EPAs.

Table 5.3: SI technologies that extension staffs train farmers on across four EPAs (n=19)

Crop	Recommendation	Gomoloti (n=6)	Kandeu (n=5)	Nsipe (n=5)	Linthipe (n=5)
Maize	One - one planting	x	x		
	Fertilizer application	x		x	x
	Manure application	x		x	x
	Early maturing varieties	x		x	x
	post- harvest handling	x		x	
	Fall army worm control	x	x	x	x
	Ridge spacing	x	x	x	x
	Proper weed management			x	
	Early planting with first rains			x	
Common Beans	Plant spacing		x	x	x
	Fertilizer application			x	
	Post- harvest handling			x	x
	Ridge spacing for pure stands			x	x
	Pest & disease control		x	x	
	Bean grading			x	
	Improved varieties		x		x
	Weeding				x
	Double row planting				x
Groundnuts	Certified seed		x	x	
	Plant spacing			x	
	Double row planting	x		x	x
	Varietal selection			x	
	Fertilizer application			x	
	Plant early with first rains			x	
	Pest and disease control		x	x	
	Weed management			x	
	Grading groundnuts for sale				x
	Post- harvest handling				x
Soya Bean	Double row spacing	x	x	x	x
	Use certified soya seed	x		x	x
	Soya bean nutrition recipes			x	x
	Ridge spacing	x	x	x	x
	Harvest methods			x	x
	Weeding	x			
Potatoes	Disease free seed selection				x
	Post-harvest handling				x
Tobacco	Use of certified seed	x			
	Uprooting of stalks -reaping	x			
Sweet Potatoes	Ridge spacing	x			x
	Pest and diseases	x			x
	Varietal selection	x			x
	Proper weed management				x
Sorghum	Crop spacing	x			
Cowpeas	Early planting	x			
	Pest and disease control	x			
	Post-harvest losses prevention	x			
Rice	Good storage practice	x			
Tomatoes	Pests and disease control	x			

5.5.1 Climate Change and Land Management

Table 5.4: Extension advice on climate change and land management across four EPAs (n=17)

	Advise	Golomoti (n= 6)	Kandeu (n= 3)	Nsipe n= (4)	Linthipe (n=4)
Climate Change	Improved cooking stoves				x
	Improved varieties	x	x	x	x
	Gullies reclamation		x		
	Rainwater harvesting	x		x	x
	Irrigation uses	x	x		
	Rainfall pattern updates		x		x
	Tree nurseries	x	x	x	
Land management	Catchment conservation	x			x
	Soil-water conservation	x	x		x

Extension staff reported to a wide range of topics and practices for climate change and land management (Table 5.4). In this Table 5.4, information given to farmers leaned towards risk and mitigation practices. Alternative use of improved cooking stoves as a source of energy, ensured that farmers will reduce deforestation. Tree planting advise was widely asked by farmers especially because some trees have multipurpose uses, that provide fuel wood as well as building materials for houses. Advice on gullies reclamation was common in Kandeu, as farmer fields are prone to flooding, and thus reclamation of areas with gullies is critical to slow soil erosion, additionally, advice on soil-water conservation on the fields by planting mixed crops and tree planting was encouraged to mitigate floods.

Farmers were keen to know about rainfall patterns as they had noticed changes in weather over the growing seasons. This information is critical as farmers also were advised on early maturing crop varieties, and when this seeds are available can mitigate against crop failure. Rainwater harvesting especially in drier areas in Golomoti and Nsipe is used for drinking for the farmers and livestock, and saves the women time to fetch water from far distances.

Catchment conservation information was given to farmers in Golomoti, and Linthipe sites, where watershed catchment areas are present and can be management for use both for growing food and water can be conversed for household use as well. Soil-water conservation information was also addressed on sites in Golomoti, Kandeu and Linthipe. Golomoti has high evapotranspiration due to its high temperatures and few tree cover, thus practices that are used to conserve moisture, such as residue management, intercropping with legumes as pigeon peas that are small bushes improves soil-water conservation.

5.5.2 Extension Training Approaches and Communication

Extension staff mostly train lead farmers who represent the farming communities in their village. Also farmer field schools are popular where farmers and extension agents come together to learn about improved farming practices. This is also similar to the farmer business school, where farmers network and learn entrepreneurial skills such as marketing of food crops, and livestock production strategies. Another method is by using the model village approach where a specific village is selected to showcase farming practices, and people from other villages come to interact and learn.

Training is also available through village authority committees, where selected members of each village are trained and then have an outreach responsibility to train the farmers in their respective villages. Most farmers and extension are also using mobile technologies and group apps for information dissemination as alternative and effective communication methods.

5.5.3 Livestock Management

Golomoti farmers were advised on construction improved livestock kraal, while Linthipe farmers were advised on increase in goat and chicken production and parasite –disease management.

Livestock production extension advice increases livestock health and productivity that bring mutual benefits to the communities, especially where livestock and farming communities have shared the landscape. Some farmers let livestock into their field after harvesting to forage, while they receive the manure from these livestock to incorporate into the soil.

5.5.4 Extension Delivery Challenges

Our findings suggest that extension delivery faces its own challenges, as they are resource based and mobility limited therefore coverage of allocated geographic locations to cater for farmers is problematic. Secondly, unbalanced extension work load with the extension to farmer ratio ranging from 1:1600 to 1:3000, contrary to the national recommendation of 1:750 – 1:850 (C. Masangano & Mthinda, n.d.) remains a key challenge.

Also, some extension staff noted that low literacy levels affect training and adoption of technologies, and resource poor farmers were limited in their ability to participate in extension activities, particularly women farmers. In some farming communities, extension staff reported that power structure between the village chiefs in the farming communities affecting the connection between extension and farmers. To mitigate this, farmers have their own associations and groups where they exchange knowledge.

5.5.5 Landscape Patterns Results

This section presents land use and landscape metrics for Dedza and Ntcheu districts between 2014, 2017 and 2019. As noted in earlier Chapter 4, caution on these class interpretations as some of the classes are produced by spectral overlap, registration or boundary problems (Howarth and Wickare 1981). Additionally, a caveat on interpretations of the mixed and bare (recently cultivated) fields are temporal, as multi-directional changes are expected from growing season to season.

