INTEGRATED REMOTE SENSING AND CROP SYSTEM MODELING FOR PRECISION AGRICULTURE ACROSS SPATIAL AND TEMPORAL SCALES

By

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ABSTRACT

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In light of global environmental change, population pressure, and food production demands, there is considerable value in mapping biogeographic crop niche and characterizing crop productivity at multiple scales to enhance the impact of agricultural improvement across Africa. Crop system research has advanced sustainable strategies for intensifying food production; however, questions regarding where to implement innovative technologies are largely unresolved.

This dissertation focuses on four geographic questions: (1) Where is the fundamental climate niche of maize, pigeonpea, and sorghum across Africa? (2) Where are marginal lands in Malawi and what are the underlying drivers of marginality? (3) Based on the drivers of marginal maize production, what are geographic scaling options for integration of pigeonpea into maize-based cropping systems? (4) What spatial resolutions are effective for conducting precision agriculture at the farm scale in smallholder systems?

Overarching themes within the geographic discipline such as the modifiable areal unit problem and ecological fallacy problem underpin this research. Marginal areas for maize are highlighted at the Africa and Malawi scales and overlain with the optimal climate niche for crops such as sorghum and pigeonpea that offer multiple ecosystem services (e.g., soil rehabilitation through nitrogen fixation). Crop productivity is evaluated at scales relative to policy making delineations in Malawi (i.e., country, district, and extension planning area) to disentangle heterogeneity at local scales that may appear homogeneous at broader scales. At the Malawi farm scale, this research included the use of a small unmanned aerial system (sUAS), national government satellites (e.g.,

Sentinel-2), and commercial satellites (e.g., SPOT 6). Spectral measurements of crop status were evaluated at multiple spatial resolutions (ranging from 0.07–20-m) to determine what spatial resolutions and what spectral indices are most effective for estimating crop yields and crop chlorophyll.

Results of this research include high spatial resolution maps of maize, pigeonpea, and sorghum suitability across Africa, indicating that pigeonpea and sorghum occupy unique agroecological zones throughout the continent (e.g., sorghum in the Sahel region). Similarly, pigeonpea suitability in Malawi occupies a greater land area than the extent to which it is currently cultivated, demonstrating that integration into maize-based cropping systems, particularly where soil is marginal, can have beneficial scaling outcomes. For the smallholder farm scale, problems of clouds and satellite revisit rates have not yet been overcome for precision agriculture. In this regard, sUAS are a promising option for relating spectral signals to on-farm measurements of crop status. Evidence from drone flights conducted at two experimental farms in the central region of Malawi (Nyambi and Ntubwi) suggest that spatial resolutions closer to the plant scale (i.e., 14–27-cm) are most effective for relating spectral imagery to crop status. Moreover, the green normalized difference vegetation index (GNDVI) and green soil adjusted vegetation index (GSAVI) were consistently correlated with crop chlorophyll and yield, illustrating that a broad range of indices should be evaluated for precision agriculture.

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INTRODUCTION

1.1 Multiscale Geographic Challenges

Continental Scale: Food Security and Climate Change—Many countries in Sub-Saharan Africa have experienced food shortages over the last several decades (Maxwell 1999; Buerkle 2005; Banda 2015; Phiri and Macharia 2016), and smallholder subsistence agriculture is increasingly stressed by population pressures, soil exhaustion, and climate change (Postel 2000; Godfray 2010). Droughts and unpredictable rainfall patterns have led to substantial fluctuations in annual agricultural output (Tadross et al. 2009), particularly in areas where biophysical conditions are suboptimal or where social factors limit productivity (Challinor et al. 2007). Moreover, there are sustainability concerns associated with the continuous production of maize consequently leading to soil nutrient and organic matter depletion (Sanchez 2002; Glasson 2010; Ngwira et al. 2012; Thierfelder et al. 2013).

Among the United Nations Sustainable Development Goals are to increase agricultural production and reduce the cases of hunger and malnutrition globally (United Nations 2018). Given the existing and anticipated concerns regarding future climate change, impacts on global food security, and the need to produce more food (Wheeler and Braun 2013), a question looms for geographers—where can new agricultural technologies be introduced, and at what scales can geospatial data be leveraged to improve agricultural production?

Elucidating the spatial organization of crop suitability across Africa is critical for resolving questions of where and how to maximize cropping system efficacy across space. At the continental scale, Africa contains many agroecological zones that can support a wide variety of crops, yet many are underrepresented by current global crop suitability models (Kane et al. 2016; Peter et al. 2017a). Promotion of ecosystem service-offering crops has taken hold; however, geospatial products designed to target implementation areas for crop system innovations are essential to successful scaling (Wood et al. 1999), yet currently lacking, particularly at regular temporal intervals. At present, evidence suggests that the production of legumes in Africa does not coincide with the biophysical extent of suitability (Snapp et al. 2019a), and that perennial grain suitability may be more geographically extensive than previously perceived (Peter et al. 2017a). In this regard, there is potential for legume diversification to enhance agroecosystem productivity in many regions of Africa (Snapp et al. 2019a), not only for soil rehabilitation, but also as complementary nutrition in household consumption (Bezner-Kerr 2007; Jones et al. 2014; Ojiewo 2015). For illustration, the geographic extent of the fundamental climate niche for common bean across Southeastern Africa is demonstrated here in Figure 1.1.

Importantly, crop technology adoption will only take place where biophysical suitability is appropriate (Kwesiga et al. 2003), and as global changes continue to occur, geospatial analytics and map outputs will need to be generated with more frequency. As global climate information is released to the public in near real-time, crop climate-suitability maps can and should be generated at the same pace. With cloud-based geographic information system platforms emerging, such as Google Earth Engine (Gorelick et al. 2017), data acquisition and geospatial analytics can be performed at unprecedented geographic scales and product delivery speeds to transform empirical spatial data into scientific and actionable knowledge.

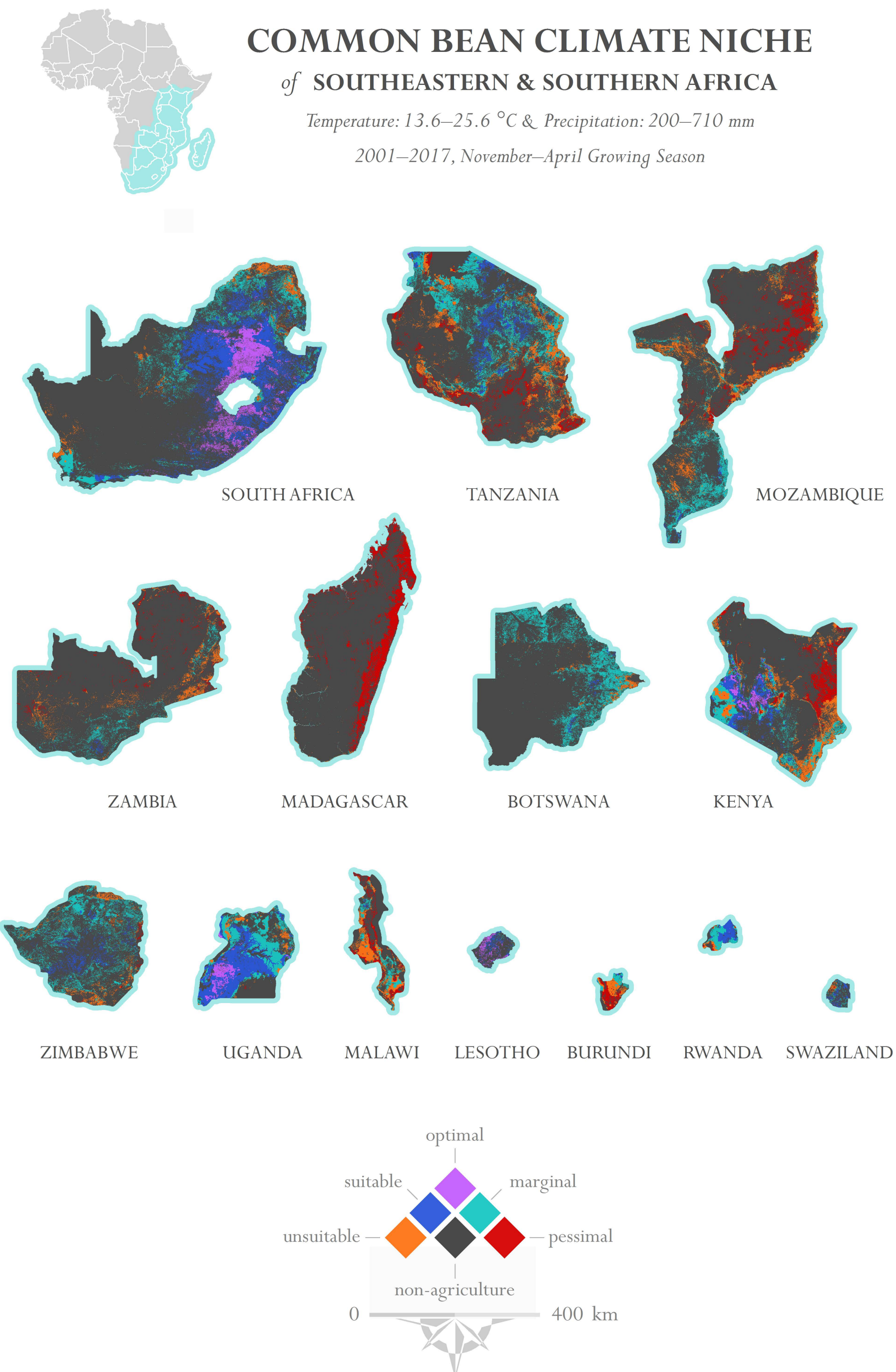

Figure 1.1. *Climate niche for common bean in Southeastern Africa.* Temperature and precipitation parameters collected from Beebe et al. (2011). Data sources: NASA MODIS Land Surface Temperature (MOD11A2) (NASA LP DAAC 2015b) and CHIRPS Precipitation (Funk et al. 2015).

Country Scale: Characterizing Marginal Lands and Informing Policy—In densely cultivated Malawi, the only options for increased production are through agricultural expansion into marginal areas or intensification of farms currently persisting on marginal lands (Kalipeni 1996; Josephson et al. 2014; Ricker-Gilbert et al. 2014). Consideration of marginal lands for agricultural sustainability is critical to national food security in Malawi as approximately 88 percent of the population lives in rural areas and many rely on subsistence farming (Malawi National Statistical Office NSO 2005; Chinsinga and O'Brien 2008). With this in mind, the focus for increased agricultural productivity revolves primarily around internal reorganization of existing farms, while simultaneously meeting goals associated with environmental conservation (Josephson et al. 2014; Ricker-Gilbert et al. 2014; Kremen 2015). However, marginal agricultural lands in need of increased production are not widely recognized as a land-use class, and despite increasing research efforts to identify marginal lands (Wood et al. 1999; Gopalakrishnan et al. 2011; Cai et al. 2011), there is not a universal definition for characterizing marginal land.

Few marginal agricultural land classifications directly address the smallholder farming context, and such studies are often limited to one scale. Problematically, marginal agricultural lands are typically presented as a singular classification and regularly conflated as unsuitable, which can divert agricultural investments away from agricultural areas in need of resources (Nalepa et al. 2017). Rather than the typical singular marginal land classification, a multi-category definition that considers the underlying factors driving marginality can inform what strategies are selected for improving crop production on smallholder farms. Locating marginal agricultural lands and identifying the drivers of marginality ensures that agricultural improvements are targeted with respect to the limiting factors of production.

Global satellites and time-series spatial information can aid in evaluating long-term agricultural system resilience (Haworth et al. 2018), as well as provide critical biophysical data for crop niche mapping. With multispectral satellite imagery, global agricultural productivity can be measured and characterized (Atzberger 2013); however, at global scales of analysis, local-scale heterogeneous landscapes can appear homogeneous (Sexton et al. 1998; Duveiller et al. 2015). This is in part a product of the modifiable areal unit problem (MAUP), popularly coined by Openshaw (1983), recognizing that pixel classifications or statistical aggregations can vary depending on the data distribution within the areal unit selected. At the pixel scale, the ecological fallacy problem also emerges, where assumptions may be erroneously applied to individual based on aggregate data (Openshaw 1983). A multiscalar challenge to overcome here is that global- and continental-scale characterizations of land in Malawi can be [mis]represented as one homogeneous category, which is ultimately not effective for country- or district-scale policy decisions, let alone an individual farm. Notably, Blaikie and Brookfield (1987) argued the importance of geographic scales and socioeconomic organizations in evaluating human-environment interactions (Nuemann 2009). To this end, policymakers will benefit from a multiscale classification approach that considers the modifiable areal unit problem and elucidates crop production variability at scales relative to multiple administrative decision levels (e.g., country, districts, and extension planning areas in Malawi).

Farm Scale: Precision Agriculture and Variable-Rate Technology—High spatial-resolution small unmanned aerial systems (sUAS) offer unprecedented levels of geospatial analytics at the farm scale. In-season crop status monitoring with these systems has become popular in industrialized agriculture, with spatial applications of crop improvement informed by spatial measurements of crop performance (known as variable-rate technology) (Sawyer 1998; Zhang and Kovacs 2012).

Precision agriculture can add value to smallholder environments in semi-arid Africa to inform timely and efficient sowing and weeding, and spatial allocation of fertilizer (Aune et al. 2017); however, there are substantial limitations to obtaining sUAS imagery across vast geographic extents. Advances in spatial and temporal resolution satellite imaging have made precision agriculture in remote areas increasingly feasible; however, cloud cover and revisit rates still pose a considerable hurdle (Mulla 2013).

With a fixed-wing craft such as the senseFly eBee equipped with a Parrot Sequoia multispectral camera, images with a spatial resolution of less than 5-cm can be achieved. The standard camera collects images at four spectral wavelengths: green, red, red edge, and near infrared, which can be manipulated to produce an extensive collection of crop status indices. At this scale, intra-farm variability can be measured and intra-farm recommendations made; however, it is well-known that the linear correlation between remote sensing-based indices and *in situ* crop measurements will vary depending on the crop evaluated, index selected, spatial resolution of the imagery, and interference of clouds, shadows, or soil (Hatfield and Prueger 2010). Two questions of interest in this research area are: What spatial resolutions (ranging from national government and commercial satellites to sUAS) are effective for conducting precision agriculture at the smallholder farm scale in Malawi?, and (2) What spectral indices are effective for informing variable-rate technologies on smallholder farms?

1.2 Multiscale Geographic Solutions

Purpose and Objectives—This research focuses on four overarching questions: (1) Where is the fundamental climate niche of maize, pigeonpea, and sorghum across Africa? (2) Where are marginal lands in Malawi and what are the underlying drivers of marginality? (3) Based on the drivers of marginal maize production, what are geographic scaling options for integration of pigeonpea into maize-based cropping systems? (4) What spatial resolutions and spectral indices are effective for conducting precision agriculture at the farm scale in smallholder systems?

Key outputs of these studies include the development of protocols and products that provide multi-scale decision guidance for improving smallholder agricultural systems in Malawi by integrating high-resolution satellite imagery, sUAS imagery, field measurements, geospatial analytics, and variable-rate technology. The project consists of the following four geographic solutions for improving agricultural production across spatial scales. Study 1: establish crop profiles and map the fundamental climate niche for maize and select perennial grains across Africa. Study 2: identify marginal maize agricultural land in Africa and Malawi based on climate niche, terrain characteristics, and measured interannual production variability. Study 3: (a) map the fundamental climate niche of pigeonpea in Malawi and (b) identify potential areas for the deployment of pigeonpea into maize-based cropping systems to illustrate geographic scalability. Study 4: evaluate a range of satellite and sUAS imagery spatial resolutions and spectral indices to determine effective spatial resolutions for precision agriculture on smallholder farms (Figure 1.2).

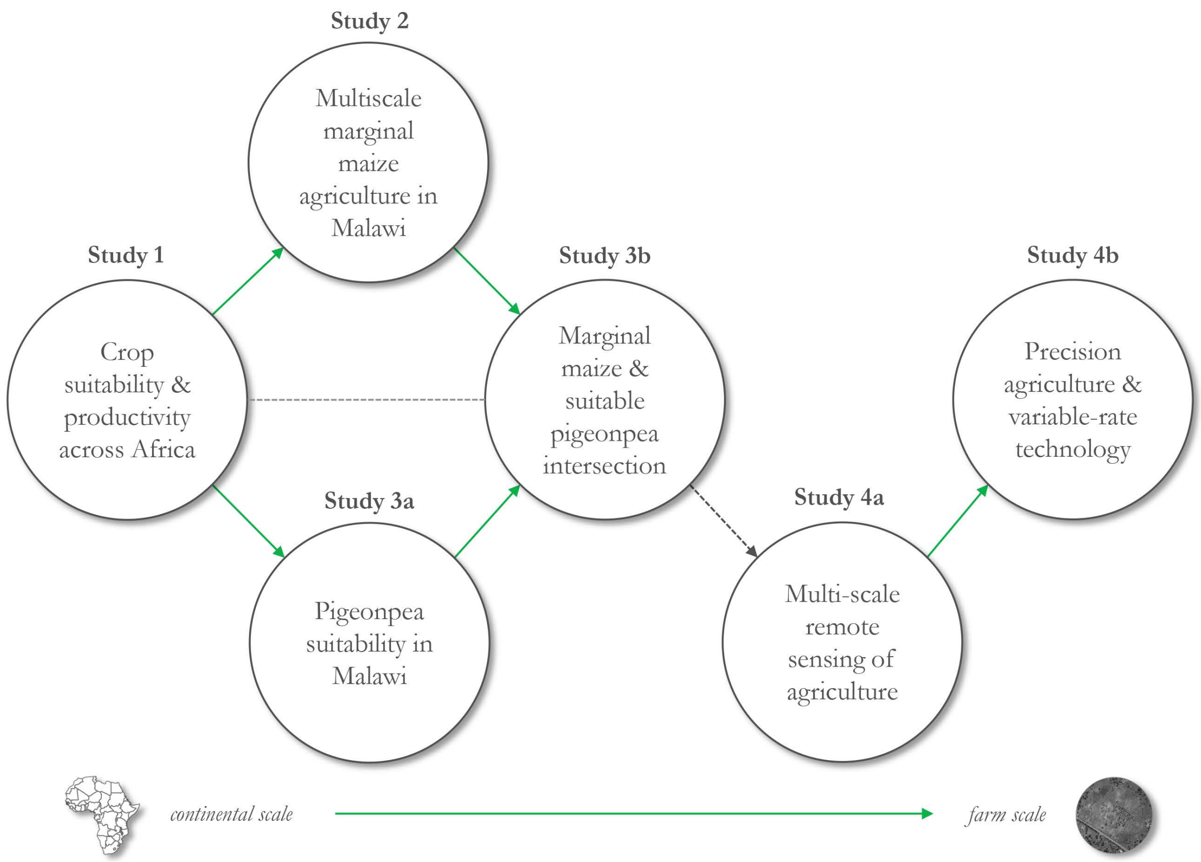

Figure 1.2. *Linking the dissertation studies.* Evaluating agricultural productivity and targeting areas for enhanced crop production across spatial scales. Study 1—Nature-Based Agricultural Solutions: Scaling Perennial Grains Across Africa; Study 2—A Multiscalar Approach to Mapping Marginal Agricultural Land: Smallholder Agriculture in Malawi; Study 3—Scaling Agricultural Innovations: Pigeonpea in Malawi; Study 4—Multi-Spatial Resolution Satellite and sUAS Imagery for Precision Agriculture on Smallholder Farms in Malawi.

Nature-Based Agricultural Solutions: Scaling Perennial Grains Across Africa (Study 1)—This study established crop profiles and mapped the fundamental climate niche for maize, pigeonpea, and sorghum across Africa using cropping parameters from a literature review of tested crop performance. In view of widespread soil organic matter depletion, nature-based solutions such as perennial grain integration into maize-based cropping systems have emerged (Maes and Jacobs 2015). Pigeonpea, for example, is resilient to marginal environments and offers nitrogen fixation, carbon sequestration, and has substantial root biomass that can aid in [re]building soil fertility (Fujita et al. 1992; Snapp et al. 2010). Sorghum, like pigeonpea, is resilient to marginal environments (Dicko et al. 2006) and is commonly used to improve field structure as a ridge crop for erosion mitigation (Okigbo and Greenland 1976).