In Table 5.5, overall changes for Dedza district from 2014 to 2019 show that shrubs and forest increased 2.8% and 10.6% respectively, while mixed, agroforestry fields decreased 9.5%, and 3.2% respectively. From 2014 to 2017 the mixed fields, agroforestry, settlement classes decreased by 14.3%, 5.7% and 0.9% respectively. While bare fields, and shrubs and forests increased by 3.1% and 17.4 respectively. In 2017 to 2019, increases were found in mixed fields, agroforestry and bare fields classes; 4.8% and 2.5% respectively.

Similarly, overall changes for Ntcheu district from 2014 to 2019 show that agroforestry fields, bare fields and shrubs and forests increased by 0.5%, 2.2% and 3.2% respectively (Table 5.6). From 2017 to 2014 the mixed fields, agroforestry, settlement classes decreased by 25%, 4.7% and 1.3% respectively. While bare fields, and shrubs and forests increased by 0.9% and 28.7 respectively. From 2017 to 2019, increases were found in mixed fields, agroforestry, bare fields and settlement classes; 5.1%, 5.2%, 1.3% and 1.3% respectively, while shrubs and forests decreased by 11.7 %.

Table 5.5: Dedza district land classes percentage

	Dedza District						Percent %	Percent %	Percent %
	2014		**2017**		**2019**		**area change**	**area change**	**area change**
LULC Class	**Area (Ha)**	**%**	**Area (Ha)**	**%**	**Area (Ha)**	**%**	**2017-2014**	**2019-2017**	**2019-2014**
Mixed fields	269308.98	52.7	196269.66	38.4	220855.59	43.2	-14.3	4.8	-9.5
Agroforestry fields	34124.4	6.7	5077.62	1.0	17982.63	3.5	-5.7	2.5	-3.2
Bare fields	11106.63	2.2	27009.81	5.3	25568.91	5.0	3.1	-0.3	2.8
Shrubs/forest	42890.13	8.4	131761.53	25.8	96873.39	18.9	17.4	-6.8	10.6
Total	357430.14	-	360118.62	-	361280.52	-	-	-	-

Table 5.6: Ntcheu district land classes percentage

	Ntcheu District						Percent %	Percent %	Percent %
	2014		**2017**		**2019**		**area change**	**area change**	**area change**
LULC Class	**Area (Ha)**	**%**	**Area (Ha)**	**%**	**Area (Ha)**	**%**	**2017-2014**	**2019-2017**	**2019-2014**
Mixed fields	244960.7	75.4	164007.4	50.5	180559.2	55.6	-25.0	5.1	-19.9
Agroforestry fields	25047.7	7.7	9886.1	3.0	26783.5	8.2	-4.7	5.2	0.5
Bare fields	4297.3	1.3	7301.3	2.2	11381.9	3.5	0.9	1.3	2.2
Shrubs/forest	41604.0	12.8	134846.9	41.5	96683.7	29.8	28.7	-11.7	16.9
Total	315909.7	-	316041.7	-	315408.3	-	-	-	-

Table 5.7, below displays the landscape metrics for Dedza district from 2014 to 2019. Here, statistics of mixed fields showed that the percentage of landscape (PLAND) index decreased from 52.7% to 43.2%, while the number of patches (NP) increased from 17,657 to 32,133 from 2014 to 2019, this suggests fragmentation of agricultural fields into smaller parcels. This is also supported by the largest patch index (LPI) that decreased from 50.4% to 30.6% and the mean patch area AREA_MN – decreased from 15.3 to 6.9, therefore fragmentation is occurring and/or that landscape heterogeneity is increasing. This is unsurprising given the land transitions narratives on fields that changes from season to season.

The agroforestry class area decreased from 34,124 to 17,982 from 2014 to 2019, the percentage landscape (PLAND) also decreased from 6.7% to 3.5% while the number of patches (NP) increased. These changes are consistent with a reduction of tree biomass in 2019, and or a change in farming practice. Shrubs/forest increased from 42,890.1 to 96,873.4 from 2014 to 2019, this increase could be due to increased biomass from 2018/2019 good rainfall season, and also improved forest management that minimized clearing of forested areas. Between 2014 to 2019, the mean nearest-neighbor distance (ENN_MN) across the classes had slight changes whereas the mean proximity index (PROX_MN) revealed that the patches less isolated for mainly for the mixed field. The observed interspersion (IJI) - distribution of adjacencies among unique patch types did not change much, but shows that the patch types are already uneven as IJI approached 0.

Table 5.7: Summary landscape structure metrics for Dedza district, 2014 and 2019

Dedza 2014 LULC Class	CA (ha)	PLAND %	NP (#)	LPI (%)	AREA_MN (ha)	SHAPE_MN (ha)	PROX_MN (m)	ENN_MN (m)	IJI (%)
Mixed fields	269309.0	52.7	17657	50.4	15.3	1.3	305368.8	69.1	76.9
Agroforestry fields	34124.4	6.7	68131	0.1	0.5	1.2	15.3	85.0	59.6
Shrubs/forest	42890.1	8.4	51970	2.4	0.8	1.2	631.1	89.9	50.8
Bare fields	11106.6	2.2	31019	0.0	0.4	1.2	1.9	129.7	43.0
Dedza 2019									
Mixed fields	220855.6	43.2	32133	30.6	6.9	1.3	97894.2	70.5	65.2
Agroforestry fields	17982.6	3.5	74571	0.0	0.2	1.1	2.0	92.3	55.7
Shrubs/forest	96873.4	18.9	56339	6.3	1.7	1.3	5511.1	85.5	52.9
Bare fields	25568.9	5.0	36437	0.3	0.7	1.2	26.4	117.0	39.9

Table 5.8: Summary landscape structure metrics for Ntcheu District 2014 and 2019

Ntcheu 2014 LULC Class	**CA (ha)**	**PLAND %**	**NP (#)**	**LPI (%)**	**AREA_MN (ha)**	**SHAPE_MN (ha)**	**PROX_MN (m)**	**ENN_MN (m)**	**IJI (%)**
Mixed fields	244960.7	75.4	9123	74.1	26.9	1.2	495373.9	63.6	68.0
Agroforestry fields	25047.7	7.7	75039	0.1	0.3	1.2	4.9	85.1	53.3
Shrubs/forest	41604.0	12.8	57436	0.3	0.7	1.3	29.1	83.9	45.6
Bare fields	4297.3	1.3	23616	0.0	0.2	1.1	0.5	152.8	53.0
Ntcheu 2019									
Mixed fields	180559.2	55.6	31696	45.9	5.7	1.3	161582.2	66.9	63.2
Agroforestry fields	26783.5	8.2	83160	0.1	0.3	1.2	5.2	83.9	53.3
Shrubs/forest	96683.7	29.8	62549	2.6	1.5	1.3	1057.6	74.6	53.9
Bare fields	11381.9	3.5	39048	0.0	0.3	1.1	2.3	119.5	49.2

Overall, the number of patches (NP) increased slightly from 217,198 in 2014 to 244,148 in 2019, suggesting high fragmentation across the landscape (Table 5.7). The SHDI and SHEI were both greater in 2019, suggesting a slight increase in landscape heterogeneity (Table 5.7).

In Table 5.8, Ntcheu district shows similarities to Dedza, such as mixed and base fields are cautiously interpreted as they show temporal changes across the year fields. Agroforestry fields increased slightly from 2014 to 2019, both in class area (CA) and percentage of landscape (PLAND), this is an interesting find, as it may suggest that efforts to increase tree planting in farmers' fields. Similarly, shrubs/forest class increased between 2014 to 2019 in CA and PLAND, and maybe due to a good rainfall event in the previous years, and /or good forest management practices minimizing clearing of forests by nearby communities. Overall, mixed fields have a decrease in largest patch index (LPI) from 74.1% to 45.9% than any other classes, and also its mean patch area -AREA_MN was slightly significant – 26.9% to 5.7% from 2014 to 2019, that suggest intensification due to these changes in patch sizes. In summary, the SHDI and SHDI show a slight increase in landscape heterogeneity.

5.6 Discussion

No clear spatial pattern observed across the sites and driven by the environmental gradient connects observed changes with agricultural extension delivery. Overall, there are minimal agricultural landscape changes, and no evidence that strategies promoted by extension have a scale effect on the landscape. The slight increase is noted in the agroforestry and shrub/forest classes that could point to efforts of tree planting in farm fields, but also good rainfall year for 2018/2019 season could have influenced the increased biomass. Overall changes in land use in Dedza and Ntcheu is low, and thus a stable system is in place.

Mungai et al., 2020, noted that across Malawi it is not uncommon to see agroforestry fields, where nitrogen fixing trees such *Faidherbia albida*, *Gliricidia sepium*, *Tephrosia vogeii*, and *Sesbania sesban* are found in mixed cropping systems. Additionally, tree planting was recommended by extension as a way to mitigate climate change. Shrubs and forests areas in in Dedza and Ntcheu has sites co-managed under the Improved Forestry for Sustainable Programme (IFMSLP) that began in 2009 assisting communities use forest based incoming generating activities as honey and timber production through proper management (Mauambeta et al., 2010). This is evident also in Southern Malawi where farming communities are stewards of the forested and woodland areas (Mauambeta et al., 2010, Zulu 2008). Extension staff trained farmers on ways to improve soil fertility by practicing intercropping with nitrogen fixing plants, ridging, residue management that can effectively manage intensification to mitigate unmanaged and unsustainable practices. Our findings show that mixed fields show some evidence of extension promoted practices.

Use of recommended farming practices should improve land resilience, as many pieces of land restoration work together to improve landscape function and thus SI of agriculture should increase landscape stability. For example, use of gullies reclamation in Kandeu (Table 5.2) can be used to manage land fragmentation, where weak soils are prone to be washed away during flooding events, and thus crops failure in such areas are likely due to lack of soil organic matter. Contrary benefits in flooding events may be observed in shrubs/forests where subsequent biomass increase is captured in 2019, that can be attributed to a climate event. Extension advice on use of irrigation farming, as a strategy to improve crop development in dry seasons is mostly beneficial especially in location with low water table, giving farmers the opportunity to improvise low irrigation systems such as drip irrigation. The above-mentioned practices are evidence of SI of agriculture as observed in the landscape. This study shows benefits of pattern metrics such as to characterize the human activities on landscapes such as use of patch sizes, Mean Euclidean Nearest Neighbor Index (ENN_NM), and Percentage Landscape (PLAND), yet limits interpretation of metrics in this study, such that lack of variations between landscape effects and its association of environmental or human activities can be assumed but not differentiated.

5.6.1 Agriculture and Extension Delivery

Our findings show when recommended practices such as ridging, intercropping, use of inorganic and organic fertilizers, weed and residue management are performed before and during planting it is possible to mitigate soil depletion and marginalization. Evidence from field work shows that most fields have ridging or some residue management practices. However, from past studies farmers are often not able to maintain these practices as they base their decisions on available input resources. The findings on land use (Table 5.5 and 5.6) suggest that changes between mixed to bare fields are temporal since farmers decisions to cultivate and sow new crops the field vary from season to season. Famers are driven by different social-economic conditions and goals, thus implementation and increase of SI practices is based on mutual benefits existing among farmers, partnerships, or extension (Hockett and Richardson 2018).

Extension delivery remain limited in terms of farmer outreach due scarce resources and also the high ratio of farmer to extension. Despite the improvement in mobile technologies where extension and farmers can interact via voice response systems using basic mobile phones (Aker 2011, Kwatani and Markon 2017). Frequent extension contact with farmers significantly influences adoption of recommended maize production technologies (Muguza-Tembo 2010). In 2017, Government of Malawi started an initiative to improve extension and advisory delivery by providing resources and promote agricultural production. Despite these efforts, connection between farmers' adoption of SI technologies based extension services remains low, and the advancement of SI technologies is likely to progress slowly where infrastructure and resources for the extension staff and farmers are lacking.

5.7 Conclusion

The agricultural landscape of central Malawi is mature and stable. With the datasets collected and presented here, there is no evidence that agricultural extension delivery improves SI of agriculture synoptically. However, landscape patterns metrics do assist in disentangling the agricultural landscape from social and biophysical drivers, and even though this study did not have evidence of improvement of SI of agriculture across the districts, it has increased understanding of the interactions found between landscape patterns measured and agricultural extension delivery.