To identify the geographic scaling potential of pigeonpea and sorghum across Africa, climate-suitability maps of each crop were constructed. There are two overarching categories, optimal and suboptimal, which are further subcategorized into a range of suitability. Following the suitability classifications of maize, pigeonpea, and sorghum, marginal maize areas were intersected with suitable sorghum and pigeonpea areas to identify areas where maize-based systems may benefit from integration of one or both perennials.

A Multiscalar Approach to Mapping Marginal Agricultural Land: Smallholder Agriculture in Malawi (Study 2)—In this study, a multiscale heuristic was designed for identifying marginal agricultural lands and the underlying drivers of marginality. Marginal agricultural lands exist as, or may emerge from, a complex combination of factors and are defined here as land characterized by variable interannual production and/or chronically low production, and suboptimal biogeographic conditions. The framework consists of measuring interannual crop productivity (and variability) of long-term farmed locations and evaluating biophysical land and climate characteristics.

Net primary productivity was used to measure time-series trends of vegetation on agricultural land, classifying pixels based on both the level of production and the productivity variance over 15 years. A methodology was developed to produce these classifications across, and relative to, multiple administrative levels (i.e., country, district, and extension planning area); however, the model devised supports any geographic delineation. This method exposes the modifiable areal unit problem, showing that classifications can change depending area and data distributions, but can also serve to manage the problem by disaggregating pixels relative to local scales where agroecologies are more commonly shared. These classifications were paired with marginal biogeographic conditions (temperature, rainfall, and soil) to address the factors that may be limiting agricultural production. In the absence of a biophysical driver explaining marginal production, it is possible that some other variable is driving marginality, namely social factors such as fertilizer availability, labor requirements, or farm management choices.

Scaling Agricultural Innovations: Pigeonpea in Malawi (Study 3)—The purpose of this study was to identify the geographic scaling potential of integrating perennial pigeonpea into maize-based cropping systems in Malawi. Since pigeonpea exhibits soil rehabilitation properties, integration of this legume into maize-based cropping systems shows a range of predictable benefits, particularly where maize production is marginal due to suboptimal soil status. Historically, pigeonpea has been cultivated dominantly in the southern region of Malawi; however, we found that climate suitability for pigeonpea spans the latitudinal extent of the country. This evidence is supported by the fact that where pigeonpea is grown in the northern and central regions of Malawi, production and yields are comparable to those in the south.

Multi-Spatial Resolution Satellite and sUAS Imagery for Precision Agriculture on Smallholder Farms in Malawi (Study 4)—This study examined a range of spatial resolution imagery over two smallholder farms in Malawi. The imagery under analysis was Sentinel-2 (20-m), SPOT 6 (7-m), Planet (3-m), Pléiades (2.5-m), and sUAS (7-cm, 14-cm, and 27-cm). A heuristic was developed to (1) automatically generate a collection of spectral indices from the initial set of spectral bands (e.g., normalized difference vegetation index [NDVI] and green soil adjusted vegetation index [GSAVI]), and (2) evaluate multiple linear regression permutations of the selected indices and proximal measurements in the field (crop chlorophyll content and crop yield).

NATURE-BASED AGRICULTURAL SOLUTIONS: SCALING PERENNIAL GRAINS ACROSS AFRICA[1]

2.1 Abstract

Modern plant breeding tends to focus on maximizing yield, with one of the most ubiquitous implementations being shorter-duration crop varieties. It is indisputable that these breeding efforts have resulted in greater yields in ideal circumstances; however, many farmed locations across Africa suffer from one or more conditions that limit the efficacy of modern short-duration hybrids. In view of global change and increased necessity for intensification, perennial grains and long-duration varieties offer a nature-based solution for improving farm productivity and smallholder livelihoods in suboptimal agricultural areas. Specific conditions where perennial grains should be considered include locations where biophysical and social constraints reduce agricultural system efficiency, and where conditions are optimal for crop growth. Using a time-series of remotely-sensed data, we locate the marginal agricultural lands of Africa, identifying suboptimal temperature and precipitation conditions for the dominant crop, i.e., maize, as well as optimal climate conditions for two perennial grains, pigeonpea and sorghum. We propose that perennial grains offer a lower impact, sustainable nature-based solution to this subset of climatic drivers of marginality. Using spatial analytic methods and satellite-derived climate information, we demonstrate the scalability of perennial pigeonpea and sorghum across Africa. As a nature-based solution, we argue that perennial grains offer smallholder farmers of marginal lands a sustainable solution for enhancing

[1] This is an Accepted Manuscript of an article published by Elsevier in *Environmental Research* on 18 August 2017, available online at doi.org/10.1016/j.envres.2017.08.011. Reference: Peter, B.G., Mungai, L.M., Messina, J.P. and Snapp, S.S., 2017. Nature-based agricultural solutions: Scaling perennial grains across Africa. *Environmental Research*, *159*, pp.283-290.

resilience and minimizing risk in confronting global change, while mitigating social and edaphic drivers of low and variable production.

2.2 Introduction

2.2.1 Adapting Agriculture in View of a Changing Landscape

Globally, there is a call to increase food production through sustainable practices, to counter the effects of climate change, rising population, land-use change, and deterioration of natural resources (Postel 2000; Godfray et al. 2010). Subsistence agriculture in Africa in particular is becoming increasingly stressed by population pressures, soil exhaustion, and climate change. Since the 1990's, the population of Africa has been growing at a rate faster than the global average (Reilly and Schimmelpfennig 1999), contributing to the conversion of land for both agricultural production and urbanization. Climate variability, such as unpredictable timing and quantity of rainfall, affect smallholder farmer crop production and farm management practices (Nelson et al. 2009), particularly in marginal environments (Reilly and Schimmelpfennig 1999). These changes, among others, have prompted increased research for agricultural intensification (Josephson et al. 2014; Ricker-Gilbert et al. 2014). Sub-Saharan African agricultural systems are among the most vulnerable systems facing these challenges (Challinor et al. 2007), and ongoing research that is both innovative and participatory will foster biodiversity and increased productivity (Snapp et al. 2010).

2.2.2 Sustainable Land Management and Emergent Nature-Based Solutions

Sustainable land management is at the foundation of societal goals to produce food, fuel, and fodder in an environmentally sound and supportable manner over the long-term. How to achieve sustainable intensified agriculture is contested, with advocates promoting such various approaches as organic agriculture, agroecology, and conservation farming (Petersen and Snapp 2015). At the same time, there are a number of sustainability principles about which consensus is emerging that can be followed regardless of the type of agriculture deployed (Robertson et al. 2014). Notable among these is the case for perennial vegetation (Pimentel et al. 1986; Glover et al. 2010). This type of plant trait ensures greater capture and conservation of resources, as living plants are continuously present to photosynthesize and foster biological processes such as nutrient recycling (Jackson 2002). Thus, a range of alternative management practices, including organic and conservation agriculture can potentially derive considerable benefit from integration of perennials. In contrast, agriculture as currently practiced involves crops with overwhelmingly annual growth habits. This leads to managed lands left bare or unproductive for much of the year, as most food crops are grown for a scant four to five months (Jackson 2002). There are sustainable alternatives to such annual-intensive production, which include mixed cropping systems that incorporate perennial plants as companion species and the development and deployment of crop plants that have perennial properties. Sorghum and pigeonpea are two such crops with perennial growth habits that allow regrowth and multiple harvests through an agronomic practice called ratooning (Rogé et al. 2016), which involves cutting the main stem(s) after reproductive maturity.

Based on agroecology and conservation agriculture principles, nature-based solutions offer sustainable qualities, such as resilience to disturbance over variable time scales and minimal input requirements, as well as an aim toward general improved human well-being (European Commission 2015; Bauduceau et al. 2015). Nature-based solutions for sustainable urbanization emerged in the European Union as a research initiative with the explicit aim of addressing environmental, social, and economic challenges sustainably (European Commission 2015; Bauduceau et al. 2015). Similarly, smallholder agricultural systems will benefit from adoption of technologies that support sustainable principles and the complex system processes of nature. At the same time, the "net benefit of nature-based solutions depends on how much non-renewable energy can be replaced without decreasing total production of ecosystem services" (Maes and Jacobs 2015: 3). Attention to resilience and resource amelioration is often overlooked in agricultural discourse in favor of the intensification of high-yield annuals, which dominates the development lexicon. In contrast to nature-based solutions that focus on economic solutions (e.g., fertilizer subsidy), nature-based solutions might be better expressed in the smallholder agricultural context through sustainable soil management strategies, field/crop organization, and local market development.

2.2.3 Perennial Grains: A Nature-Based Approach for Africa

Pigeonpea (*Cajanus cajan* (L.) Millspaugh) is a perennial leguminous shrub commonly cultivated and consumed by smallholder farmers in the tropical and often marginal environments of Africa (Kumar Rao and Dart 1987). Pigeonpea is biologically suited to production as an intercrop, as a slow initial growth habit minimizes competition for resources with a primary crop (Sakala et al. 2000). Farmers typically grow pigeonpea as a mixed cropping system, producing two or more food products while simultaneously building soil fertility through biological processes (e.g., nitrogen fixation and carbon sequestration) (Fujita et al. 1992; Snapp et al. 2010). Sorghum (Sorghum bicolor (L.) Moench) is a grass with perennial properties commonly grown by smallholder farmers in semi-arid regions of Africa (Doggett 1988; Paterson et al. 2009). The cultivation of sorghum occurs primarily in dryland areas and hot, semi-arid tropical environments (Dicko et al. 2006), though there are sorghum species that grow in wetter regions (Harlan and Stemler 1976). Sorghum has deep and spread roots and a solid stem (Buchanan, 1885), and it is common to grow sorghum along field ridges, as this helps prevent soil erosion (Okigbo and Greenland 1976). Pigeonpea and sorghum are generally drought-tolerant and resilient in dryland environments, and in perennial forms maintain these desirable traits (Parr et al. 1990).

A research gap that has not been addressed is the spatial assessment of suitability for diversification of nature-based solutions. In this paper, we consider the phenology of two perennial crops, pigeonpea and sorghum, both of which offer soil rehabilitation properties and are tolerant to marginal environments (Okigbo and Greenland 1976; Snapp et al. 2010). The unique properties of these crops enhance sustainability of cropping; however, they face biophysical constraints and require an appropriate socio-economic context to achieve successful adoption. Our overall objective is to identify appropriate integration properties and delineate the climate niche for deployment of these sustainable perennials within existing maize-based smallholder farms. From an agroclimatology perspective, we explore areas suitable for the cultivation of perennial sorghum and pigeonpea, and highlight the geographic potential for perennial grains to scale across Africa. Remotely-sensed imagery such as those presented here allow for global observation of the environmental and biophysical factors that influence perennial development and adaptation and their spatial organization. Identifying biogeographic conditions in which sorghum and pigeonpea can prosper is crucial for effective integration and scaling of these perennial grains (Wood et al. 1999).

This work builds on other global and continental suitability maps (e.g., the Global Agro-Ecological Zones (GAEZ) database (Fischer et al. 2008; IIASA/FAO 2012)) by highlighting the intersection between marginal dominant crop conditions (in this case maize) and optimal perennial crop conditions (in this case pigeonpea and sorghum), ultimately targeting areas where maize-based systems are likely to benefit from perennial integration. More, the data presented here are unaltered and at the remote sensing pixel level, providing a direct link to the farmer experience and offering a level of transparency (in terms of background variables) commonly masked by data aggregations and complex zoning classifications. We use geospatial technologies and techniques to (1) explore suitable (and optimal) climate conditions for pigeonpea and sorghum across Africa,

(2) assess marginal maize conditions and historic agricultural productivity, and (3) identify areas where existing maize-based agricultural systems are likely to benefit from integration of sorghum or pigeonpea.

2.3 Methods

2.3.1 Fundamental Climate Niche: Maize, Pigeonpea, and Sorghum

The methodology presented here consists of three major components. First, we identify the fundamental climate niches for maize, pigeonpea, and sorghum. Second, we present a range of suitability (and optimality) for each crop based on temperature and precipitation conditions. Third, we locate the intersection between marginal maize areas and the optimal pigeonpea or sorghum climate niche.

The fundamental climate niche (i.e., temperature and precipitation) used for maize, pigeonpea, and sorghum is based on a literature review of tested crop performance (Table 2.1). Pigeonpea is tolerant to variable rainfall, from very low to high amounts ranging from 350 to 2000 mm during a growing season (Kimani 2001; Valenzuela and Smith 2002; Wood and Moriniere 2013; Houérou, n.d.), and produces grain even during dry spells, unlike other legumes (Okiror 1986). The crop prefers temperatures ranging between 20.0 °C and 35.5 °C (Omanga et al. 1996; Carberry et al. 2001; Silim and Omanga 2001; Sardana et al. 2010; Wood and Moriniere 2013). Suitable growing season conditions for sorghum consist of rainfall between 150 and 950 mm (Chipanshi et al. 2003; Du Plessis 2008; Mishra et al. 2008; Wood and Moriniere 2013) and temperatures between 20.0 °C and 35.0 °C (Du Plessis 2008; Wood and Moriniere 2013; FAO, n.d.-a).

Crop	Temperature (°C)	Precipitation (mm)
Maize*	23.8–32.2	750–1217
Pigeonpea**	22.7–30.9	544–1263
Sorghum***	22.1–33.7	317–833

Table 2.1. *Optimal temperature and precipitation ranges for maize, pigeonpea, and sorghum*. Sources: *(Pingali 2001; Wood and Moriniere 2013; Sanchez et al. 2014; Infonet 2016; FAO, n.d.-b). **(Omanga et al. 1996; Kimani 2001; Carberry et al. 2001; Silim and Omanga 2001; Valenzuela and Smith 2002; Sardana et al. 2010; Wood and Moriniere 2013; Houérou, n.d.). ***(Chipanshi et al. 2003; Du Plessis 2008; Mishra et al. 2008; Wood and Moriniere 2013; FAO, n.d.-a)

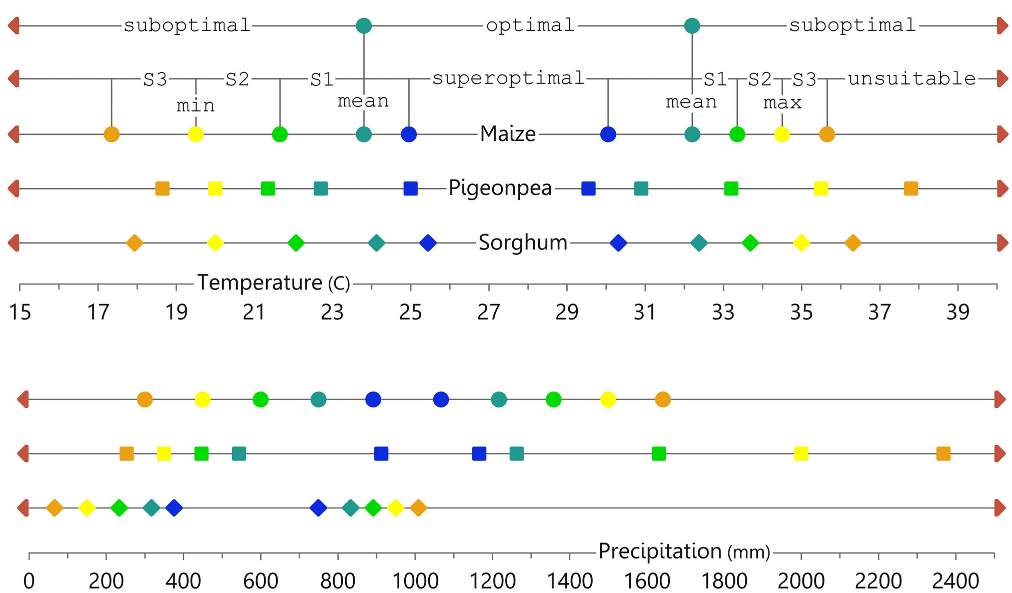

Figure 2.1. *Diagram of the maize, pigeonpea, and sorghum temperature and precipitation suitability classification thresholds*. Classifications include optimal and suboptimal, which were further subcategorized into a range of suitability: superoptimal, optimal, suitable 1 (S1), suitable 2 (S2), suitable 3 (S3), and unsuitable. Maize, circle; pigeonpea, square; sorghum, diamond. Suitability classification color scheme used in Figs. 3 and 4.

For the optimal range, we calculated a mean low-value and mean high-value from all optimal temperature and precipitation ranges collected in our review. From the values presented in Table 2.1, there are two basic categories, optimal and suboptimal, which were further subcategorized into a range of suitability: superoptimal, optimal, suitable level 1 (S1), suitable level 2 (S2), suitable level 3 (S3), and unsuitable (Figure 2.1). We used equal intervals from the mean low-value and high-value outward, depending on the range between the minimum or maximum value, to designate thresholds for levels of suitability. We extrapolated one step inward (toward superoptimal) and one step outward (toward unsuitable) in order to highlight an additional level of spatial variability. The same protocol was applied for classifying precipitation. The categories were constructed in this manner so that precipitation and temperature tolerance (or intolerance) would be considered when moving outward from optimal.

2.3.2 Spatial Distribution of Climatic Variables

The spatial distribution of climate variability was acquired using two remotely-sensed NASA products. Temperature data were gathered from NASA MODIS Land Surface Temperature (LST—MYD11B3) (NASA LP DAAC 2015a) and precipitation from NASA/JAXA Tropical Rainfall Measuring Mission (TRMM—3B43) (NASA/JAXA TRMM 2016). Mean annual temperature and accumulated annual rainfall values were calculated between 2003 and 2014 and a conditional statement applied to classify the ranges of suitability as shown in Table 2.1. In order to generate suitability maps that consider both temperature and precipitation, the individual suitability maps of temperature and precipitation were overlain and reclassified so that each pixel was represented by the most unsuitable factor.

Marginal agricultural lands are those places with suboptimal temperature and precipitation conditions for the dominant crop (e.g., maize), as well as places with chronically low production levels and/or high interannual variability in production (Peter et al., in preparation). Marginal maize agricultural land is identified here using suboptimal temperature and precipitation ranges for maize (Table 2.1, Figure 2.1), in combination with an interannual variability model that identifies areas where agricultural production is historically low and/or highly variable (Peter et al., in preparation). The model uses time-series Net Primary Productivity (NPP—MOD17A3) (NASA LP DAAC 2015c) to categorize individual pixels based on regional productivity trends, highlighting three levels of production and two types of interannual variability. Six results are returned: Low-Stable (LS), Low-Variable (LV), Medium-Stable (MS), Medium-Variable (MV), High-Stable (HS), High-Variable (HV) (Peter et al., in preparation). From these classifications, we considered areas that are historically low and/or variable (LS and LV) to be marginal, as well as areas that are historically medium and variable (MV). Combining suboptimal temperature and precipitation conditions with marginal historic productivity reveals the spatial organization of various combinations of marginality and suboptimality, and serves to disentangle possible drivers of underproduction (Figure 2.4). In order to delineate areas by agricultural land, we used a global cropland percentage map developed by Fritz et al. (2015).

Areas likely to receive maximum benefit from perennial deployment exist at the intersection between marginal dominant crop conditions (i.e., maize) and the optimal climate niche for perennial grains (i.e., pigeonpea and/or sorghum) (Peter et al. 2017b). We identify this intersection by overlaying optimal perennial pigeonpea or sorghum conditions with the marginal maize areas identified above (Figure 2.4). These are areas where perennial properties may serve to improve existing maize-based agricultural systems.

2.4 Results

2.4.1 Spatial Organization of Crop Suitability

Suitable temperature and precipitation conditions for maize, pigeonpea, and sorghum are spatially organized across Africa, following well-established agroecological zones (e.g., IIASA/FAO 2012) (Figure 2.2). Marked temperature suitability differences exist in the Southern and Central regions of the continent. Suitable precipitation ranges vary significantly by crop, and clear regional delineations are revealed when mapped. In terms of precipitation, sorghum, for example, is highly suitable in Southern Africa, Northern Africa (i.e., Northern Algeria, Morocco, and Tunisia), parts of Eastern Africa (i.e., Kenya and Tanzania), the Horn of Africa (i.e., Somalia, Ethiopia, Djibouti, and Eritrea), and a horizontal stretch along the Sahel. Precipitation in these areas is uniquely suitable for sorghum and is largely suboptimal or unfavorable for pigeonpea and maize. Pigeonpea has a breadth of rainfall suitability that covers much of Africa south of the Sahara. Unlike sorghum and maize, pigeonpea suitability, particularly in terms of precipitation, covers a large land area in the Central region of Africa (i.e., the Democratic Republic of Congo and adjacent countries).