The findings area an opportunity to consider that successful extension delivery of innovative technologies that not only boosts SI of agriculture but should be measured in the landscape patterns. Our study informs Malawi's Ministry of Agriculture and Extension Services on current sub-regional landscape status and these landscape pattern measurements can be used to improve resource priorities for extension and farmers across the districts.

6. CONCLUSIONS

This research uses a multi-scale lens to assess indicators of Sustainable Intensification (SI) for smallholder agriculture in Malawi by identifying spatial patterns and human–environment agents of agricultural intensification over time and spatial scales. Understanding the multi-scale aspects of SI of agriculture for smallholder systems in Malawi is imperative to improve our understanding of the processes and drivers that play a role in agricultural productivity and the emergent or coincident variations therein.

The first study assessed the spatial patterns of Malawi’s agricultural productivity trends from 2006 to 2017 and identified areas of positive trends that are not influenced by climate and edaphic factors signaling potential human induced intensification. Also, the spatial distribution of farmer reported maize yields and farmer input resource practices enhanced our understanding of variability in yields and farmer resource management. At the national level, the long-term data showed a decline in productivity and maize yields, concentrated in the south. The hot spots that show positive trends not influenced by climate typically had medium-large scale farming of crops such as sugar cane, tea and other cash crops. Some of these locations have irrigation systems, unlike the areas with low yields. Despite the government input subsidies, it is evident that the inorganic fertilizer and maize seeds are not enough to sustain food production. Low maize yields are often indicative of marginal/poor soils under continuous cultivation. The low use of diversified farming systems such intercropping with soil improving crops, agroforestry for soil and water conservation, and best practices in residue and compost management contribute to low yields and unsustainable systems.

The second study; a baseline characterization of local farmers in the four study sites, highlighted current farmer demographics, resources and farm practices to understand smallholder farmer potential for SI of agriculture. Typically, the local people were subsistence farmers and consumed most of the food that they grew in each season. The baseline study showed that these farmers have no resources to improve their food production and are highly depended on government fertilizer and seed subsidies. In addition, extension services are not able to reach all farmers, and thus information on crop and farm practices improvement is limited to easily accessible areas. There are few public and private partnerships, and infrastructure is lacking with few community distribution centers. Aside from these issues, this research also looked into the human activities on the landscape that that could point to intensification of agriculture. The third study analyzed regional Land Use Land Cover Change (LULC) for Dedza and Ntcheu districts in Central Malawi based on three growing seasons (2014, 2017, and 2019) to quantify land-use patterns. Landscape structure was also examined to determine the nature of these patterns as linked to the human-environment processes of agricultural intensification. Both Dedza and Ntcheu districts showed land classes such as mixed and bare/cultivated fields to be the most common across the years. Less frequently, were agroforestry fields. There are seasonal variations across the agricultural fields between 2014, 2017 and 2019. Farmers make decisions on field area to cultivate each season and also which plots based on seed and labor availability. In many areas in Ntcheu, fields were left fallow, especially where farmers had insufficient labor to clear and prepare the fields for the next season. Both Dedza and Ntcheu have high field and landscape fragmentation. This is not a surprise, especially in areas where farmers search out fertile soils to cultivate, and, due to the traditional land tenure systems, farmers are able to find fields within their own village sections or rent out fields to others. Overall, similar farming practices are usually transferred to new fields, and there is not much change in either local or regional productivity.

In the fourth study, there was need to understand the agricultural extension service delivery and associate its role to the landscape patterns identified in study three above, that are manifestations of SI of agriculture. Identifying the types of information and training that extension workers give to farmers is key to understanding whether the delivery is making an impact in the fields and overall landscape. Based on the surveys collected from extension workers, we found that the extension trainings and information can fall under sustainable intensification and also risk mitigation methods. Prior to our survey, the assumption has been that extension services are geared towards sustainable intensification, however, our evidence shows that the services are broader, and thus a keen interest on what farmers' are asking from extension workers shows that farmers are asking for local solutions based on what is happening within and around their farm areas and can differ from season to season. The types of trainings given to farmers are also limited to available resources (materials and staff availability), and thus this resource cap is one of the disadvantages to scaling of innovations both from the extension delivery and the farmer livelihood.

The main conclusions are, overall Malawi agricultural productivity has been declining across time between 2006-2017, and is trend is supported by national farmer reported yields that showed low yields across Malawi, especially Southern region of Malawi displayed lowest yields. Low productivity is mainly driven by untimely access of affordable input resources, lack of credit access to assist in buying resources, and lack of information to deal with the season to season problems driven by external factors, as well as low adopt SI technologies.

Land Use and Land Cover (LULC) change findings show few changes from 2014 to 2019 across both Dedza and Ntcheu districts. Land in agricultural production is stable. There are few changes in infrastructure development, and thus most rural areas remain inaccessible. Land fragmentation increased between 2014 to 2019 and may be indicative of underlying intensification processes. Agricultural fields (mixed and bare) are seasonal depending on farmer decisions. Despite the lack of clear evidence of effective extension delivery of SI techniques and trainings, the agricultural landscape studied was stable. Understanding extension delivery responsibilities and public-private partnerships can help to disentangle information that is most beneficial to farmers across seasons, and thus when innovations in sustainable agriculture are implemented consistently, they can then be captured in the landscape.

Malawian farmers show great potential in sustainable food production, and thus more work is needed to understand farming across agro-ecologies across Malawi. Improvements in resource availability and innovative solutions for accessible extension delivery to improve soil fertility, crop production and livelihood is a step towards progress. Innovative systems approaches that integrate field work and big data at multiple scales will assist stakeholders target locations where climate and edaphic factors are optimal for different types of crops as well as places where smallholder farmers need assistance to move towards sustainable agriculture.

6.1 Future Recommendations

- This research used a multi-scale lens to understand Malawi's agricultural production across national, sub-regional and local scales, giving a deeper understanding on the variations of SI of Agriculture across spatial-temporal scales. The use of spatial-temporal scales to study smallholder farming systems is a novel approach in global food security studies and should be applied often to understand the variability of agriculture production within locations and across regions. Future research suggestions are as follows:
- Landscape pattern metrics should be applied to future studies of SI of Agriculture in other parts of Sub-Saharan Africa, particularly for small-holder agriculture.

- Future work should consider seasonal variations analysis that drives productivity across agro-ecologies to recommend SI technologies that are location specific to improve sustainable food production. Location-specific agricultural advice should be based on local bio-geographical and social-economic factors as we as take into consideration farmer goals for crop production and the adaptation capacities of farmers.
- Model agricultural extension innovative services associated to farmer practice as found in the landscape as a way to monitor extension delivery across Malawi.
- Integrate spatial-temporal agricultural information across administrative levels.
- Invest in extension services through partnerships with local and private organizations and improve farming community engagement by investing in farmer-led businesses to improve farmer livelihood, especially during droughts.
- This study is significant as it provides stakeholders with information to understand agricultural production in Malawi across scales, via a systems approach to elucidating intensification of agriculture through an interdisciplinary lens.

APPENDIX

APPENDIX

Notes: Central Malawi (Dedza and Ntcheu Districts), survey instruments used in this dissertation are part of Africa RISING (Research in Sustainable Intensification for the Next Generation) project. Permission from Africa RISING is needed to access the datasets.

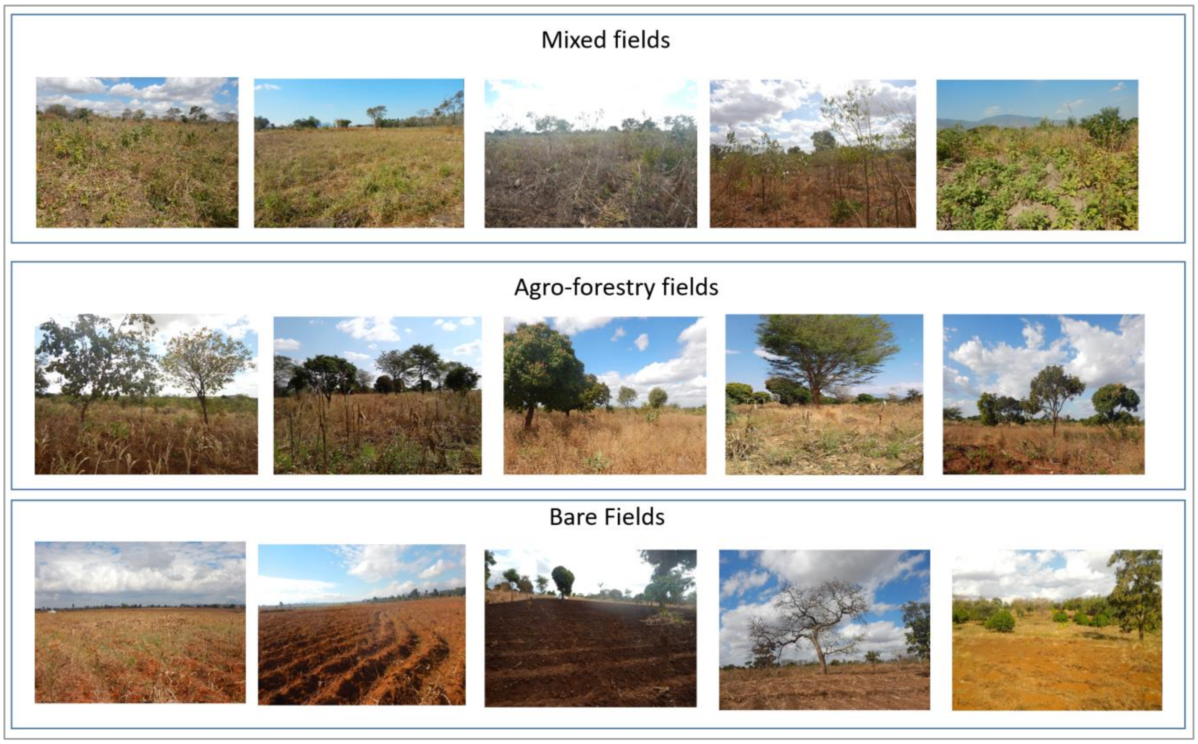


Figure A4.1: Geo-tagged photos of diverse types of agricultural fields in Dedza and Ntcheu District (Photo credit: Leah Mungai)