Since suitable temperature ranges are similar among the crops under study, precipitation is the primary determinant of continental-scale suitability; however, temperature does reveal its importance when combined with precipitation, particularly at fine spatial scales (Figure 2.3). The most notable distinction is that temperature restricts the suitability of sorghum in the Southern tip of Africa, as well as the North western portion of the continent (i.e., Northern Algeria, Morocco, and Tunisia); maize and pigeonpea are affected in these areas, as well.

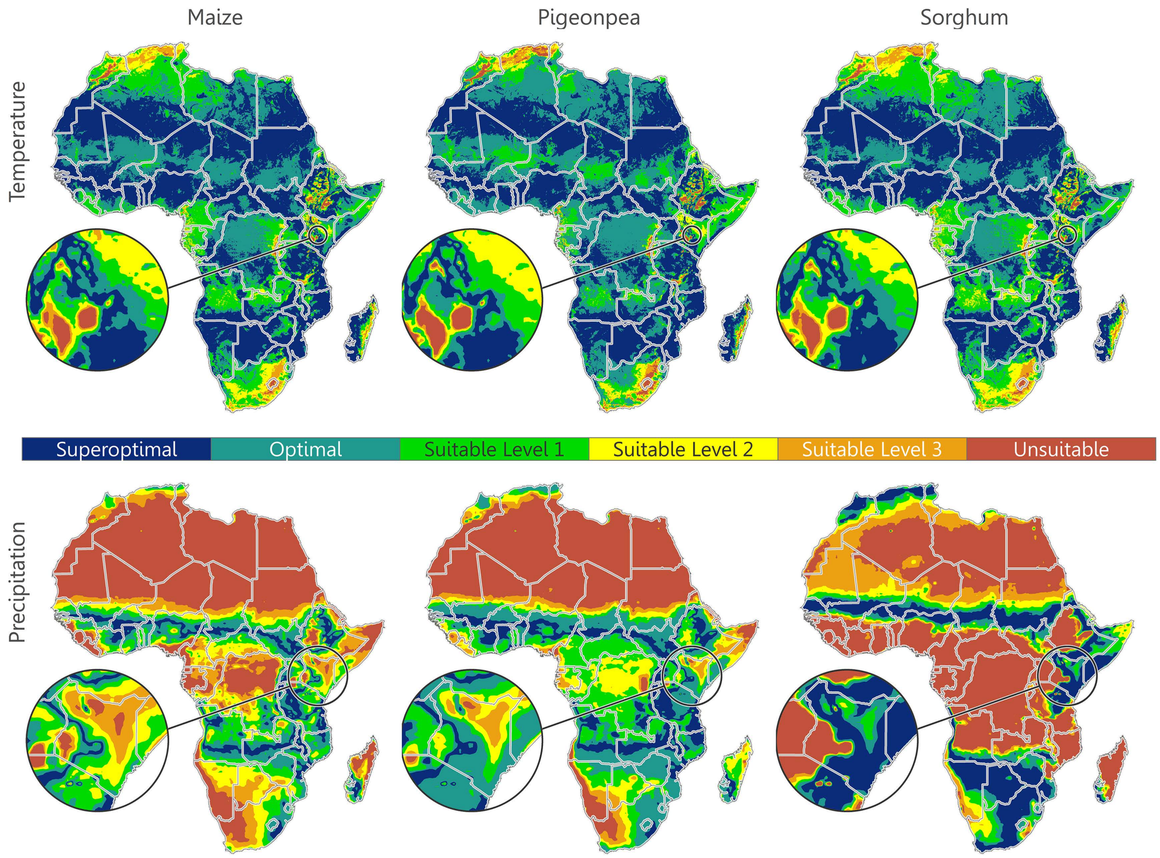

Figure 2.2. *Temperature and precipitation suitability for maize, pigeonpea, and sorghum.* Kenya is highlighted in order to show local spatial variability.

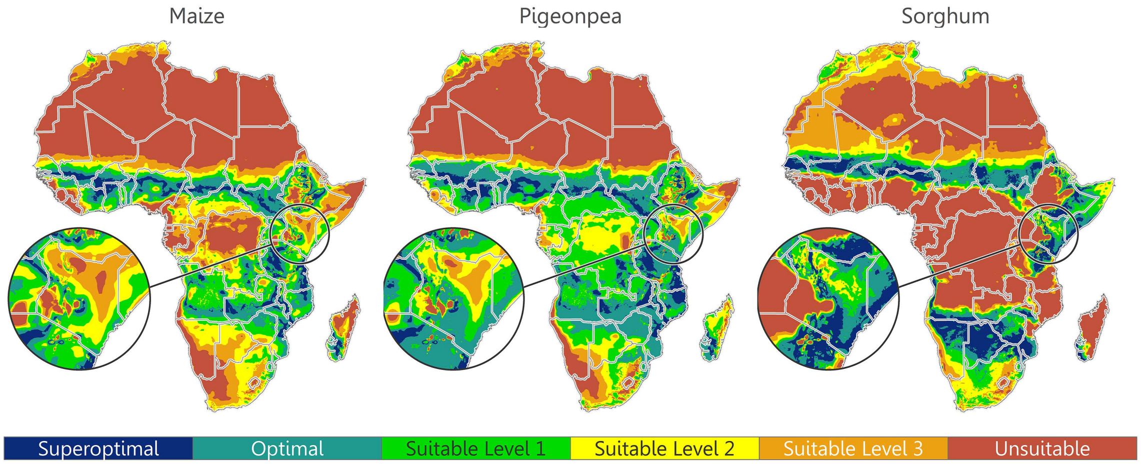

Figure 2.3. *Combined suitability of temperature and precipitation suitability for maize, pigeonpea, and sorghum.* Kenya is highlighted in order to show local spatial variability.

Crop	Superoptimal	Optimal	Suitable Level 1	Suitable Level 2	Suitable Level 3	Unsuitable
Maize	8.1%	20.0%	21.9%	22.0%	15.4%	12.6%
Pigeonpea	11.3%	33.4%	26.4%	15.5%	7.7%	5.7%
Sorghum	12.6%	11.7%	8.0%	9.5%	9.1%	49.1%

Table 2.2. *Agricultural land area proportions for each category (suitability classifications).* Global cropland percentage map by Fritz et al. (2015) used to delineate areas by agriculture.

Overall, we found that maize production is optimal on approximately 28.1 percent of agricultural land across Africa, suitable on 59.3 percent, and unsuitable on 12.6 percent (Figure 2.3, Table 2.2). Pigeonpea is optimal on 44.7 percent of agricultural land across Africa, suitable on 49.6 percent, and unsuitable on 5.7 percent. Sorghum is optimal on 24.3 percent of agricultural land across Africa, suitable on 26.6 percent, and unsuitable on 49.1 percent. Sorghum is the least suitable in terms of land area; however, conditions are optimal for its cultivation where maize and pigeonpea are not. Optimal pigeonpea conditions occupy the greatest land area, and optimal conditions for maize are surprisingly low given the extent to which it is cultivated.

2.4.2 Scaling Perennial Innovations for Maximum Benefit

Within the optimal pigeonpea niche, 24.9 percent exhibits marginal agricultural productivity and suboptimal rainfall conditions for maize, 41.6 percent exhibits sole marginal agricultural productivity, and 20.9 percent exhibits optimal conditions for maize (Figure 2.4, Table 2.3). Within the optimal sorghum niche, 71.4 percent exhibits marginal agricultural productivity and suboptimal rainfall conditions for maize, 18.2 percent exhibits sole marginal agricultural productivity, and only 4.6 percent exhibits optimal conditions for maize. Areas that exhibit sole marginal agricultural productivity are areas where marginality may be driven by social or other biogeographic factors (e.g., soil quality and land management practices). In areas where maize conditions are suboptimal and/or agricultural productivity is marginal, and pigeonpea or sorghum climate conditions are optimal, integration of these crops is likely to benefit existing maize-based agricultural systems.

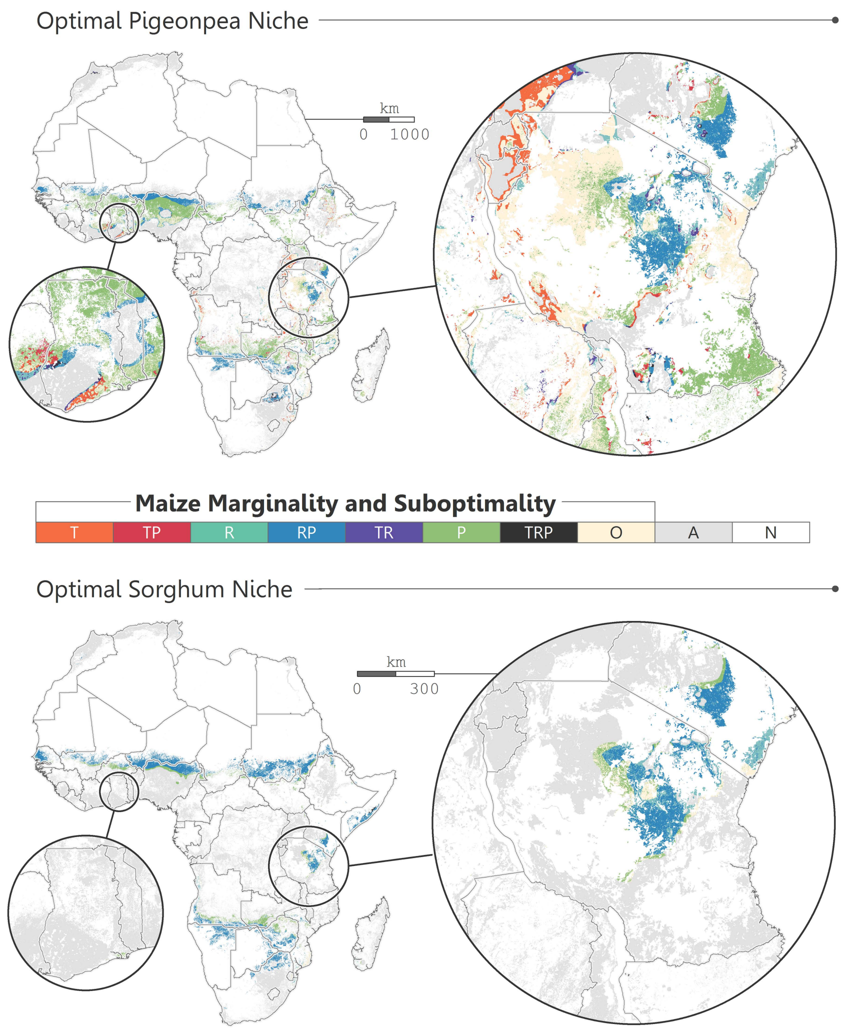

Figure 2.4. *Intersection of marginal maize and optimal pigeonpea or sorghum.* Areas presented in color exhibit optimal temperature and precipitation conditions for pigeonpea or sorghum. Suboptimal temperature and precipitation legend classifications are associated with the fundamental niche for maize: T = suboptimal temperature; TP = suboptimal temperature and marginal productivity; R = suboptimal rainfall; RP = suboptimal rainfall and marginal productivity; TR = suboptimal temperature and suboptimal rainfall; P = marginal productivity; TRP = suboptimal temperature, suboptimal rainfall, and marginal productivity; O = optimal; A = other agriculture (i.e., suboptimal for pigeonpea or sorghum); N = non-agriculture. Global cropland percentage map by Fritz et al. (2015) used to delineate areas by agriculture.

Crop	T	TP	R	RP	TR	P	TRP	O
Pigeonpea	4.3%	1.2%	5.2%	24.9%	1.0%	41.6%	1.0%	20.9%
Sorghum	<0.1%	<0.1%	5.4%	71.4%	<0.1%	18.2%	0.3%	4.6%

Table 2.3. *Agricultural land area proportions for each category (marginal/optimal intersection).* Proportions presented only within the optimal pigeonpea or sorghum niche; other agricultural land not included. Global cropland percentage map by Fritz et al. (2015) used to delineate areas by agriculture.

2.5 Discussion and Conclusions

2.5.1 Promoting a Sustainable Future

Historically, most smallholder farmers in Africa have depended on intensively managed maize systems as a cash crop and staple food (Byerlee and Heisey 1996); however, taking a closer look reveals frequent and continual cultivation of, and dependence upon, pigeonpea and/or sorghum for food security (Rufino et al. 2013). Many African households are familiar with cultivation needs of perennial grains through generational knowledge (Rufino et al. 2013; Rogé et al. 2016), yet there is little academic attention given to perennial management practices (e.g., ratooning) of perennial grains (Kane et al. 2016). In Africa, there is potential to revitalize perennial crops such as pigeonpea and sorghum through innovative practices that offer multiple benefits (e.g., ecosystem improvements, crop water-use efficiency, and improved cultivars that enhance nutrition) (DeVries and Toenniessen 2001; Cox et al. 2006; DeHaan et al. 2007).

Perennial grains offer benefits that encompass rural and marginal environment smallholder farming contexts, and should be promoted in locations where labor constraints reduce agricultural system efficiency, or where topography and farming practices increase erosion or depletion of soil organic matter. Integration of perennial pigeonpea or sorghum into maize-based farming systems shows wide spatial applicability across Africa. Though the optimal land area for sorghum cultivation appears of moderate size, low rainfall requirements permit it to fill a spatial niche that pigeonpea does not. This regional delineation of crop suitability between sorghum and pigeonpea is particularly evident along a horizontal stretch of the Sahel (Figure 2.4). This is a marginal area for which there are few suitable crop options, and sorghum is often overlooked in a maize-centric agricultural development agenda (Hellin et al. 2012). Overall, conditions are optimal for pigeonpea cultivation on approximately 45 percent of agricultural land across Africa, and optimal for sorghum on 24 percent (Figure 2.4). Between the two crops, approximately 53 percent of African agricultural lands are likely to benefit from their integration. There are certainly other perennials that may be promoted in Africa (e.g., rice), and there is considerable potential to improve maize-based farming systems through integration of semi- and fully perennial crops that provide multiple ecosystem services (Glover et al. 2010).

Pigeonpea diversification offers unique environmental benefits, particularly in locations where soil fertility decline is limiting crop yields. The ability of pigeonpea to biologically fix nitrogen has been proven to function in a smallholder farm context across a range of soil types, rehabilitating soils through input of 70–100 kg of nitrogen per hectare annually (Myaka et al. 2006). Given the overlap between the pigeonpea and maize niche across large swaths of agricultural lands, this could potentially address a substantial portion of the nitrogen deficit that is a primary yield limiting factor on African smallholder farms (Vanlauwe et al. 2011). Sorghum is more drought-resistant than maize, yet it has been replaced by maize in areas such as Northern Malawi (Bezner-Kerr 2014). Where it is still grown, farmers in Malawi ratoon by cutting the stem to extend production for more than one season, and have reported that ratooning also saves labor and seeds (Rogé et.al 2016). Smallholder farmers typically cultivate sorghum in mixed cropping systems where the spatial arrangement of crops plays a major role. In Malawi, for example, farmers have reported growing sorghum on soils that are marginal for maize (Rogé et al. 2016). In North-

Central Nigeria, sorghum has been reported to be intercropped in combinations with millet, groundnut, and/or cowpea (Okigbo and Greenland 1976). Due to current global climate impacts on crops, there have been partial efforts for breeding of sorghum (ICRISAT, n.d.), and research shows that breeding sorghum can produce varieties adaptable to climate variability and pests (Haussmann et al. 2012).

Despite the legacy cultivation of maize across much of Africa, and recent expansion into new areas of West and North Africa (Blackie and Dixon 2016), there are large areas that are suboptimal environments for maize growth. The decision to cultivate maize in these areas reflects socioeconomic factors such as market demand and farmer preference, and may also be influenced by the superior calories per unit input that maize offers (Snapp and Silim 2002). Interestingly, our analysis shows that the Horn of Africa is largely unsuitable for maize production and optimal for sorghum, yet maize is being widely promoted. One study found that one-third of farmers ratoon sorghum for perennial production in lowland areas of Ethiopia (Mekbib 2009), yet surprisingly little research focuses on this drought-adaptation option, even in the center of origin for the crop. Overall, our findings highlight the role that both sorghum and pigeonpea could play in improving food security and resilience across marginal swaths of Africa. This is further evidence that the crop has been understudied, particularly for novel perennial genotypes and historically important ratooned types (Paterson et al. 2014).

2.5.2 Conclusions

Sustainable land management is at the forefront of agronomic research, and nature-based solutions are emerging as long-term subsistence strategies. Following nature-based models, sustainable agricultural solutions for smallholder farms are innovations inspired by nature. Though many nature-based solution initiatives in the European context have been urban-centric (Nesshöver et al.

2016), the core sustainable intensification concepts have broad potential. In rural Africa, where land availability and fertilizer access are often limited, smallholder farming systems may benefit from the sustainable cropping methods and synergistic crop choices that nature-based solutions promote. As arable, fertile land continues to diminish and population growth continues to drive production demand, proactive strategies for increased and sustainable production need to be considered. There are certainly other perennials that may be promoted in Africa, and the potential to improve maize-based farming systems through perennial integration is substantial, and underappreciated. Though we present the spatial suitability of maize, pigeonpea, and sorghum in Africa, the heuristic proposed is generalizable and not limited to any particular set of crops or region. We recommend that policy- and decision-makers utilize information and techniques such as these to intelligently target areas that may benefit from perennial integration. As pigeonpea, sorghum, and other perennials are reintroduced to parts of Africa where perennial production has been neglected in preference for maximizing maize yields, it is crucial to promote cultivation of these environmental options in areas where climate conditions are conducive to prosperous and synergistic growth.[2]

[2] This research was supported by the Perennial Grain Crops for African Smallholder Farming Systems project, Grant #OPP1076311, funded by the Bill & Melinda Gates Foundation, and through support of the United States Agency for International Development, AID-OAA-A-13-00006. The opinions expressed herein are those of the authors and do not necessarily reflect the views of the US Agency for International Development or the US Government. We thank the organizers of the special issue for the invitation and for highlighting the importance of this topic.

A MULTISCALAR APPROACH TO MAPPING MARGINAL AGRICULTURAL LAND: SMALLHOLDER AGRICULTURE IN MALAWI[3]

3.1 Abstract

Marginal agricultural lands are defined here by suboptimal biophysical conditions and historically variable or low agricultural production. We characterize these areas using remotely sensed information to disentangle the biophysical and possible social factors driving marginality. Considering both the modifiable areal unit problem and the ecological fallacy problem, the heuristic we propose is generalizable across geographies and scales and provides information at multiple decision-making levels through a multiscalar interannual variability model. We present results from our study of Malawi, where the landscape is densely cultivated and smallholder farmers frequently occupy marginal lands, to illustrate the potential of a multiscalar analysis in a place where food insecurity alleviation is needed and where remote sensing can provide necessary information. Our framework for identifying marginal agricultural lands consists of (1) locating long-term agricultural land, (2) measuring interannual productivity of long-term farmed locations, and (3) assessing marginal biophysical land characteristics and the fundamental climate niche for the dominant crop (in this case maize). Productivity and marginality in Malawi are spatially organized, and an assessment of productivity at multiple scales highlights the importance of presenting both global and local spatiotemporal variability for managing agroecological variance. By disaggregating broad classes of historically marginal production and the underlying drivers of marginality, different intervention efforts can intelligently target areas most likely to receive maximum benefit. These

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methodologies can be applied by both policy-makers and scholars to identify and target marginal agricultural areas for improved productivity and for the support of smallholder farmer livelihoods.

3.2 Introduction

Marginal agricultural lands are dynamic and in many places and contexts represent the dominant form. Whether through cause or consequence, sustainability of smallholder farming systems is inextricably linked with agricultural marginality. Assuming a normative case for sustainable production of most smallholder farms, marginal agricultural lands become so either by bringing marginal land into production or by adopting management models that degrade the respective potential of existing agricultural land.

Marginal agricultural lands exist as, or might emerge from, a complex combination of factors and rarely have a singular driver. The Consultative Group for International Agricultural Research (CGIAR) defined land marginality as dependent on biophysical characteristics, proximity to infrastructure, and population pressure (Nelson et al. 1999). Kang et al. (2013) characterized marginal land as areas with low productivity and reduced economic return. Lantican et al. (2003) referred to marginal land as "the world's [unfavorable] dry and difficult cropping environments" (353). Others consider marginal land to be entirely unsuitable and too fragile for cultivation (James 2010). Stimulating controversy, some national governments (e.g., Philippines, Cambodia, and Ethiopia) conflate marginal land classifications with wastelands or barren land, partitioning them off for corporations or agribusinesses that benefit the state and potentially negatively affect local rural populations (e.g., displacement and reduced resource allocation; Borras et al. 2011; Nalepa and Bauer 2012; Nalepa et al. 2017). Notably, "big data" methodologies have been used to identify and classify global marginal lands as prospects for agrofuel development (e.g., Cai et al. 2011).