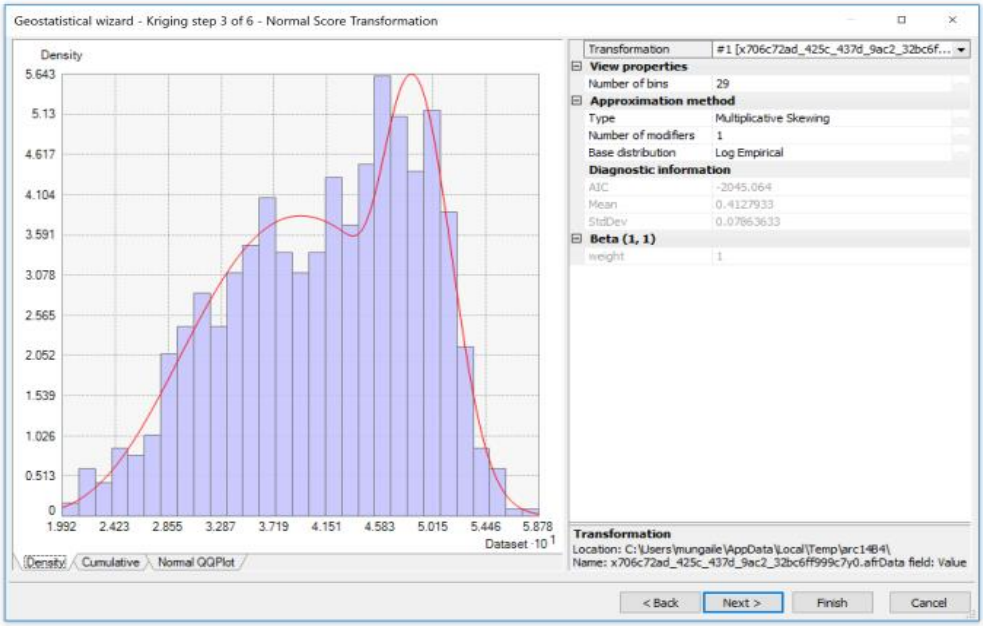


Figure A4.2: Landsat 250m rescaled imagery geostatistical process in ArcGIS

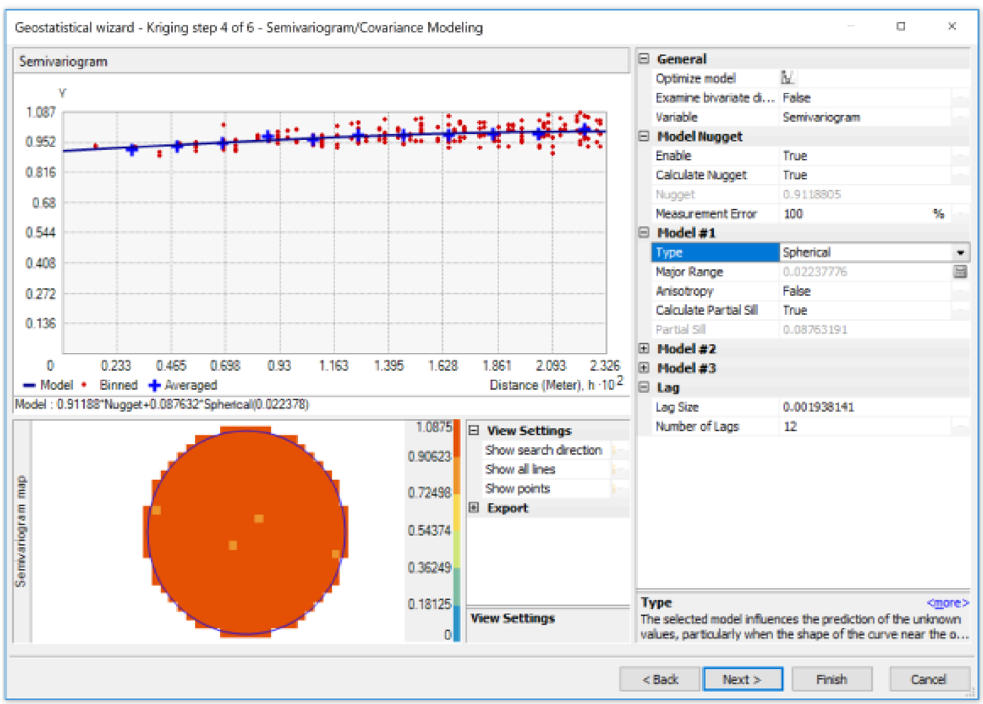


Figure A4.3: Landsat 250m semi variogram geostatistical process in ArcGIS

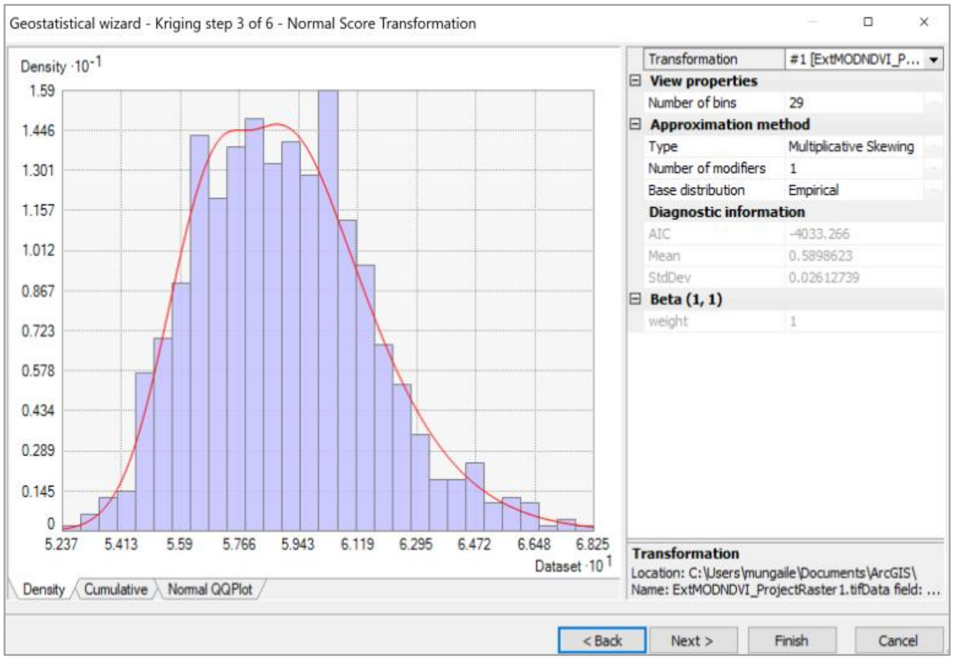


Figure A4.4: MODIS NDVI imagery Geostatistical process output in ArcGIS

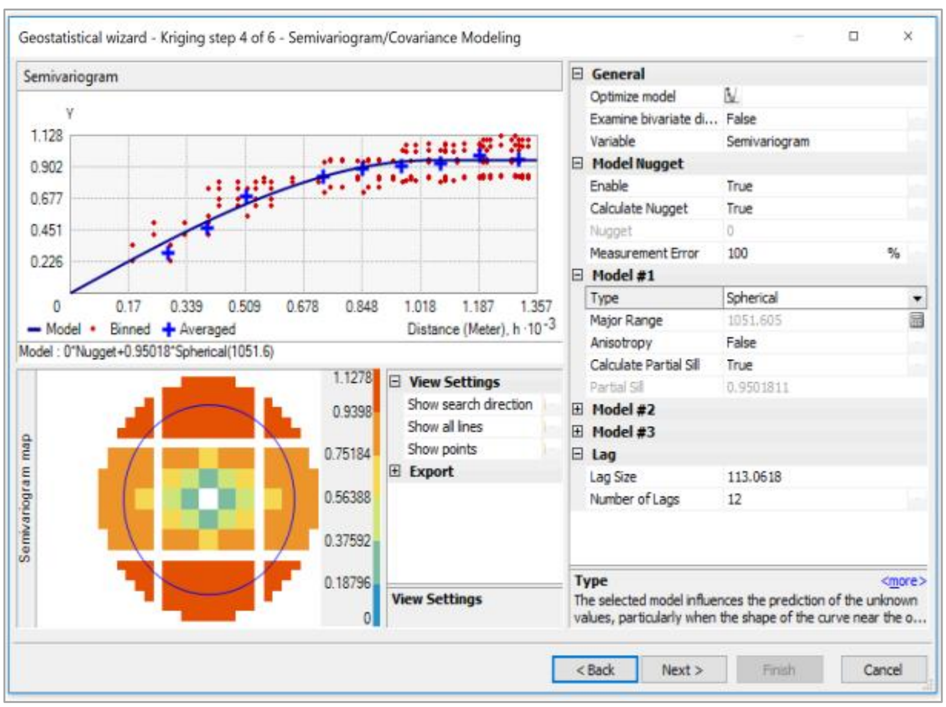


Figure A4.5: MODIS NDVI imagery Semivariogram Geostatistical process in ArcGIS

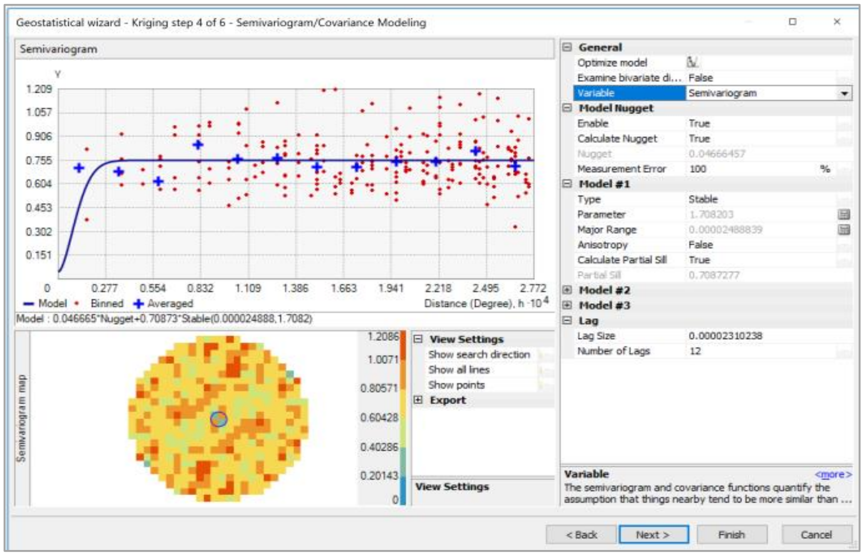


Figure A4.6: Linthipe 2m resolution imagery Geostatistical process output in ArcGIS

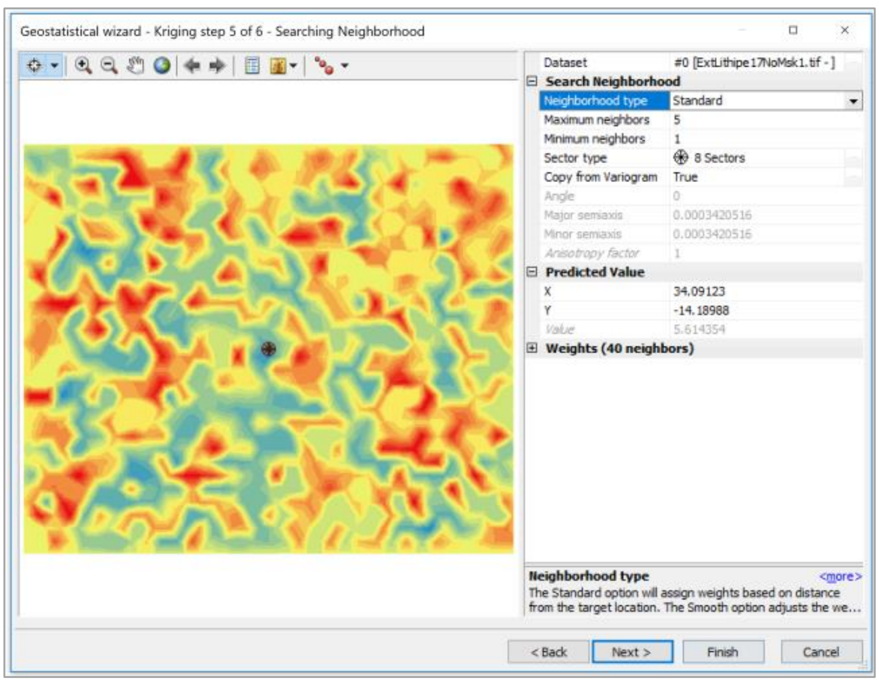


Figure A4.7: Linthipe 2m resolution prediction map Geostatistical process output in ArcGIS

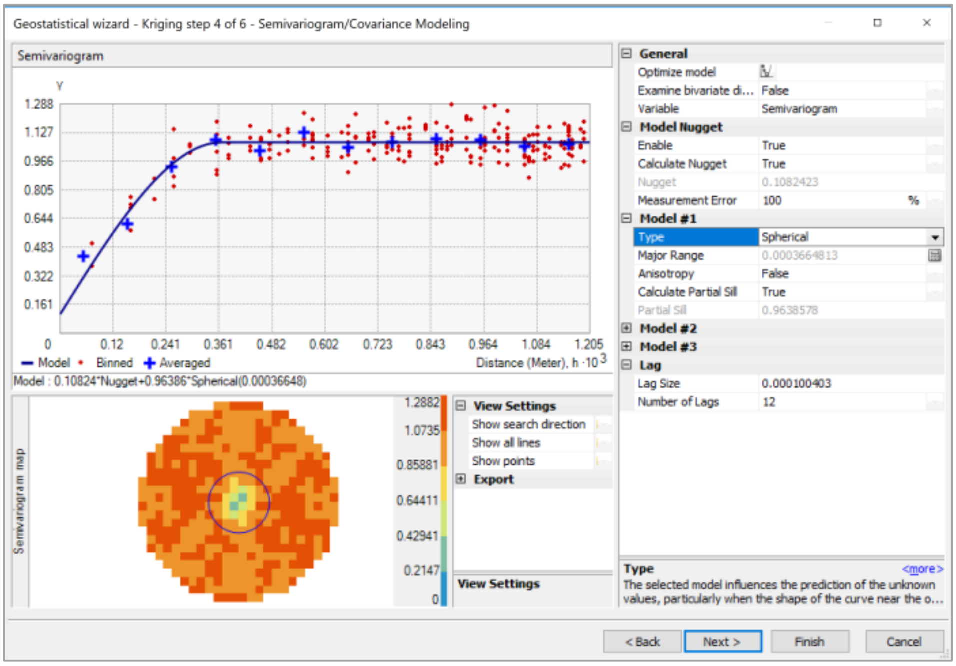


Figure A4.8: Golomoti 5m imagery original and rescaled geostatistical output in ArcGIS