Pursuits to maintain and reclaim ideas about marginal land as a category for smallholder agricultural improvement are present, and research efforts to identify and locate marginal lands have proliferated in recent years (e.g., S. Wood et al. 1999; Gopalakrishnan et al. 2011). Still, marginal agricultural lands, particularly those in the smallholder rural context, are in need of more research wherein the focus on marginal land classifications is more closely tied to smallholder agricultural improvement, rather than partitioning for other activity. This is especially important in rural Africa, where much of the smallholder agriculture takes place in marginal environments. In Malawi, for example, a survey conducted by the Malawi National Statistical Office (NSO 2005) estimated that approximately 88 percent of the population lives in rural areas with the majority smallholder subsistence farmers (Chinsinga and O'Brien 2008). In sub-Saharan Africa, the International Fund for Agricultural Development (IFAD 2001) estimated that 73 percent of the population were smallholder farmers (Morton 2007). Farming on marginal lands warrants particular attention because (1) marginal land is frequently occupied by smallholder farmers dependent on consistent production for subsistence, (2) considerable resources are required to transform marginal land out of marginality, and (3) marginal areas are particularly vulnerable to abrupt changes in climate and at market (Morton 2007). Moreover, in densely populated and cultivated countries such as Malawi, internal reorganization and occupation of marginal and protected lands remain the only expansion or intensification options (Kalipeni 1996).

Despite increasing attention, marginal agricultural land is not a widely recognized land-use class and is not identified as such on any of the commonly used land-use/land-cover (LULC) maps. Even locating agriculture, particularly in low-intensity areas and smallholder farming contexts, presents a challenge. There are numerous land-use datasets readily available (e.g., global, continental, and country specific), yet there are clear and nontrivial inconsistencies among them

(Messina et al. 2014). Haack et al. (2015) discussed inadequacies associated with both traditional LULC classifications and remote sensing models. Inevitably, errors of commission (i.e., inclusion of non-agriculture features within an area classified as agriculture) will propagate in most LULC models.

Remote sensing has been used in myriad ways to identify and map marginal agricultural lands. Gopalakrishnan et al. (2011) used remote sensing to map marginal agricultural lands in Nebraska on the basis of soil health, current land use, and environmental degradation. S. Wood et al. (1999) used remote sensing and other spatial data to identify marginal agricultural lands, categorized by levels of suitability, with the explicit aim of targeting agricultural development. Cai et al. (2011) used remote sensing to map cross-continent marginal agricultural lands by integrating global data (i.e., soil properties, terrain characteristics, temperature, and humidity) in a fuzzy logic model; in the final marginal agricultural land map, the majority of Malawi is classified as marginal. Yield gap models have been used to identify marginal production areas (e.g., Neumann et al. 2010), but crop simulation products often do not provide access to the biophysical and social drivers of marginality.

Following on this research, there is a need to classify marginal land for the smallholder farming context. Few studies have considered definitions that disentangle the underlying biophysical factors (i.e., temperature, precipitation, and soil) driving agricultural marginality. Rather than the typical singular marginal land classification, a multi-classification approach allows consideration of all possible marginal combinations of the variables under study. This approach is critical to inform policy and provide insights of value to sustainable development of smallholder agriculture. For example, a parcel of land simply classified as marginal might be perceived as fit for biofuel production (Cai et al. 2011), whereas the same parcel of land classified as marginal with regard to temperature or precipitation might be ideal for promotion of climate-resilient varieties of crops. Areas marginal in terms of soil fertility could be viewed as a prospect for intensification of crop production through nutrient replenishment.

Moreover, the model presented here provides a heuristic to measure agricultural productivity at multiple scales to enhance decision making across administrative levels and geographies and allows for land management across spatially variable agroecosystems. At global and country-wide aggregations, remotely sensed measures of crop productivity could be indicative of global processes and variable agroecosystems. By aggregating remotely sensed measures of crop productivity at local levels, marginality of agriculture could be assessed relative to shared agroecological conditions; that is, areas of homogeneity at the country level become heterogeneous when observed at a local scale (Sexton et al. 1998). With multiscalar information presented, national and local administrative units (e.g., districts and extension planning areas in Malawi) can direct resources and technologies in an informed manner, relative to actionable levels. The multiscalar methodology presented here also allows for assessment of marginal agriculture across (agro) ecosystems, where LULC (e.g., crop choices, tree type, tree density) is highly variable and inevitably included in remote sensing spectral signals of agriculture.

To summarize, there are two overarching themes driving this research and two fundamental questions asked. First, classifications of marginal agricultural lands that include the underlying drivers of marginality can serve to emphasize the smallholder farming context. Second, the scale of observation matters for making decisions at actionable levels. Regarding these themes, we pose two research questions: (1) What measurable, biophysical conditions constitute marginal agricultural land across space, time, and scale? (2) Where are the variable types of marginal agricultural land located?

3.2.1 Mapping Global Marginal Agricultural Lands for the Smallholder Context

Here, we define marginal agricultural land as land that has variable interannual production or is chronically low-producing, driven by poor biogeographic conditions or social factors. This definition is directly translatable to the farmer experience and can be measured using remote sensing. For subsistence farmers, low productivity translates to insufficient food supply and variable production translates to unpredictable harvests. Marginality is further characterized here by crop climate niche (in this case maize) and soil suitability. The definition of marginal agricultural land outlined is one that we argue can be measured using remotely sensed time-series information and is generalizable across geographies and scales.

In this study, we identify the spatial organization of marginal agricultural land in Malawi by disentangling the biophysical factors driving marginality, as well as possible social factors by deduction (i.e., measured marginal productivity but no explanatory variable). We approach identifying these marginal areas through a strictly biophysical perspective, and the data we employ are primarily remotely sensed products. Moving beyond the either–or debate, we present all possible marginal combinations of the variables under study. Combinations of marginality presented here include (1) suboptimal temperature, (2) suboptimal precipitation, (3) marginal soil suitability, and (4) marginal interannual productivity. Additionally, we propose that measures of productivity and interannual variability are relative to the scale and geography under observation. Our framework consists of locating long-term agricultural land, measuring interannual productivity (and variability) of long-term farmed locations, and assessing marginal biophysical land characteristics and the fundamental climate niche for the dominant crop, in this case maize.

Because our definitions and measures of productivity are relative to the scale and geography under observation and the data we employ are global, the methodology herein can be used to reveal the spatial organization of marginality at any decision-making or administrative level. By presenting information at multiple scales and administrative boundaries, we aim to manage some issues manifested by the modifiable areal unit problem (MAUP) and the ecological fallacy problem. The MAUP arises when classifications or aggregations change based on differences in areal selection and scale (Openshaw 1983). The ecological fallacy problem occurs when inferences are made about an individual instance based on aggregate data (Openshaw 1983). The five major components of the model are as follows: (1) locating long-term agricultural land and minimizing errors of commission, (2) measuring historic productivity and interannual variability of agriculture, (3) calibrating the model to field observations, (4) identifying crop niche and mapping marginal land, and (5) extending the interannual variability model to possess multiscalar capabilities.

3.2.2 Malawi as a Bellwether for Identifying Marginal Agricultural Lands

Malawi is presented here as a bellwether for identifying marginal lands in the smallholder, rural context. Historically, marginal agricultural lands in countries with low population densities move into and out of production as prices change, labor shifts, and when climate signals encourage planting and land clearing. Malawi faces different challenges. The country is largely settled with very little suitable land available for new agriculture, and dense population reduces farm size and limits fallowing options (Ricker-Gilbert and Jumbe 2014). Moreover, the Malawian landscape is mosaicked with mixed land use, regional land-use variance, and relatively small fields, making agricultural land difficult to discern from other land-use types in most singular global land-cover products. This long-term use of marginal lands and the spatial arrangement of cultivation is unique, and marginal agricultural lands in Malawi are particularly important because the current intensive use reflects population pressures that will emerge in many other regional countries. In neighboring Zambia, for example, the coupling of large-scale investments in agricultural land

(Nolte 2014) and population increases will restrict fallowing options for smallholder farmers, demanding more food production on already continually harvested fields (Schneider et al. 2011).

Information-driven targeting for new or different agricultural practices is essential to successful scaling (S. Wood et al. 1999), and adoption will only take place where biophysically feasible (Kwesiga et al. 2003). To date, efforts to identify marginal agricultural lands specific to Malawi are thinly scattered. Remotely sensed data offer a solution to this problem, particularly in areas where fine-resolution crop information is unavailable. Depending on the platform, such data can be cost-effective and cover entire landscapes, improving on regional- or administrative-level development strategies. Remotely sensed imagery can also be used to measure crop response to various development strategies. The Fertilizer Input Subsidy Programme (FISP) in Malawi, for example, was popularly recognized as initiating an "African green revolution" (Sanchez 2015), but recent studies suggest that it might not have been effective at reaching those most rural, and production might have been overestimated (Holden and Lunduka 2012; Chinsinga and Poulton 2014; Messina et al. 2017). Moreover, remote sensing offers a partial solution to targeting resource delivery. Recurring food insecurity in Malawi and the country's position in the global market have prompted regular aid initiatives from both nongovernmental organizations and international governments; however, resource allocation is the subject of much scrutiny and resource need might not always be a major driver in resource allocation across all sectors (Dionne et al. 2013).

	Precipitation	**Soil suitability**	**Temperature**	**Productivity**
Source	NASA/JAXA	Li et al. 2017a	NASA MODIS	NASA MODIS
Product	TRMM 3B43	—	MOD11A2	MOD17A3
Spatial resolution	~27-km	90-m	1-km	1-km
Temporal resolution	Monthly	—	8-day	Annual

Table 3.1. *Biogeographic data sets used to determine marginality and suboptimality of maize agriculture.*

3.2.3 The Malawian Landscape: Cultivation, Climate, and Population

In Malawi, "maize is life"; it is the most frequently cultivated and consumed cereal crop in the country, commonly taking form as nsima, a dried, finely ground, and reconstituted dense porridge—a staple of the Malawian diet. Production of maize is widely distributed throughout Malawi and, according to the United Nations World Food Programme (WFP 2016), 80 percent of Malawians are smallholder subsistence farmers. Of the farming population, approximately 97 percent of farming households cultivate maize, and its consumption comprises 60 percent of the total caloric intake (Denning et al. 2009). According to Kassie et al. (2012), 70 percent of smallholder agricultural land is cultivated for maize production. Smallholder farmers rely on the success of the maize harvest for subsistence, and national food security depends on consistent domestic agricultural productivity. Presently, pressures from rising population, climate change, unsustainable agricultural practices, and deterioration of natural resources all pose major threats to Malawi's maize production (Postel 2000; Godfray et al. 2010).

There are underlying agricultural sustainability concerns associated with widespread, continuous production of maize with limited use of soil amendments (e.g., fertilizer; Thierfelder et al. 2013). Malawi's long history of unsustainable agricultural practices (e.g., monocrop maize systems, residue mismanagement, and extensive cultivation; Glasson 2010; Thierfelder et al. 2013; Mungai et al. 2016) has contributed to widespread soil nutrient and organic matter depletion (Sanchez 2002; Ngwira et al. 2012). Monocropping of maize with little or no inputs is common throughout Malawi, resulting in diminishing yields over the last several decades (Thierfelder et al. 2013). Residue management is variable across Malawi, depending on the presence of livestock and access to other biomass sources, and legumes are commonly neglected as a source for residue biomass (Valbuena et al. 2015; Mungai et al. 2016). Intercropping (e.g., maize with pigeonpea) and other rehabilitation strategies (e.g., conservation agriculture) are frequently offered through extension efforts, but adoption is generally poor or might be rejected outright (Schulz et al. 2003; Bezner-Kerr et al. 2007; Snapp et al. 2010). Despite implementation of the FISP, an initiative put forth by the Malawian government in response to record low production, soil degradation remains a wide-spread concern and food insecurity persists (Ecker and Qaim 2011; Messina et al. 2017).

Demands for increased production continue as Malawi's population continues to grow. On average, the national population increased by approximately 2.9 percent each year between 2000 and 2014 (World Bank 2016). Concerns related to population growth in Malawi are not new. In fact, House and Zimalirana (1992) warned of Malawi's rapid growth, lack of resources (e.g., access to fertilizer, seed, capital, and labor), and pressures on the land (and human needs) before the turn of the century, when the population was only 9.7 million (World Bank 2016). In 2014, Malawi reached a total population of 16.7 million a 3.1 percent increase from the previous year and up from 11.2 million in 2000 (World Bank 2016). Such population pressures and increased production demands have contributed to the exhaustion of agricultural lands in Malawi, largely due to over-cultivation of maize (Manyonda 1998; Thierfelder et al. 2013).

Unpredictable climate events can lead to significant fluctuations in agricultural output, affecting both smallholder livelihoods and national food security. During the last two decades, Malawi has been afflicted by both severe droughts and floods, threatening the nation's ability to sustain its large, growing population (Devereux 2007; Pauw et al. 2011). In 2002, Malawi was stricken with a record drought (Syroka et al. 2010), resulting in 32 percent less reported production than the previous maize harvest, placing the country in a food insecure "state of disaster" (Devereux 2002; Frize 2002). In 2005, Malawi "faced its worst food crisis in more than a decade," with more than 34 percent of the population in need of food aid (Buerkle 2005). In 2015, record floods displaced nearly 70,000 people (Banda 2015). In 2016, Malawi's President Peter Mutharika declared a national disaster in response to prolonged drought and a devastated maize harvest (Phiri and Macharia 2016). Twenty-five of Malawi's twenty-eight districts were affected, leaving the country with a 1.2 million metric ton maize deficit (Kandaya 2016; Phiri and Macharia 2016). Overall, droughts and floods contribute to an approximately 1.7 percent loss in gross domestic product each year (Pauw et al. 2011). Moreover, seasonal shifts and changes in rainfall pattern leave the optimal timing of planting and fertilizing uncertain each year (Tadross et al. 2009; Extension Planning Area Officers, personal communication 2015). Smallholder farmers occupying marginal agricultural areas are most vulnerable to abrupt climatic and biophysical changes, as well as socioeconomic shifts (e.g., fertilizer and seed access, poverty, and health). These issues are not expected to subside or resolve with imminent global environmental change and steady population growth.

Product	**Temporal range**	**Spatial resolution**	**Source**
Global Land Cover	2000	986-m	ESA (2005)
GlobCover	2005–2006, 2009	920-m	ESA (2008); ESA (2010)
World land use–land cover	2002	920-m	IFPRI (2002)
Land Cover and Land Cover Change of Malawi	2000 & 2010	30-m	FAO (2013)
NASA MODIS Land Cover Type (MCD12Q1)	2001–2012	500-m	NASA LP DAAC (2015d)

Table 3.2. *Land-use products incorporated in errors of commission-managed agricultural land-use map.* Temporal range under study: 2000–2014.

3.3 Methods

3.3.1 Remotely Sensed Data Products and Preprocessing

Precipitation data were acquired from the NASA/ JAXA Tropical Rainfall Measuring Mission (TRMM–3B43) via the NASA Mirador Web portal (Table 3.1; NASA/JAXA TRMM 2016).

TRMM data require a precipitation rate conversion to retrieve monthly rainfall amounts. We converted monthly precipitation rates to accumulated growing season rainfall (November–April; Jayanthi et al. 2013; FAO 2016b) for each year between 2000 and 2014. For both temperature and precipitation, we opted to use only growing season data so that postharvest measures were not included (Zhang and Oweis 1999).

Soil suitability was assessed using a product developed by Li et al. (2017)—a multimethod approach utilizing a suite of landform characteristics and soil properties (i.e., slope, erosion hazard, organic matter, cation exchange capacity, texture, pH, and drainage) to score and rank soil suitability. There are two marginal categories—marginally suitable and marginally unsuitable. Other categories include highly suitable, moderately suitable, and permanently unsuitable (e.g., forest reserves or urban areas; Li et al. 2017a). Land surface temperature (LST) data were acquired from the NASA Moderate Resolution Imaging Spectroradiometer (MODIS–MOD11A2) via the NASA Reverb Web portal (NASA LP DAAC 2015b). Annual productivity (net primary productivity [NPP]) data were acquired from NASA MODIS (MOD17A3) via the NASA Reverb Web portal (NASA LP DAAC 2015c). For the MODIS products, we selected the Terra satellite for its daytime temperature accuracy in southeast Africa (DeVisser and Messina 2013). We elected to use the annual NPP product because the trendline tracks reported yields more closely than growing season gross primary productivity (GPP) (Messina et al. 2017).

To identify long-term farmed locations, we developed a composite agricultural land-use map utilizing a suite of widely recognized products (GLC2000, GlobCover 2005/06 and 2009, IFPRI 2002, FAO 2000 and 2010, and NASA MODIS LC 2001–2012; Table 3.2). We elected to use the MODIS Land Cover Type product (MCD12Q1) because the temperature and productivity measures used here come from the MODIS sensor and it covers a large temporal range (2001–

2013; NASA LP DAAC 2015d); GlobCover because it is well recognized and covers two time steps within the temporal range under study (2000–2014; ESA 2008 2010); GLC2000 because it is well documented and widely used (ESA 2005); IFPRI because it has a relatively unconstrained definition of agriculture (i.e., we know from field experience that Malawi is cultivated extensively, and this product reflects a high amount of agricultural land area; IFPRI 2002); and FAO because it offers a fine spatial resolution Malawi-specific data set and covers two time steps (2000 and 2010) within the temporal range under study (2000– 2014; FAO 2013; see Table 3.2).

3.3.2 Locating Long-Term Agricultural Land: Minimizing Errors of Commission

Before identifying marginal agricultural land, all agricultural lands across the production spectrum must be identified. The approach taken here shares conceptual and methodological similarities (i.e., integration of a suite of land-cover products) with those of a global cropland percentage map developed by Fritz et al. (2015), as well as a global cropland extent map produced by Pittman et al. (2010); however, we developed our methodology independently and the output categorizations are of a different type. The logic here is that locating areas where multiple land-cover products agree (across space and time) will illuminate areas that are routinely and intensively cultivated, exhibit minimal land-use mixing, and have been historically used for agriculture.

Each land-cover classification system (Table 3.2) was reclassified into a binary system (agriculture or non-agriculture), resampled (nearest neighbor resampling method) to the finest resolution of the inputs (30 m), and aggregated (overlain and summed) to create one land-use map. The resulting product is an ordinal ranking of values ranging from zero to five; zero represents areas where none of the classification systems classify an area as agricultural land and five represents an area where all five classification systems agree that a particular area is agriculture. Finally, majority resampling was used to generate rankings at a 1-km spatial resolution, coinciding with the resolution of many MODIS products (e.g., LST and NPP; Figure 3.1). To represent the actual land area devoted to agricultural production, we selected a number of pixels equal to the average FAO-reported agricultural area between 2000 and 2013—approximately 5.25 million hectares (52,510 km^2 pixels or 55.7 percent of the total land area; FAOSTAT 2016).

We used all pixels from ranks 3, 4, and 5, and added in 7,072 unconstrained random pixels from rank 2 so that the total agricultural area would equal 52,510 km^2. We refer to the final product as our errors of commission-managed agricultural land-use map. This grid was used to demarcate agriculture in the marginal agricultural land model. There are undoubtedly marginal agricultural lands that exist within ranks 1 and 2, and biophysical suitability could be assessed; however, historic productivity in these areas cannot be measured confidently because of changes in land use over time and the resolution of the NPP product used here (1-km). These areas commonly exhibit mosaicked land use, particularly mixed forest and agriculture (e.g., Kasungu National Forest in central-western Malawi).