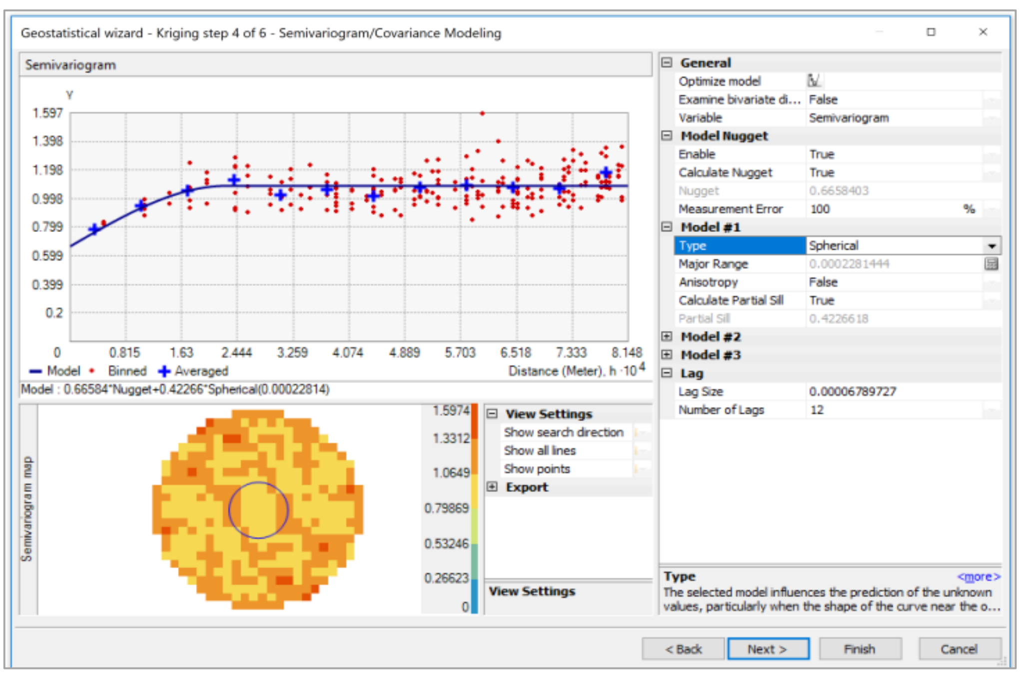


Figure A4.9: Golomoti 5m imagery original and rescaled geostatistical output in ArcGIS

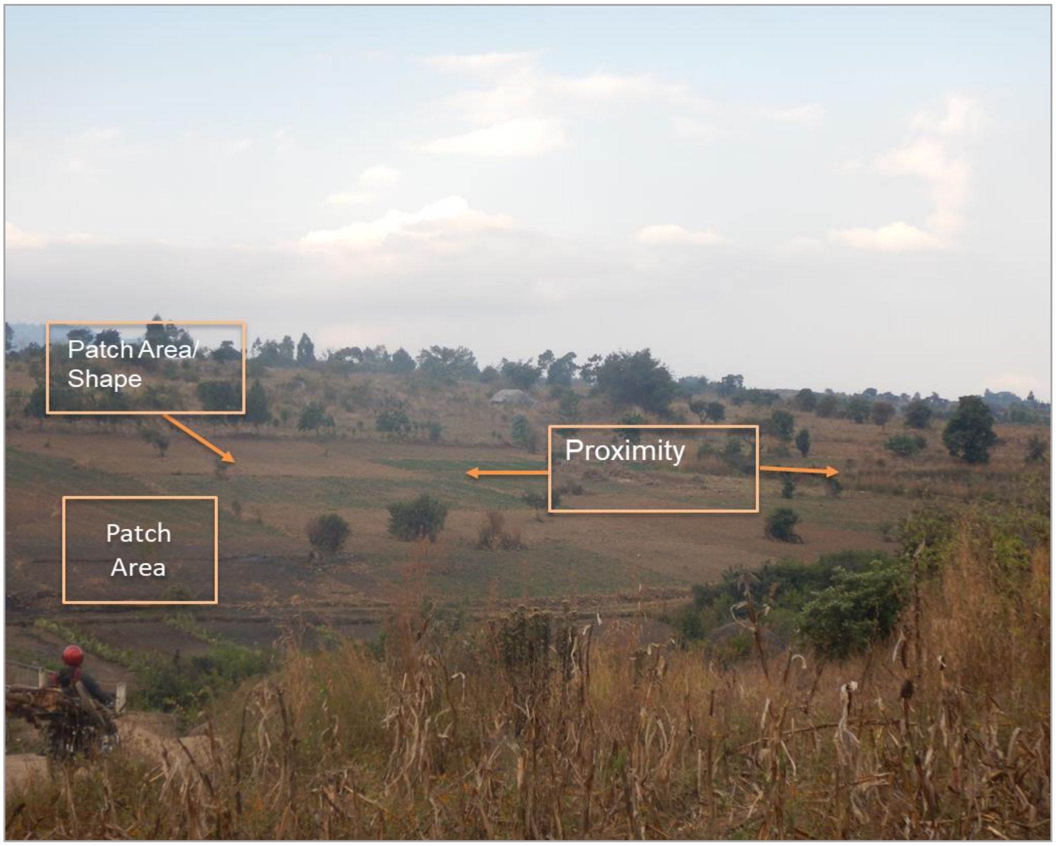


Figure A4.10: Example of landscape metrics (adapted: source Frazier, A. (2019)).

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