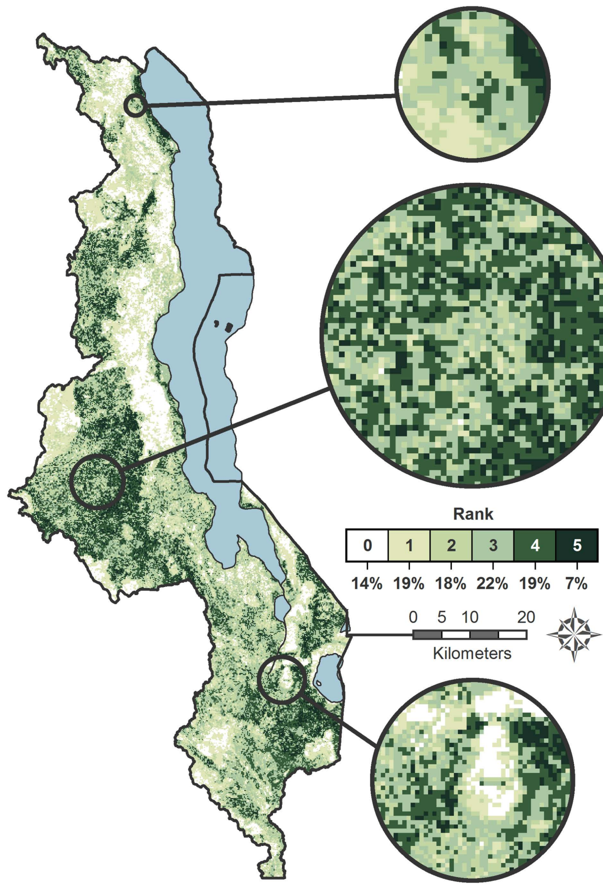

Figure 3.1. *Errors of commission–managed agricultural land–use map.* 1-km spatial resolution.

3.3.3 Measuring Historic Productivity and Interannual Variability of Agriculture

Marginal agricultural lands are defined here by suboptimal biophysical conditions and historically variable or low agricultural production. Using this definition, we created a model that categorizes time-series data, classifying individual pixels relative to spatially structured distributions and administrative delineations. Our methodology considers three levels of production (low, medium, or high) and two types of interannual variability (stable or variable). We use NPP (kg C m^{-2}) as our indicator of production because it has a direct relationship with agricultural output (Heinsch et al. 2003; Reeves et al. 2005; Lobell 2013a; Messina et al. 2017).

First, to generate levels of production, we calculated the average value of each pixel using the time-series NPP (2000–2014). Any pixel with a value of zero for any year between 2000 and

2014 was excluded so that only land under regular cultivation would be considered; this involves excluding pixels that were not productive for any range of years within the time frame. The level of production is derived from a quantile (equal area) classification algorithm; we use three categories to represent low, medium, and high levels of production. Optionally, the model allows for selection of alternative classification systems (e.g., Jenks [1967] natural breaks). Second, to measure interannual variability, we calculated the variance of each pixel using the time-series NPP (2000–2014). We used the quantile classification algorithm with two categories to disaggregate the two temporal trends (variable or stable). Again, the classification system here is optional. The resulting six categories are low-stable (LS), low-variable (LV), medium-stable (MS), medium-variable (MV), high-stable (HS), and high-variable (HV) (Figure 3.2).

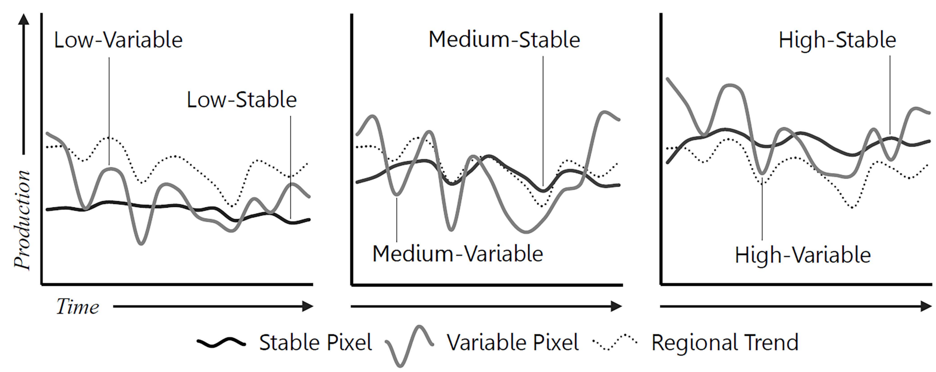

Figure 3.2. *Illustrative diagram of the six interannual variability trends.* Net primary productivity trends measured between 2000 and 2014 for all of Malawi and individual select depictive pixels. The regional trend (shown as a dotted line) is the average of all pixels within the selected region (Malawi in this case). Gray and black continuous lines are select pixels that exhibit the six types of trends.

Crop	Temperature (°C)	Precipitation (mm)
Maize (marginal)	$23.8 > M_m > 32.2$	$750 > M_m > 1217$

Table 3.3. *Marginal temperature and precipitation parameters for maize.* Note: Temperature data acquired from NASA MODIS LST (MOD11A2). Precipitation data acquired from NASA/JAXA TRMM (3B43). Precipitation requirements are represented as accumulated growing season rainfall. Pingali (2001), L. Wood and Moriniere (2013), Sanchez et al. (2014). L. Wood and Moriniere (2013), Infonet (2016), FAO (n.d.-b).

3.3.4 Calibrating the Model to Field Observations

In 2015, prior to the development of the marginal land model, we visited 200 sites in thirty-three farming regions across the extent of Malawi to conduct a land-cover assessment. We devised a stratified random sampling scheme binned by distance to roads and access to local authorities (i.e., extension planning area officers). Extension planning areas (EPAs) are local administrative zones situated within districts. We visited sites ranked between 3 and 5 on the errors of commission–managed agricultural land-use map to increase the likelihood of sampling on agriculture under regular cultivation. Interviews were held with farmers and EPA officers for inquiry of the primary drivers (and limiters) of production, as well as crops grown and land-use history.

Agriculture dominates the Malawian landscape. Of the 200 sites we visited, we found that only ten were either nonagricultural or experienced dominant land-cover change since 2000. Of these ten, only five were misclassified (one barren or forest, one village center, two pastures, and one reed field), two were sparsely cultivated (one mountainous region, one rapidly urbanizing), and three experienced major land-use change (two became maize agriculture, one became government housing for police; Messina et al. 2017). Between ranks 3 and 5 on the errors of commission–managed agricultural land-use map, 95.0 percent (190/200) of locations visited were long-term farmed locations; 91.5 percent (183/200) were long-term maize dominant. The seven fields not dominated by maize were sugarcane (three) and tobacco (two) estates and rice irrigation (two).

During our interviews, we found that the majority of responses for primary drivers of production were related to soil quality or suboptimal precipitation. Temperature and agricultural management practices were seldom reported as limiting factors for production (<1 percent and 1 percent, respectively). The most commonly driven narrative of yield limitations in Malawi is soil degradation (i.e., loss of nutrients and soil organic matter). Approximately 50 percent of interviewees reported that soil quality (i.e., soil degradation, lack of fertilizer, soil infertility, soil suitability, or soil type) was the primary driver limiting yield, with occasional secondary and tertiary factors; 75 percent overall reported soil quality as one of the drivers of low production. Another common observation in Malawi, which is gaining increasing attention in the literature, is that the rainy season is shortening (i.e., starting later and ending earlier; Tadross et al. 2009; Vizy et al. 2015; EPA Officers, personal communication 2015; Sutcliffe et al. 2016) and that rainfall patterns are erratic, yet the overall amount of precipitation has not changed drastically (EPA Officers, personal communication 2015). A sole mean descriptive statistic does not capture this phenomenon. Approximately 50 percent of interviewees reported erratic rains or changing rainfall patterns as one of the drivers limiting yields; 40 percent of interviewees reported rainfall (erratic rains or precipitation amount) as the primary driver limiting production. For this reason, we include rainfall variability in our definition of suboptimal precipitation (refer to the appendix for more discussion on this topic).

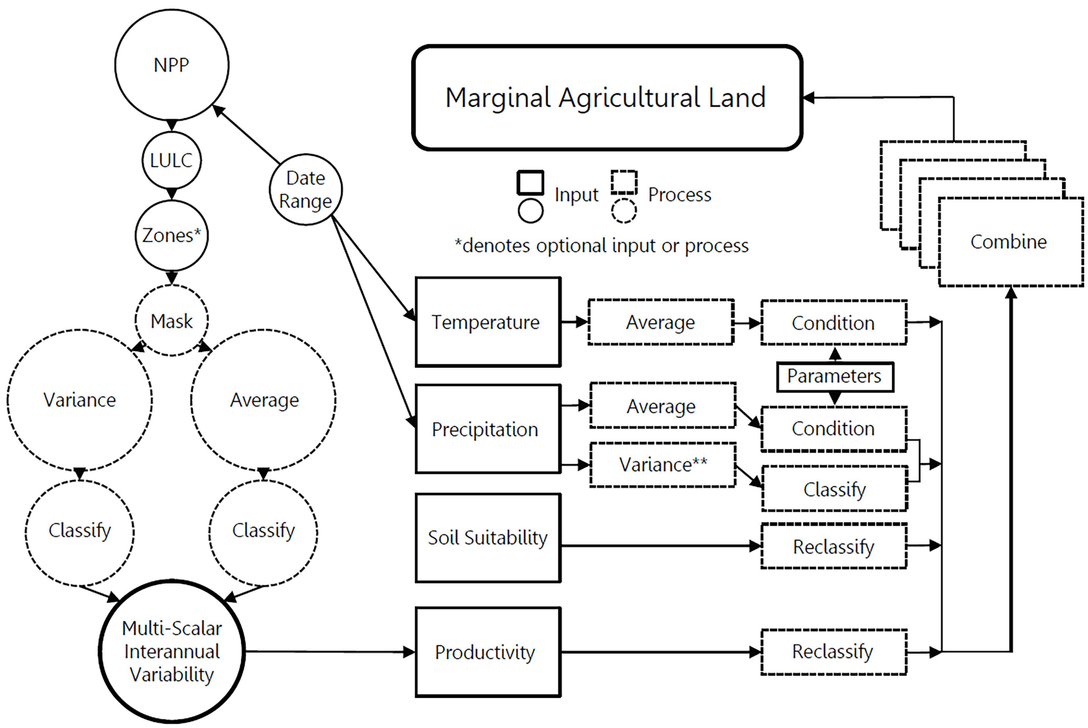

Figure 3.3. *Multiscalar interannual variability and marginal agricultural land model.* *The zones input provides an optional multiscalar calculation. **The precipitation variance was calculated here uniquely for Malawi. NPP = net primary productivity; LULC = land use–land cover.

3.3.5 Identifying Crop Niche and Mapping Marginal Maize Agricultural Land

Marginal maize agricultural land is defined here, in part, by suboptimal LST and suboptimal precipitation. We adopted widely accepted temperature and precipitation ranges for maize to determine suboptimality (Table 3.3). We calculated a singular average LST value (per pixel) across all 2000 to 2014 growing seasons and, using the parameters from Table 3.3, created a binary grid for temperature—either suboptimal or not. Our definition of suboptimal precipitation is a coupling of variable precipitation (determined using our interannual variability model; quantile classification, two classes—either variable or not) and accumulated rainfall outside the optimal range of values (Table 3.3).

In terms of productivity, we consider LS, LV, and MV (gathered from the interannual variability model) as marginal categories. The soil suitability grid provides various levels of suitability, two of which are marginal (marginally suitable and marginally unsuitable; Li et al. 2017a). Interannual productivity and soil suitability were reclassified into binary grids—either marginal or not. All marginal and suboptimal grids were combined so that all possible combinations of marginal maize agriculture (temperature, precipitation, soil suitability, and productivity) would be revealed (Figure 3.3). Input parameters are time-series spatial data (raster data structure), classification method, and boundary data; worth mentioning is that the model is not restricted to NPP and any spatial data could be considered (e.g., rainfall and temperature).

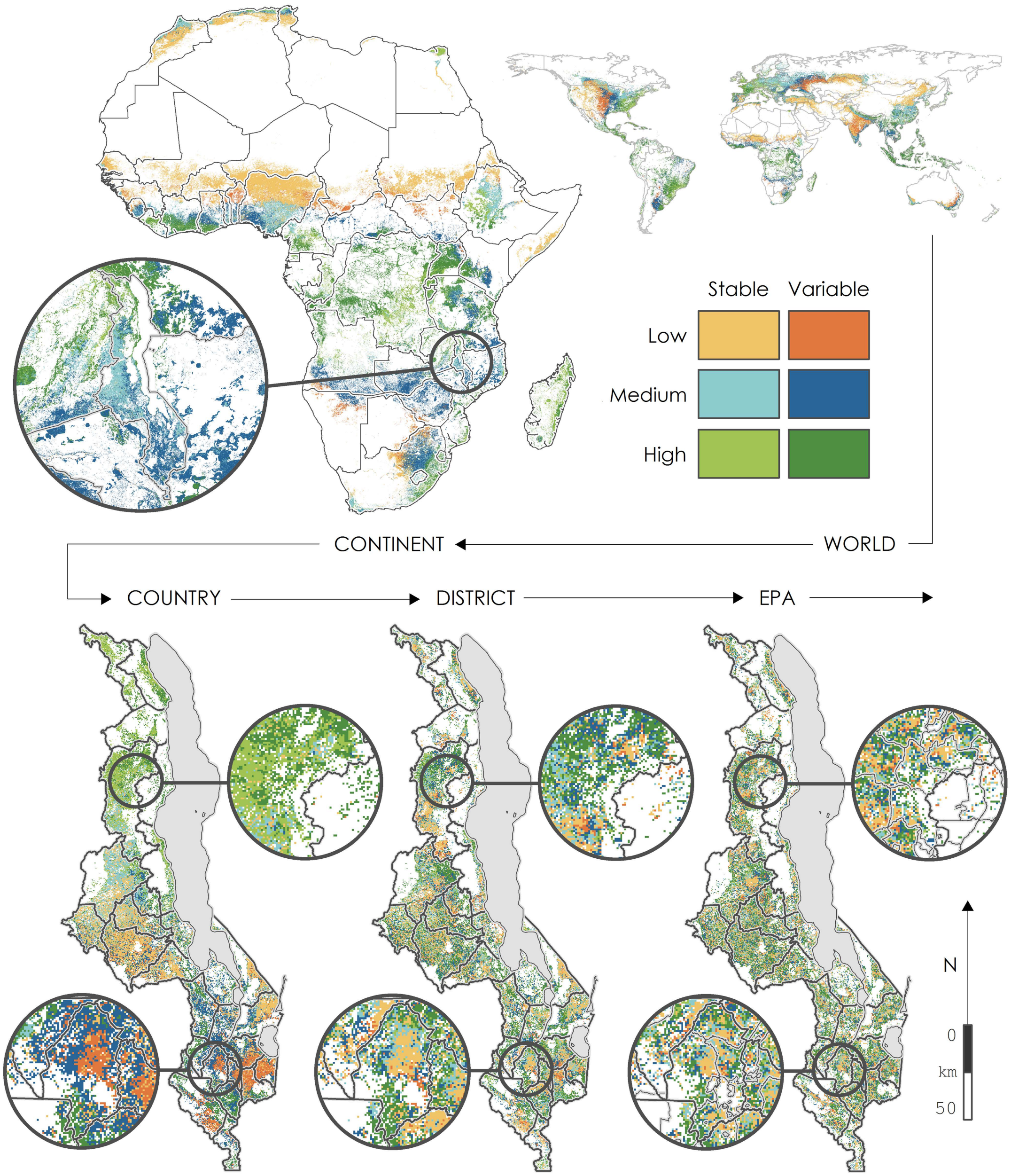

Figure 3.4. *Multiscalar interannual variability: low-stable (light orange), low-variable (dark orange), medium-stable (light blue), medium-variable (dark blue), high-stable (light green), and high-variable (dark green).* Fritz et al.'s (2015) global cropland percentage map used to delineate areas by agriculture on the global and continental maps; the errors of commission–managed agricultural land-use map was used for Malawi. Scale bar applies to Malawi inset maps. EPA = extension planning area.

3.3.6 Devising a Multiscalar Marginal Land Model

We adapted the productivity and interannual variability methodology into a dynamic, multiscalar model. Decision making often takes place at varying administrative levels and performing multiscalar analyses can provide additional levels of insight. The model is generalizable across all geographies, scales, and temporal ranges and is equipped to automatically generate classifications for any geographical boundary and subset boundaries (i.e., country, district, or EPA). The zones input is an optional selection that will generate the six-classification (LS, LV, MS, MV, HS, and HV) map for each subset region (e.g., country, district, or EPA; Figure 3.4).

3.4 Results and Discussion

3.4.1 Multiscalar Interannual Productivity and Variability of Agriculture

Agricultural productivity across Malawi is spatially organized and relative to the scale under observation. There is a clear regional delineation between relative high primary productivity in the north and low productivity in the south. The central region of Malawi is a mix of low and medium productivity. The district- and EPA-level maps reveal additional levels of information (i.e., areas that are homogenous on the country-wide map exhibit heterogeneity at the district level; Figure 3.4). Important to acknowledge is that productivity on a global and continental scale looks expectedly similar to precipitation maps. This is due to global processes driving productivity (precipitation is a calculation input for NPP) and the homogenization of data based on scale. Modifying the scale to the country, district, and EPA levels reveals local processes driving variability (e.g., topography, precipitation, temperature, and soil).

3.4.2 Map of Marginal Maize Agricultural Land in Malawi

Marginal conditions for maize are spatially structured in Malawi. Presented are all possible combinations of marginality and the amount of land area each category occupies (Figure 3.5).

Suboptimal temperatures and marginal productivity are prominent in the central region, marginal productivity and marginal soil in the south, and marginal soil and suboptimal temperatures in the north. Clusters of other combinations are scattered throughout. We found that marginal soils (pertaining to any agricultural activity) occupy 40 percent of Malawi's agricultural land; suboptimal temperatures (pertaining to maize) occupy 52 percent of agricultural land; and suboptimal precipitation (pertaining to maize) occupies 59 percent of agricultural land (approximately 19 percent of the suboptimal precipitation is the result of too much rainfall). Forty-seven percent of agricultural land is characterized by marginal interannual variability and marginal production levels. Despite maize being the dominant crop, only 5 percent of Malawi's total agricultural area is optimal for maize. Also uncovered in this map are possible regions where social factors are driving marginality. These are areas that have marginal productivity not explained by one of the biophysical drivers under study, classified solely as marginal productivity (category P, 5 percent of the agricultural land area; Figure 3.5). These areas might benefit from extension and market development.

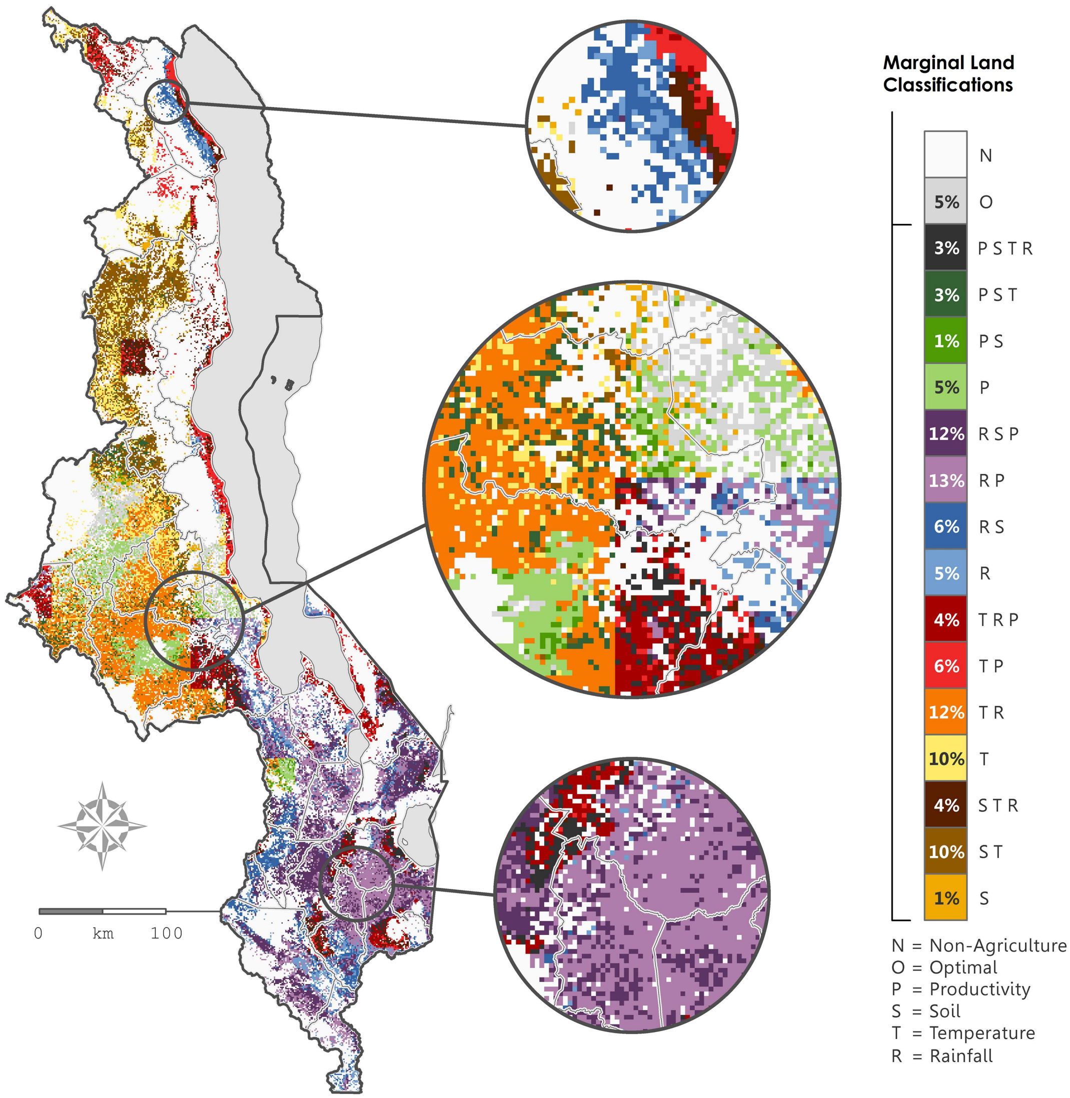

Figure 3.5. *Marginal maize agricultural land (2000–2014).* All possible marginal combinations of the variables under study: productivity (P), soil (S), temperature (T), and rainfall (R). Percentages indicate the proportion of agricultural land that each combination occupies. Letter codes for the various combinations of marginality are listed below the legend. Colors presented are semi-arbitrary and nonhierarchical.

3.4.3 Geographic Themes

There are two distinctly geographic themes underlying this work: the MAUP and the ecological fallacy problem. To recount, the MAUP arises when classifications or aggregations change based on differences in areal selection and scale, and the ecological fallacy problem occurs when inferences are made about an individual instance based on aggregate data (Openshaw 1983). Consider the Malawi country-level map, for example (Figure 3.4). If there are resources available for distribution (e.g., fertilizer or seed subsidies), the southern region with LV interannual variability seems to be an ideal area for focus. Indeed, the southern region warrants particular focus; however, we know that in Malawi, the rural poor across the country are facing similar challenges at local levels. The district- and EPA-level maps manage the country-level homogenization and identify the marginal agricultural lands with respect to variable regional agroecosystems.

Regional land-cover and land-use variation accounts for much of the country-level variation in the productivity signal. For example, fields in the northern region of Malawi are largely composed of maize and cassava, whereas the central region is dominated by maize supplemented with groundnut and beans. In the southern region, maize-based systems commonly include pigeonpea (VAC 2005). The multiscalar map presented here accounts for these regional variations in LULC by presenting measures relative to the differing regional conditions and agroecosystems. In terms of policy, if there is to be an equitable spatial distribution of resources, it is critical to understand variability at multiple aggregations (i.e., country, district, and EPA). If resources (e.g., fertilizer or seed packets) are available for distribution in each district, the question then would be where to deliver the resources within each district. A district-level aggregation provides the necessary information that the country level does not. Without maps like these, policy decisions would be made with incomplete information. Because much agriculture development in Malawi takes place at the EPA level, information at this scale can equip extension officers with additional targeting capabilities.

The MAUP is indeed illuminated here, and we argue that taking a multiscalar approach is one way of managing the problem. There is no single global standard or threshold that would effectively describe low, medium, and high productivity across geographies or scales. If we were to consider the Africa-wide map on its own, nuanced productivity within Malawi would not be observed. Similarly, if observations are only made at the country level, within-district heterogeneity would be missed. Ultimately, no scalar presentation of marginality is better than another irrespective of context, but depending on resource allocation or research purpose, one map (or a suite of maps) might be better equipped for the task.

3.4.4 Reclaiming Marginal Lands

To date, the concept of marginal land has been elaborated largely in the context of biofuel advocacy within both academia and government, with some attention given to assessing where biofuel crops might be grown without disrupting agricultural subsistence and income-generating crops (Cai, Zhang, and Wang 2011). Biofuel advocacy ignores the pivotal role that marginal lands play in agricultural production across sub-Saharan Africa and beyond. As global population continues to increase and land under cultivation is exhausted, more attention must be paid to how to manage marginal agricultural land for improved productivity and sustainability.

Agrobiodiverse, sustainable agricultural practices suited to conserving marginal agricultural lands in a productive manner have become an active area of research in the African development context (Khumalo et al. 2012). Specific examples of how marginal land mapping can help target development strategies are illustrated here for Malawi. Technologies for soil rehabilitation include pigeonpea-based systems, for example, as a tool to foster more resilient maize production (Snapp et al. 2010; Ngwira et al. 2012; Mhango et al. 2013). Illuminating areas that are marginal for maize agriculture (driven by poor soils) but that are suitable for pigeonpea is a novel approach for identifying locations where targeted policy and education would have maximum benefit. Areas where marginality is driven by temperature or precipitation might benefit from climate-resilient crop varieties. Although we focus on maize here, the model is equipped to assess marginal agricultural land for any crop. Marginal lands identified here might also be candidates for promotion of agroforestry, particularly those where human population density is sufficient enough to support the labor requirements of planting, pruning, and managing trees within agricultural landscapes. The protocols presented here can identify the intersection of marginal drivers and suitable conditions for select intervention efforts and crops.

More attention must be given to the potential for remote sensing to characterize marginal land as a prospect for increased yields, improved smallholder farmer subsistence, and overall long-term agricultural system improvement in Malawi. Intervention targeting (i.e., bringing development initiatives to places in need of support and where benefits are predictable) is often overlooked and seldom mapped. As mentioned, one prospect in Malawi is targeted integration of pigeonpea in maize-based cropping systems for soil rehabilitation in locations where conditions are optimal for its cultivation. Remotely sensed spatial information and maps such as those presented here can provide necessary information to target areas in need, particularly in areas most rural where other forms of climate information are unavailable. Moreover, we see considerable value in addressing the biophysical and possible socioeconomic constraints at multiple scales, as illustrated here. In doing so, we aim to overcome some of the hurdles associated with coarse data and characterization of marginal lands by applying big data to a smallholder farming context.

3.4.5 Social Factors Driving Marginal Productivity

The marginal agricultural land map presented here highlights areas where social factors might be playing a role in marginal productivity. Remotely sensed data do not explicitly capture social drivers of farm productivity (e.g., exogenous economic factors or endogenous agricultural management practices); however, we hypothesize that areas where interannual productivity is low or variable but biophysical conditions are optimal are areas where social factors might be dominant factors in marginal productivity. These areas (category P) represent 5 percent of agricultural land on the marginal maize agricultural land map (Figure 3.5). Soil suitability is invariably linked to management practices; however, they are categorized separately here because (1) the soil suitability map used here does not cover a temporal range, making management practices difficult to untangle or verify; (2) the product itself is largely based on terrain characteristics and gross single measurement period soil characteristics; and (3) soil degradation or soil quality (e.g., soil texture) might be beyond the management capacity of the individual farmer. Moreover, it is often the case that farmers are cultivating and managing fields in concordance with agricultural extension-recommended practices, but soil suitability is a production driver often operating on timescales beyond the seasonal or soil degradation is embedded in the soil suitability feedback system. Bringing marginal land out of marginality or degrading status requires resources that are nontrivial to obtain.

Somewhat surprising temperature and agricultural management practices were rarely reported as drivers of marginality (<1 percent and 1 percent, respectively). The most commonly driven narrative of yield limitations in Malawi was soil degradation (i.e., loss of nutrients and soil organic matter). Importantly, there is a prevailing narrative of soil degradation and changing rainfall patterns that is delivered from the top down in Malawi (country/district/EPA). EPA officers carry out missions in concordance with government objectives and soil and precipitation responses might have been given when the primary limiting factor of production was not known. It can certainly be argued that current and recommended management practices are suboptimal, thus contributing to continual soil degradation; however, this situation would not elicit an interviewee response for inadequate management practices. Agricultural extension officers typically referred to management practices as a primary driver of low and variable yields when a farmer did not implement advice from extension, although sometimes insufficient labor or capital were the reasons. Still, it is possible that another factor not presented here is driving marginality. We recommend that areas where interannual productivity is marginal but all biophysical conditions under study are optimal (i.e., temperature, precipitation, and soil suitability) receive further research attention to unpack the social variables (or other biophysical drivers) that might be contributing to marginal production in these areas. In this case, market conditions might be one possible avenue for future research. Areas where interannual productivity is marginal but temperature and precipitation are optimal (and soil suitability is marginal) could also be considered for research on farm management.

Despite widespread maize agriculture in Malawi, conditions are not optimal for its cultivation. This phenomenon is widespread, as many crops are grown far outside of their optimal niche, in terms of both environment and socioeconomic contexts. An increasingly narrow range of crops is dominant in the region and across the African continent. Maize is a clear example, and it continues to expand in production area, becoming a larger presence in semiarid areas of West Africa and Ethiopia, which historically did not grow maize due to local food preferences. This raises questions related to which agronomic traits support this dominance, such as biological properties, which we hypothesize might be related to a superior ability to convert photosynthate into calories, and robust tolerance to weeds and other pests. Socioeconomic conditions might also favor some crops over others, such as market price support and the fertilizer subsidies that are critical for production of cereals. Resilience of farming systems and the environment are supported by agrobiodiversity, and research attention is urgently needed to understand the drivers and geographical patterns that appear to support a countertrend of narrowing of crop diversity.

3.5 Conclusions

Identification of marginal agricultural land is essential for resource conservation and the successful deployment and scaling of innovative technologies and development strategies. Our model provides a generalizable and multiscale heuristic for locating marginal agricultural land and disentangling the factors driving marginality. Further, we propose that areas exhibiting marginal productivity are regions where attention is most needed and indicate the underlying drivers of marginality to reveal where different intervention efforts would prove most effective. The results presented here illuminate the role that spatiotemporal mapping can play in shifting contentious debates to more informed, constructive engagement. Policymakers and scholars can use such mapping exercises to elucidate impacts of agricultural development efforts, and plan effective ways to conserve the environment while supporting farmer livelihoods and services for societal benefits. As pointed out by Kremen (2015), moving beyond the either–or debate to a better understanding of vulnerable lands is key to informing policies that protect natural areas while enhancing food production in a conservation-sensitive manner.[4]

[4] This research was supported by the Perennial Grain Crops for African Smallholder Farming Systems project, Grant #OPP1076311, funded by the Bill & Melinda Gates Foundation, and through support of the U.S. Agency for International Development, AID-OAA-A-13-00006. The opinions expressed herein are those of the authors and do not necessarily reflect the views of the U.S. Agency for International Development or the U.S. government. We thank the Lilongwe University of Agriculture and Natural Resources (LUANAR) in Malawi for facilitating research in the field and M. N. Kakwera for his assistance and expertise, as well as the EPA officers who offered their valuable insight. Additional thanks go to the Environmental Science and Policy Program at Michigan State University for their continued support.

SCALING AGRICULTURAL INNOVATIONS: PIGEONPEA IN MALAWI[5]

4.1 Abstract

Successful scaling of agricultural development strategies is fundamental to increased production and yields, yet targeting efforts frequently fail to fully consider the underlying biophysical drivers of agricultural marginality, particularly at fine spatial resolutions. We present a heuristic for intelligent targeting, utilizing remotely sensed information to identify the intersection between marginal conditions for performance of a staple crop and the optimal niche for technologies that improve crop performance. Here, we explore the geographic potential of maize diversification with pigeonpea, a crop with soil productivity enhancing properties. Overall, 79 percent of agricultural land in Malawi exhibits climate conditions optimal for pigeonpea cultivation and, in total, approximately 51 percent of Malawian maize-based farming is expected to receive some benefit from pigeonpea integration, with 9 percent receiving predictable and substantial benefits. These findings illustrate the geographic scaling potential of pigeonpea in Malawi and provide direction for informed pigeonpea deployment and market development across the country.

4.2 Introduction

In view of widespread food shortages and rural poverty across Africa, scaling innovations to boost agricultural productivity is a global priority and essential to meeting many of the United Nations Millennium Development Goals (Sachs 2005). Although definitions of scaling vary, achieving effective agricultural development involves innovations that have positive impacts on productivity. Scaling in development is both vertical and horizontal. Vertical scaling includes institutionalization

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or decision making at higher levels and often involves sectors and stakeholder groups in the expansion process (Pachico and Fujisaka 2004). Horizontal scaling, also known as scaling out, refers to geographical spread (Snapp and Heong 2003; Pachico and Fujisaka 2004). In practice, horizontal scaling translates to the widespread spatial adoption of new behaviors or technologies through expansion, replication, and adoption of projects, programs, or policies (Linn 2012). Adoption of new technologies, both inputs and practices, along with the innovative use of existing technologies, is vital to achieving agricultural sector growth. These developments aim to increase land and labor productivity, the effective use of natural resources, and farmer income potential, with market solutions (USAID 2014).

Understanding the drivers that prompt farmers to adopt a new product, process, or practice is an essential part of designing a successful scaling strategy. Adoption is a dynamic process, one that is location specific, and influenced by a wide range of biophysical and socio-economic factors (Feder, Just, and Zilberman 1985). Not only does technology performance matter, but there is also a need to consider social context, including input and output market opportunities, farmer priorities, and perceptions of performance. This is illustrated by adoption and disadoption of drought-tolerant maize varieties by smallholder farmers in Malawi, as nationally representative survey data illustrate that this varies with location, as well as with farmer perceptions of drought risk, and yields of modern maize varieties (Fisher and Snapp 2014). Overall, adoption of sustainable agriculture technologies in Africa has been shown to depend on biophysical performance, which influences profitability, and a complex milieu of land and labor availability, knowledge, extension, technology availability, and policy (Hazell and Wood 2008; Muyanga and Jayne 2014).

Approaches to scaling agricultural productivity commonly address and sometimes mix intensification and extensification. In intensified systems, efforts are made to generate more product on land currently under cultivation. Increasing production is achieved through changes in system inputs (i.e., seed, fertilizer, land, labor, time, or feed; Food and Agriculture Organization of the United Nations [FAO] 2004). Other land-use decisions include the displacement of one commodity for another, where the economic outcome is comparable or greater (Govereh and Jayne 2003). As consideration is given to the importance of agricultural systems in a global context, emphasis is increasingly being given to sustainable intensification practices. Thirty-eight percent of the world's agricultural area has become degraded through poor natural resource management, particularly in Africa, where up to 65 percent of agricultural land suffers from degradation (Feed the Future 2015). With little room to expand agriculture into new areas due to poor suitability, access, or limited availability, there is an increasing focus on intensified agricultural productivity (USAID 2016).

Extensification involves introducing agricultural production into land areas that have been previously unused or used for less intensive purposes (Impact Assessment Group 2000). These land areas are often marginal and might require substantial inputs to bring them into production. High population density and limited land availability, however, is widespread in Malawi, limiting extensification options (Ricker-Gilbert and Jumbe 2014). Between 1990 and 2013, forest cover in Malawi decreased by 23 percent (FAO 2016a), attributed in part to agricultural extensification by smallholder farmers and population increase (Government of Malawi 1998; Chibwana, Jumbe, and Shively 2013). As of 2013, agriculture occupied approximately 61 percent of Malawi's total land area, with forest cover diminishing to 34 percent of the total land area (FAO 2016a). Consequently, options for extensification have been largely reduced to protected or marginal areas, neither of which are viable or sustainable for long-term production demand. Thus, intensification has become the primary focus for soil rehabilitation and increased production.

4.2.1 Prospect for Soil Rehabilitation in Malawi

Malawi is facing recurrent food security crises due in part to long-term unsustainable agricultural practices (Glasson 2010; Mungai et al. 2016). There are other contributing factors, such as historical inequities in resource distribution and minimal investments in infrastructure, research, and education. From a biophysical standpoint, the continuous production of maize over the last several decades has fostered widespread soil nutrient and organic matter degradation (Sanchez 2002; Ngwira, Aune, and Mkwinda 2012; Thierfelder et al. 2013). In the past, emphasis has been placed on fertilizer substitution (e.g., Denning et al. 2009); however, the success and long-term viability of such a solution is widely debated (Chinsinga and Poulton 2014; Messina et al. 2017), and seemingly ineffective for the rural poor in Malawi (Holden and Lunduka 2013).

Pigeonpea has been proposed as a mitigation strategy for combating soil degradation with its large root system, copious vegetative biomass, and superior ability to fix nitrogen and enhance phosphorus solubilization for soil rehabilitation (Snapp et al. 2010; Ngwira, Aune, and Mkwinda 2012; Mhango, Snapp, and Phiri 2013). The benefits of pigeonpea, grown in combination with maize, or as a doubled-up legume system (i.e., pigeonpea and an understory of soybean or groundnut), rotated with maize, have been proven in country-wide trials (Snapp et al. 2010; Snapp et al. 2014). Perennializing agriculture through growing perennial legumes complementary to existing maize-based farming systems is at the foundation of many such sustainable practices, yet adoption across Africa has been limited (Schulz et al. 2003; Bezner-Kerr et al. 2007; Snapp et al. 2010). In Malawi, uptake of legume biodiversity is commonly hindered by profitability and farmer preference; however, trials in northern Malawi show promise for semi-perennial legume adoption (Snapp et al. 2010).

Pigeonpea is commonly integrated in maize systems in the southern region of Malawi, yet farmers in the northern and central regions have historically elected not to grow pigeonpea, choosing other legumes (e.g., groundnut, soybean, common bean, and cowpea) and other forms of crop diversity (e.g., cassava; Malawi Vulnerability Assessment Committee [VAC] 2005; Simtowe et al. 2010). This regional delineation of crop choice does not appear to be dictated explicitly by biophysical conditions. In terms of temperature and precipitation, 79 percent of southeast Africa (Kenya, Tanzania, Malawi, Mozambique) is suitable for pigeonpea cultivation (Snapp et al. 2019b). Rather than climate, pigeonpea presence in Malawi might be dictated largely by social factors (e.g., market conditions, culture, extension, labor, preference, or pressure to produce cash crops; Snapp and Silim 2002).

4.2.2 Horizontal Scaling of Pigeonpea in Malawi

Targeting is crucial to the successful deployment and scaling of development strategies and innovation technologies (S. Wood et al. 1999). Although agricultural improvement efforts frequently take place at the local level (e.g., Giller et al. 2006), scaling is typically targeted by region and absent the local context (e.g., Millar and Connell 2010). More regional approaches to scaling agricultural technologies are often unilateral (i.e., focus is given to a singular metric—e.g., sustainability), neglecting to fully address the underlying combinations of biophysical and social factors driving marginality, particularly at fine spatial resolutions. For intervention initiatives to succeed, they need to be delivered in areas where benefits would be substantial and predictable (e.g., biophysical conditions must be considered), and where farmer adoption is realistic (Kwesiga et al. 2003). Here, we focus primarily on the biophysical suitability of pigeonpea across Malawi. This means promoting pigeonpea and encouraging market development in regions and sites where (1) cli-mate conditions are optimal for pigeonpea, and (2) maize suitability and maize production are marginal.

Remotely sensed data offer cost-effective, fine spatial and temporal resolution data to uncover the complex dynamics of agricultural production across the landscape and in remote places on earth. These data allow for intelligent targeting of development strategies beyond administrative levels and beyond often arbitrary decision-making processes unrelated to *in situ* conditions. Other agricultural improvement initiatives have employed remotely sensed information for targeting deployment of new technologies (e.g., Bellon et al. 2005; Muthoni et al. 2016). Bellon et al. (2005) used remotely sensed climate data in combination with demographic information to target agricultural advancements for poverty alleviation of farmers in Mexico. Muthoni et al. (2016) used a suite of biophysical and socioeconomic variables to recommend zones for sustainable intensification efforts in Tanzania. Our work complements studies such as these and is differentiated by providing a framework to disentangle the complex combinations of the underlying biophysical and possible social factors driving marginality, supplying information and recommendations at a fine spatial resolution, and on a pixel basis. Highlighted here are areas and sites where pigeonpea integration will provide predictable and substantial benefits in a classification format readily usable by policymakers, decision makers, and scholars.

We propose a heuristic for assessing the horizontal scaling potential of pigeonpea in Malawi using a comprehensive suite of remotely sensed measures of agricultural productivity, climate conditions, and land suitability. First, we identify locations where climate conditions are optimal for the cultivation of pigeonpea, based on fundamental niche. Second, we evaluate areas where biophysical conditions for maize are suboptimal and productivity is historically marginal. Finally, the intersection of soil-driven maize marginality and the optimal pigeonpea niche reveals "better bet" locations for predictable and beneficial integration outcomes. We present a range of scaling outcomes and propose areas where pigeonpea will provide positive results based on biophysical suitability, as well as areas that might benefit from extension and market development.

4.3 Methods and Data

4.3.1 Pigeonpea Niche

To identify locations suitable for pigeonpea cultivation, we used two remotely sensed products: (1) NASA MODIS Land Surface Temperature (LST— MOD11A2) for temperature (NASA LP DAAC 2015b), and (2) NASA/JAXA Tropical Rainfall Measuring Mission (TRMM—3B43) for precipitation (NASA/JAXA TRMM 2016). Thresholds for optimal pigeonpea conditions are based on widely accepted and tested temperature and precipitation ranges (Table 4.1). We calculated the average value for each pixel across all years under study (2000–2014) for the November through April growing seasons (Jayanthi et al. 2013; FAO 2016b). Only areas where temperature and precipitation were both optimal were considered for the optimal niche.

4.3.2 Targeting Development Strategies

To identify areas where agricultural production is historically poor and soil is likely driving underproduction, we used a Malawi maize suitability map that disaggregates broad classes of suboptimal biophysical conditions and agricultural productivity (Peter et al. 2018). The map depicts all combinations of suboptimal temperature, suboptimal precipitation, soil suitability, and agricultural productivity. The dominant focus here is soil quality and pigeonpea integration. Legumes are generally tolerant to low soil fertility (Snapp and Silim 2002) and are commonly grown in marginal soil environments (Kumar Rao and Dart 1987), whereas maize growth is impaired by marginal, resource-poor soils (Heisey and Edmeades 1999). Pigeonpea can grow effectively on marginal soils and its integration with maize cropping systems can provide soil nutrient enrichment, resilience, and improved maize yields (Snapp et al. 2010). Because pigeonpea has these soil rehabilitation properties, a reclassification of the marginal maize map tailored to soil marginality reveals areas where pigeonpea deployment would prove most effective. This reclassification is one that can be easily interpreted and readily used by policymakers and academics to intelligently target research and development scaling initiatives.

Crop	**Temperature (°C)**	**Precipitation (mm)**
Pigeonpea (optimal)	22.7–30.9	544–1263

Table 4.1. *Optimal pigeonpea climate niche*. Note: Temperature data acquired from NASA MODIS LST (MOD11A2). Precipitation data acquired from NASA/JAXA TRMM (3B43). Precipitation requirements are represented as accumulated growing season rainfall. L. Wood and Moriniere (2013); Sardana, Sharma, and Sheoran (2010); Valenzuela and Smith (2002); Carberry et al. (2001); Silim and Omanga (2001); Kimani (2001); Omanga, Summerfield, and Qi (1996); Houérou (n.d.).

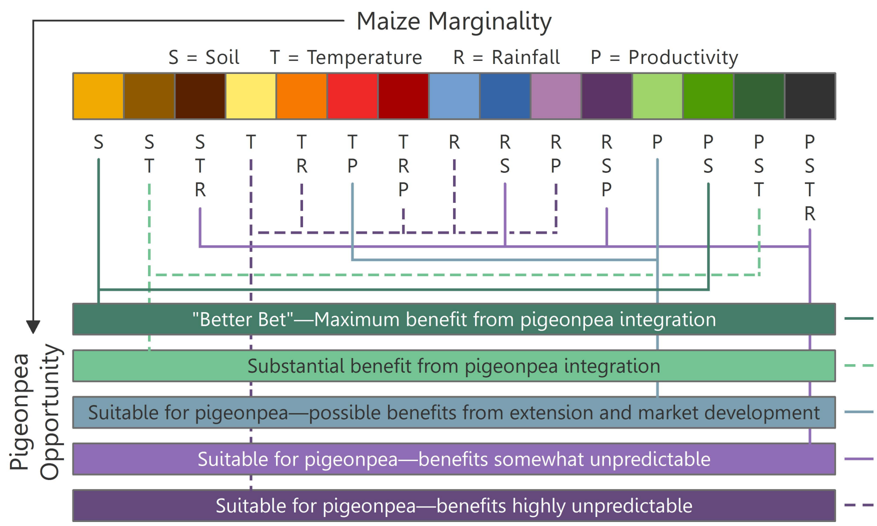

Figure 4.1. *Reclassification diagram: Transforming maize marginality into pigeonpea opportunity.*

Potential areas for pigeonpea deployment are defined as the intersection between soil-driven marginal areas for maize and the optimal climate niche for pigeonpea. Locations where marginality is related to soil (solely or in combination with marginal productivity) were reclassified to a "better bet" option for maximum benefit from pigeonpea integration. In this case, because soil is the only factor (of those under study) driving marginality, positive outcomes from pigeonpea integration are expected. Locations with marginal production, but where low productivity is not explained by any of the explanatory drivers, are areas where marginality might be driven by social factors and would likely benefit from extension and market development. It is also possible, however, that another factor not under study is driving marginality. Marginal productivity and suboptimal temperature regions were also considered potential areas for extension and development.

Other reclassifications include locations that are suitable for pigeonpea, but benefits are somewhat unpredictable because marginality is associated with other factors in combination with soil and might require alternative solutions (e.g., climate-resilient crop varieties). Areas where pigeonpea is suitable, but soil is not a driver of marginality, are classified as highly unpredictable. The following are the resulting categories: (1) Better Bet—maximum benefit from pigeonpea integration; (2) substantial benefit from pigeonpea integration; (3) suitable for pigeonpea— likely benefits from extension or market development; (4) suitable for pigeonpea—benefits somewhat unpredictable; and (5) suitable for pigeonpea—benefits highly unpredictable (Figure 4.1). The last resulting category (6) includes areas unsuitable for pigeonpea or nonmarginal for maize.

4.3.3 Field Survey and Data Acquisition

In 2015, we conducted a country-wide field survey in which we spoke with extension officers in thirty-three farming regions (extension planning areas [EPAs]) across the extent of Malawi. We visited nine EPAs in the north, eight in the south, and sixteen in the central region, conducting interviews and land-cover/land-use assessments at 200 sites. At each site, we inquired about crops grown and cropping system patterns (e.g., sole crop and intercrop). In addition to our interviews, we acquired EPA-level crop production metrics from the Malawi Ministry of Agriculture and Food Security (MoAFS), which covers the years between 2005 and 2012. These data, along with the interviews, allow us to cross-reference reports of regional crop delineation (VAC 2005;

Simtowe et al. 2010), as well as reveal the spatial distribution of pigeonpea production and yield at the local scale. Regional and administrative boundaries are presented here for reference (Figure 4.2).

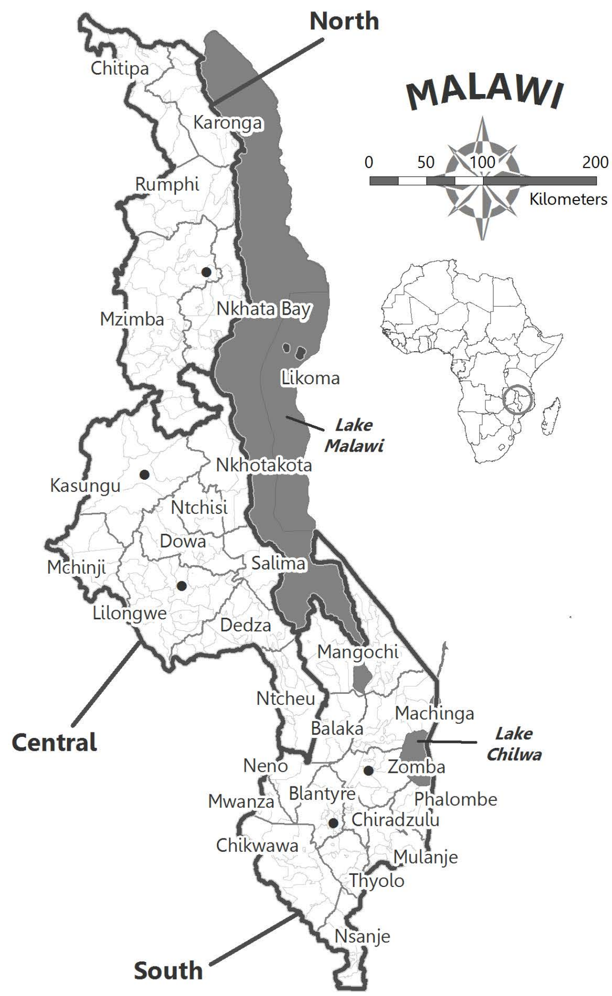

Figure 4.2. *Study area map highlighting the northern, central, and southern regions of Malawi and the contained districts and extension planning areas.*

4.4 Results

4.4.1 Spatial Distribution of Pigeonpea in Malawi

Here we present data on pigeonpea production and yield by administrative unit (EPA) across Malawi for 2005 and 2012; these years represent the greatest temporal range in the data available.

There is a clear regional pattern of pigeonpea presence in the southern region of Malawi (Figure 4.3). In 2005, the southern region of Malawi produced 92 percent of the national pigeonpea total (compared with less than 1 percent in the north). In 2012, the southern region of Malawi produced 89 percent of the national pigeonpea total (compared with less than 1 percent in the north). For instances where pigeonpea is grown in the northern and central regions, however, yields are comparable to those observed in the south (Figure 4.4). In 2005, pigeonpea yields in the southern region averaged approximately 430 kg ha^{-1}, and in the northern region, pigeonpea yields averaged approximately 440 kg ha^{-1}. In 2012, pigeonpea yields in the southern region averaged approximately 980 kg ha^{-1}, and in the northern region, pigeonpea yields averaged approximately 700 kg ha^{-1}. Pigeonpea is scarce in the central region; however, in 2005 pigeonpea yields averaged approximately 470 kg ha^{-1} and in 2012 pigeonpea yields averaged approximately 900 kg ha^{-1}. Coinciding with government reports, our field survey shows an overwhelming presence of pigeonpea in the southern region of Malawi. Of our 200 sites visited (in thirty-three farming regions), we were able to confirm pigeonpea cultivation at forty sites. Of these sites, pigeonpea was grown at only three sites in the north, four in the central region, and thirty-three in the south.

4.4.2 Pigeonpea Niche and Deployment Potential

Malawi's climate is highly suitable for the cultivation of pigeonpea. In terms of both temperature and precipitation, 79 percent of agricultural land exhibits climate conditions optimal for pigeonpea growth (Figure 4.5). Approximately 3 percent is optimal only for temperature and 17 percent is optimal only for precipitation, so only 2 percent of Malawi's agricultural area is entirely suboptimal for pigeonpea.

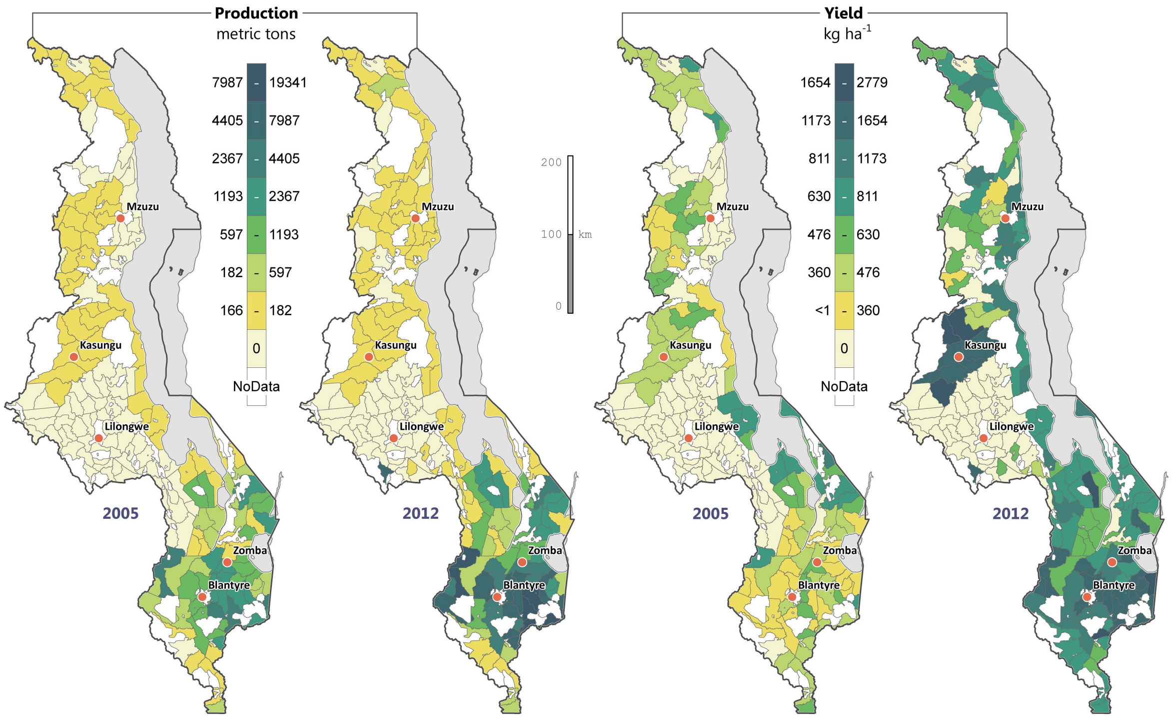

Figure 4.3. *Map depicts the spatial distribution of pigeonpea production and yield in 2005 and 2012 by extension planning area.*

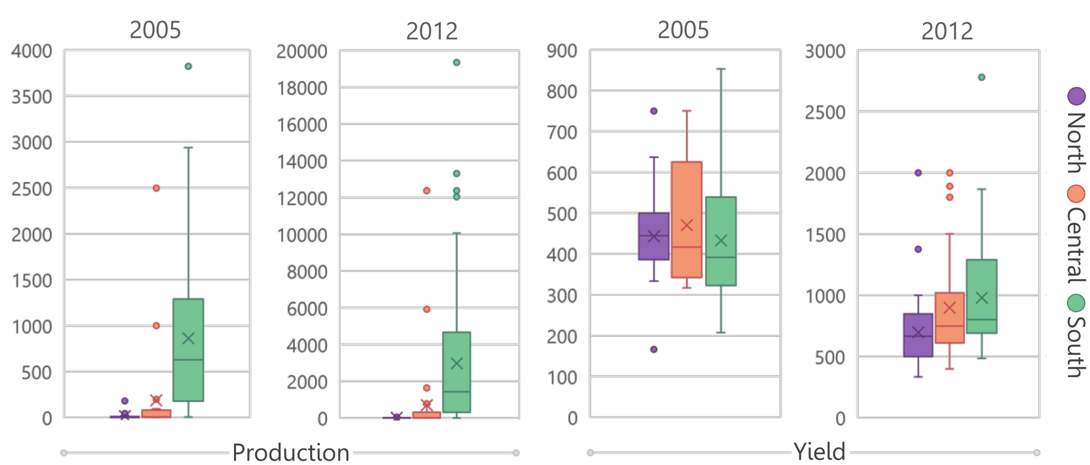

Figure 4.4. *Regional descriptive statistics: Box and whisker plot of pigeonpea production and yield in three major regional subdivisions of Malawi (north, central, and south) for 2005 and 2012.* Production in metric tons and yield in kg/ha. Note that y-axes vary.

The intersection of marginal maize and optimal pigeonpea covers 74 percent of agricultural land in Malawi (Figure 4.6). Within this intersection, 46 percent of maize marginality is attributed to soil (solely or in combination with other drivers). Our findings suggest maximum benefit from pigeonpea integration occurring on 2 percent of agricultural land. These are areas where soil suitability is the sole driver of marginality. Seven percent of marginal agricultural land is expected to receive substantial benefit from pigeonpea integration. These are areas where soil suitability is a primary driver of marginality, along with suboptimal temperature conditions. Another 7 percent is suitable for pigeonpea and might benefit from extension and market development. These are areas where productivity is measurably low, yet there is either no observable limiting driver of productivity (of those under study), or temperature is the sole factor. We found that 37 percent of the country is suitable for pigeonpea, but soil is not the sole driver of marginality and benefits are less predictable. Twenty-one percent is suitable for pigeonpea but soil is not a driver of marginal maize; therefore benefits are highly unpredictable. Twenty-six percent is unsuitable for pigeonpea or nonmarginal for maize. Overall, approximately 51 percent of Malawian agriculture is likely to receive benefits from pigeonpea adoption, with varying degrees of predictability and effectiveness, at least 9 percent of which should receive highly predictable and beneficial outcomes from pigeonpea integration.

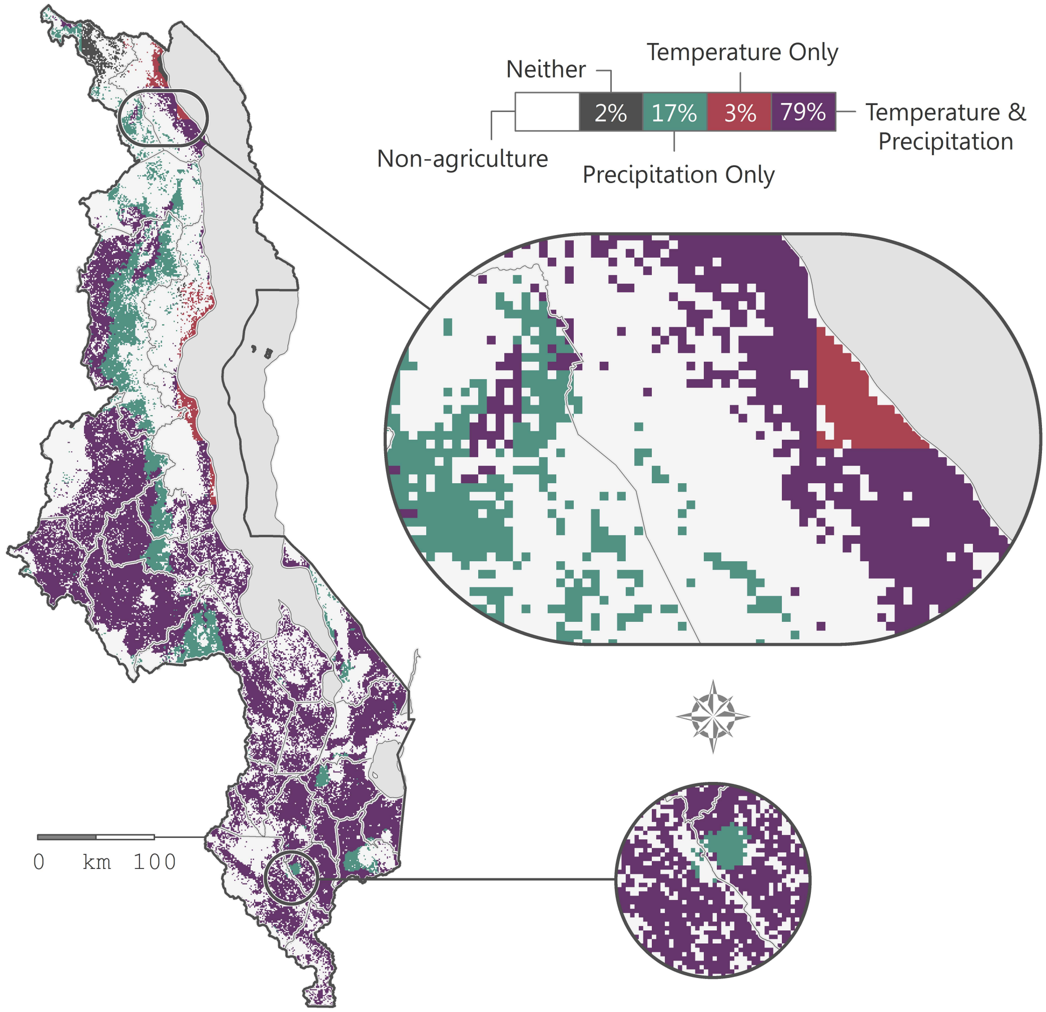

Figure 4.5. *Pigeonpea climate niche: Optimal temperature and precipitation (2000–2014).* Data sources: NASA MODIS LST (MOD11A2) and TRMM (3B43). Inset maps selected to highlight local spatial variability.

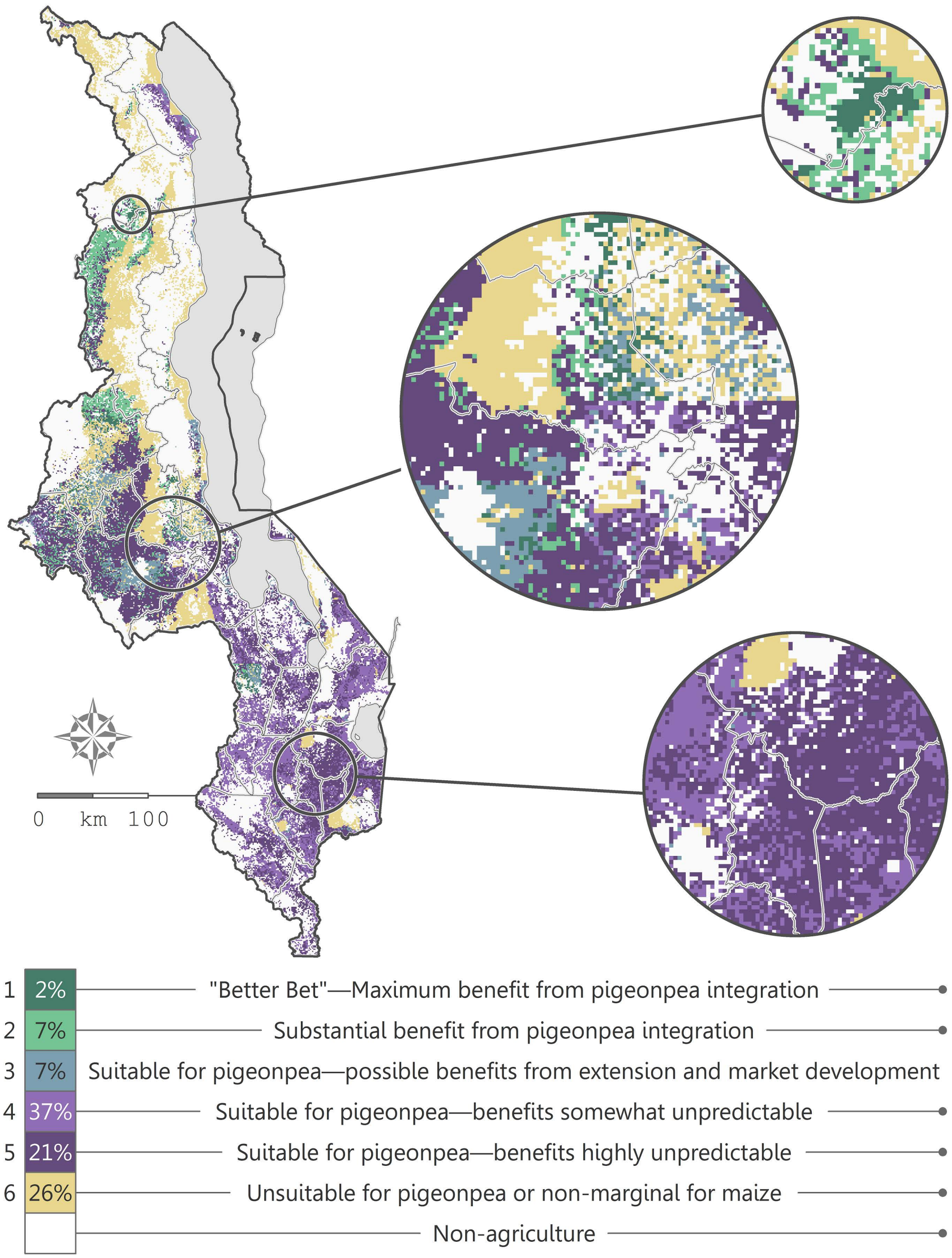

Figure 4.6. *Potential areas for deployment of pigeonpea and market development.* Inset maps selected to highlight local spatial variability.

4.5 Discussion

4.5.1 Targeting Investments in Sustainable Agriculture Technologies

It is urgent to reverse the soil degradation trend in Malawi and support sustainable agricultural practices and higher production levels. Agricultural development will not be successful unless sustainable management of the underlying soil resource is addressed, nor will investments in agricultural subsidies achieve profitable returns. To build soil organic matter requires sufficient organic matter inputs, delivered efficiently from leguminous plant roots (Puget and Drinkwater 2001; Kong and Six 2010). In Malawi, sustained effort to improve soil organic carbon is also required. There is a growing body of evidence that the surest way to achieve soil organic matter gains, in a manner that ensures ease of farmer adoption, is to promote crops that are shrubby, such as pigeonpea, in contrast to growing exclusively annual crops that have limited life spans, limited aboveground biomass, and meager root systems (Snapp et al. 2010; Glover, Reganold, and Cox 2012).

Over the long term, technologies such as residue mulch systems, agroforestry, and intensified livestock systems that transfer manure to crop fields are all expected to play a role in building soil productivity in Malawi. Some of these systems, however, have been shown to require substantial labor investments, as well as food production opportunity costs, at least in the short term (Sirrine et al. 2010). The combination of near-term options, such as diversification with pigeonpea, and more long-term, radical options all need to be considered as means to build soil organic matter. This is essential to ensure crop response and profitable use of investments in improved seed and fertilizer. We recommend the Malawi government extension consider innovative approaches to targeting intervention efforts, such as the example presented here that assesses where pigeonpea can be most effectively deployed. To complement long-term investments, we propose immediate research and extension attention be given to multipurpose legumes, such as pigeonpea, in the "better bet" areas we have highlighted.

It is clear that pigeonpea is preferred in the southern region of Malawi, based on the quantity of production; however, in instances where pigeonpea is grown in the northern and central regions, it performs quite well and yields are comparable to those in the south (Figure 4.4 and Figure 4.5). These findings support the spatial extent of pigeonpea optimality and the potential for widespread integration (Figure 4.3). Pigeonpea is largely absent in most of the central region; however, the confirmation of overlapping optimal niche and reported high productivity leads to a reasonable assumption that pigeonpea could be grown successfully in the northern and central region EPAs. In Figure 4.3, we show that much of the northern region is suitable for pigeonpea, and, based on the drivers of marginality for maize, would receive maximum or substantial benefit from pigeonpea integration. These areas in the northern and central regions are high-priority areas for the scaling and market development of pigeonpea.

4.5.2 Drivers of Pigeonpea Production

This article documents the spatial extent of soil and temperature properties that condition pigeonpea growth and compares this to the actual pigeonpea distribution. It is clear that pigeonpea is underrepresented in terms of biophysical suitability, but is an expanding crop in Malawi. Production area has increased at a rate of about 5.5 percent per year between 2006 and 2014; over the same time period, production has increased at a rate of about 5.6 percent per year, and yield at a rate of about 11.4 percent per year (FAO 2016a). The maps of pigeonpea production and yield presented (MoAFS) are consistent with FAO-reported trends of continually increasing production and productivity in Malawi. Indeed, 2005 was a particularly low producing year due to severe crop response from poorly timed rains (Buerkle 2005); however, there is still a considerable annual yield increase (8.1 percent on average, 2000–2014; FAO 2016a). The maps and reported figures also demonstrate that pigeonpea responds similarly to rainfall stress across regions. Somewhat surprisingly, this rapid upward production and yield trend holds true for many of Malawi's primary crops (e.g., maize, rice, groundnut, soybean, and tobacco). Despite reported production and yield gains across crops, the fact remains that widespread food insecurity persists throughout rural Malawi (Messina et al. 2017).

A driving factor of increasing pigeonpea production might be the growing international market opportunities occasioned by large and consistent pigeonpea import demands from the Indian subcontinent (Simtowe et al. 2010). Emergent pigeonpea success in neighboring Mozambique and Tanzania (Walker et al. 2015) make it increasingly important for Malawi to situate itself within the pigeonpea export arena. There is somewhat contradictory evidence regarding market demand, which appears to be highly variable in Malawi, as several reports have highlighted farmer concerns with pigeonpea market access limitations outside of southern Malawi (Rogé et al. 2016; Waldman et al. 2017). The central region of Malawi, where the country capital of Lilongwe is situated, is largely undiversified, with maize and tobacco dominating the agricultural landscape (VAC 2005), and pigeonpea is largely absent (Snapp et al. 2003). Conversely, southern districts such as Zomba have a market structure that encourages pigeonpea production and integration (Ortega et al. 2016; Waldman et al. 2016). In Malawi, variability of the pigeonpea market over space and time might drive increased production in some areas and years, and limit it in others, with an overall positive impact on pigeonpea production. Socioeconomic contexts (e.g., market structure and farmer preference) are impeding pigeonpea scaling across much of Malawi. Another barrier to pigeonpea production is the extent of free-ranging livestock in northern and central Malawi. Compared to southern Malawi, there are few community norms that ensure year-round livestock control, which is key to growth and survival of long-lived semi-perennial crops such as pigeonpea (Rogé et al. 2016). Taken together, this is suggestive that agricultural development efforts that involve pigeonpea promotion will need to pay attention to livestock control and market policies, as well as biophysical suitability for pigeonpea.

4.6 Conclusions

Maize produced in optimal areas with recurring high yields will never be replaced by pigeonpea—the calorie yield difference is simply too great. The strengths of the model proposed here, however, lie in its ability to transform marginality into opportunity with predictable outcomes. Smallholder farmers are generally risk averse. Here, we provide evidence that pigeonpea is a promising and scalable option for soil rehabilitation, nitrogen fixation, and improved maize yields across many specific locations in Malawi. The maps and methodology herein are resources that might be used to intelligently target locations in need of intervention, where benefits will meet expectations and minimize risk. The fine spatial and temporal resolution data we employ allow policymakers and decision makers to focus efforts beyond the regional level, removing some uncertainty in extension delivery and promotion of new practices. Although we focus on maize and pigeonpea here, the model is not limited to a particular crop and could be generalized across geographies, crops, scales, and innovation strategies. Reclassifying the underlying drivers of marginality, tailored to specific technologies, will allow for a wide array of potential for agricultural innovations to scale and improve agricultural systems across Malawi.[6]

[6] This research was supported by the Perennial Grain Crops for African Smallholder Farming Systems project, Grant #OPP1076311, funded by the Bill & Melinda Gates Foundation, and through support of the U.S. Agency for International Development, AID-OAA-A-13-00006. The opinions expressed herein are those of the authors and do not necessarily reflect the views of the U.S. Agency for International Development or the U.S. government. We would like to thank the Lilongwe University of Agriculture and Natural Resources and Africa RISING for facilitating research in the field, as well as the Global Center for Food Systems Innovation at Michigan State University.

MULTI-SPATIAL RESOLUTION SATELLITE AND sUAS IMAGERY FOR PRECISION AGRICULTURE ON SMALLHOLDER FARMS IN MALAWI[7]

5.1 Abstract

A collection of spectral indices derived from a range of remote sensing imagery spatial resolutions are compared here to on-farm measurements of crop yield and crop chlorophyll at two trial farms in central Malawi. The primary objective of this analysis was to evaluate what spatial resolutions are most effective for relating multispectral images with crop status. Single and multiple linear regressions were tested for spatial resolutions ranging from 7-cm to 20-m using a small unmanned aerial system (sUAS) and satellite imagery from Planet, SPOT 6, Pléiades, and Sentinel-2. Evidence presented here suggests that imagery with spatial resolutions nearest the plant scale (i.e., 14–27-cm) are most effective for relating spectral signals with crop status on smallholder farms in Malawi. Moreover, green-band indices were more consistently correlated with crop chlorophyll and yield than conventional red-band indices such as NDVI, and multivariable models often outperformed single variable models.

5.2 Introduction

5.2.1 Precision Agriculture and sUAS

Precision agriculture has become a prominent subject of research for remote sensing of cropping systems since the advent of individual-use small unmanned aircraft systems (sUAS) (Zhang and Kovacs 2012). While national governments have been monitoring agricultural production via satellite since the 1970s, coarse spatial resolutions, cloud cover, and infrequent collection has rendered much of these image data unfit for the needs of small-scale farmers (Mulla 2013). Now, the

[7] This is an Unpublished Manuscript. Reference: Peter, B.G., Messina, J.P., Carrol, J., Lin, S., Chikowo, R., Zhi, J., and Snapp, S.S. 2019, In Preparation. Multi-spatial resolution satellite and sUAS imagery for precision agriculture on smallholder farms in Malawi.

use of quadcopters and fixed-wing drones for precision farming continues to grow as sUAS technologies become increasingly cost effective and programmatic operations are developed that streamline the process of collecting imagery and generating map outputs (Floreano and Wood 2015). Many drones, such as the senseFly eBee fixed-wing aircraft with eMotion, no longer require manual piloting and can be launched with pre-programmed flight plans. Moreover, associated software such as Pix4D (Pix4D SA 2017) can handle many of the previously arduous image pre-processing tasks, such as image mosaicking, geometric correction, orthorectification, and radiometric calibration. These advancements have made precision agriculture accessible to users with minimal to no experience with aerial vehicle piloting and remote sensing-based crop analytics. Continuing the precision autonomous farming trends, large-scale agribusinesses have begun to leverage GPS enabled systems to deliver fertilizer and water relative to spatial need as measured via sUAS (Eaton et al. 2008).

Typical agricultural-use sUAS multispectral cameras will acquire red, green, and blue (RGB), red edge, and near-infrared (NIR) imagery (e.g., Parrot Sequoia multispectral camera) (Parrot Drones SA 2017), and more sophisticated cameras with a broader range of spectral bands can record shortwave and thermal infrared (SWIR and TIR) (Stark et al. 2015), which are critical for monitoring crop water stress (Ceccato et al. 2001). With the visible spectrum (RGB) and NIR, a broad range of crop status indices can be calculated. Most notable is the normalized difference vegetation index (NDVI) (Tucker 1979). This metric is widely used as a measure of crop health—a healthy plant will absorb visible light (especially blue and red), while the fortified leaf structure will reflect a high amount of NIR. NDVI calculation is simply (NIR–red)/(NIR+red), returning values between -1 and 1, ranging from non-vegetated (water or barren) to healthy crops and plants with a high leaf area index (LAI). Beyond being a metric for crop health, NDVI is frequently correlated with crop production and yield, thus many farmers find value in mapping NDVI across their fields (Wall et al. 2008).

5.2.2 Variable-Rate Technology and Spectral Signals of Farm Productivity

Perhaps the most common use of drone imagery on-farm is the application of variable-rate technology. This is the term coined to describe farm productivity improvement applications that are informed by spatiotemporal measurements of crop performance (Sawyer 1994). In the case of NDVI being used as an indicator of crop productivity, fertilizer may be applied proportionately across a field depending on the spatial organization of measured crop status. Similarly, maximum efficiency applications may be deployed that consider the nitrogen use efficiency (NUE) at various stages of crop growth (i.e., fertilizer applied to a moderately healthy plant may have a greater return than fertilizer applied to an unhealthy plant) (Cassman 2002). NDWI (normalized difference water index), a ratio of the SWIR and NIR bands (Gao 1996), can be used to inform water distribution across a field, supplying water to areas where crops are experiencing water stress and restricting the amount delivered to areas at risk of waterlogging. Depending on the spatial resolution, an image interpreter may be able to visually detect areas that are experiencing leaf damage from pests and identify invasive plants and weeds between row crops (Hunt and Daughtry 2017). Further, elevation point clouds derived from drone imagery can be used to identify sloping terrain prone to erosion and areas susceptible to pooling, which can be managed by manipulating the field structure or by integrating crops with substantial root biomass (Pineux et al. 2017).

While NDVI is an extensively used vegetation index, it is well known that it does not always emerge as having the strongest correlation with on-farm yields or leaf chlorophyll and is often outperformed by other remote sensing indicators (Hatfield and Prueger 2010). Spectral indices in relation to crop status can vary substantially due to differences in crop leaf structure, planting density, soil and shadows, and image spatial resolution. Other indices that are often used to correlate spectral signals with crop status include GNDVI (green normalized difference vegetation index), SAVI (soil adjusted vegetation index), GSAVI (green soil adjusted vegetation index), GCI (green chlorophyll index), RVI (ratio vegetation index), CVI (chlorophyll vegetation index), and MCARI1 (modified chlorophyll absorption ratio index 1). Zhu et al. (2012), for example, found that the soil adjusted vegetation index (SAVI) was effective for estimating leaf nitrogen content of wheat. Shanahan et al. (2001) found the green normalized difference vegetation index (GNDVI) to be highly correlated with corn grain yields, particularly during midgrain filling. Similarly, Panda et al. (2010) found the red- and NIR-based perpendicular vegetation index (PVI) reliable for predicting corn yields. Mulla (2013) supplies a comprehensive list of remote sensing-based indices used in precision agriculture contexts.

5.2.3 National Government and Commercial Satellites

While drones are an increasingly viable option for industrial farms and many small-scale operations, there is still a considerable financial and infrastructural barrier to entry in remote areas. As such, national government and commercial satellites play an integral role in scaling agricultural technologies and improving crop production worldwide. MODIS (250-m), Landsat (30-m), and Sentinel-2 (20-m) are national government satellites that offer global coverage at regular temporal intervals. Finer spatial resolution governmental and commercial satellites collect quasi-global imagery and can be commissioned for specific missions. Notably, SPOT 6/7 (7-m), Planet (3-m), WorldView-2 (2-m), and Pléiades (2.5-m) satellite constellations offer regional, inter-farm, and intra-farm multispectral imagery to measure crop status, though none at the individual maize plant scale with multispectral bands. In contrast, sUAS can provide intra-farm measurements for individual plants down to the leaf scale. For maize, a 30-cm spatial resolution image will capture a complete plant and 7-cm is fine enough to evaluate individual leaves. Though MODIS, Landsat, and Sentinel-2 are free to the public, finer spatial resolution images require purchase. A cost per resolution curve of multispectral imagery from the Apollo Mapping repository (Apollo Mapping 2018) is plotted here for comparison in Figure 5.1.

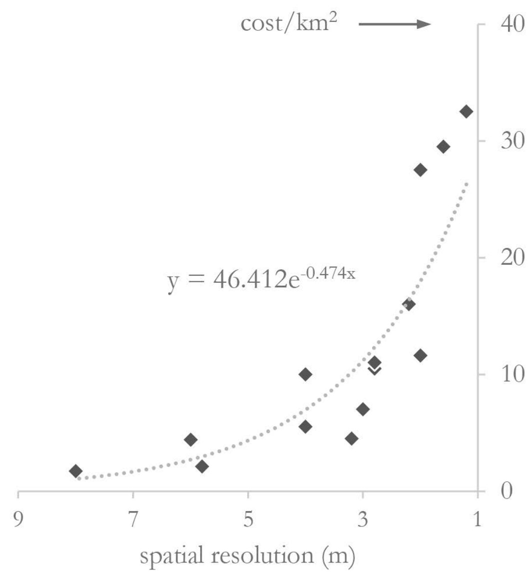

Figure 5.1. *Spatial resolution and cost per square kilometer curve.* Costs listed are for the multispectral products available from the Apollo Mapping archives. Prices were retrieved from the 2018 mono high and medium-resolution satellite imagery price list (archive ≤ 90 days) (Apollo Mapping 2018).

5.3 Methods

The objective of this study was to evaluate the linear relationship between *in situ* farm measurements (crop chlorophyll and yield) and spectral indices of crop status across multiple spatial resolutions. Spatial resolutions included in this analysis are 7-cm, 14-cm, and 27-cm (sUAS), 2.5-m (Pléiades), 3-m (Planet), 7-m (SPOT 6), and 20-m (Sentinel-2). The workflow consisted of (i) sUAS image collection and satellite image acquisition, (ii) image mosaicking, radiometric calibration, orthorectification, and geometric correction, (iii) index calculation (NDVI, GNDVI, SAVI, GSAVI, GCI, RVI, CVI, and MCARI1), (iv) mean zonal statistic calculations by plot for each index, (v) single and multiple linear regression permutations of all selected indices compared to crop chlorophyll and crop yield, (vi) regression model rankings using Akaike information criterion (AICc), and (vii) comparison of correlation results across all spatial resolutions under analysis (Figure 5.2). The performance of each spectral index in relation to on-farm crop measurements was also evaluated.

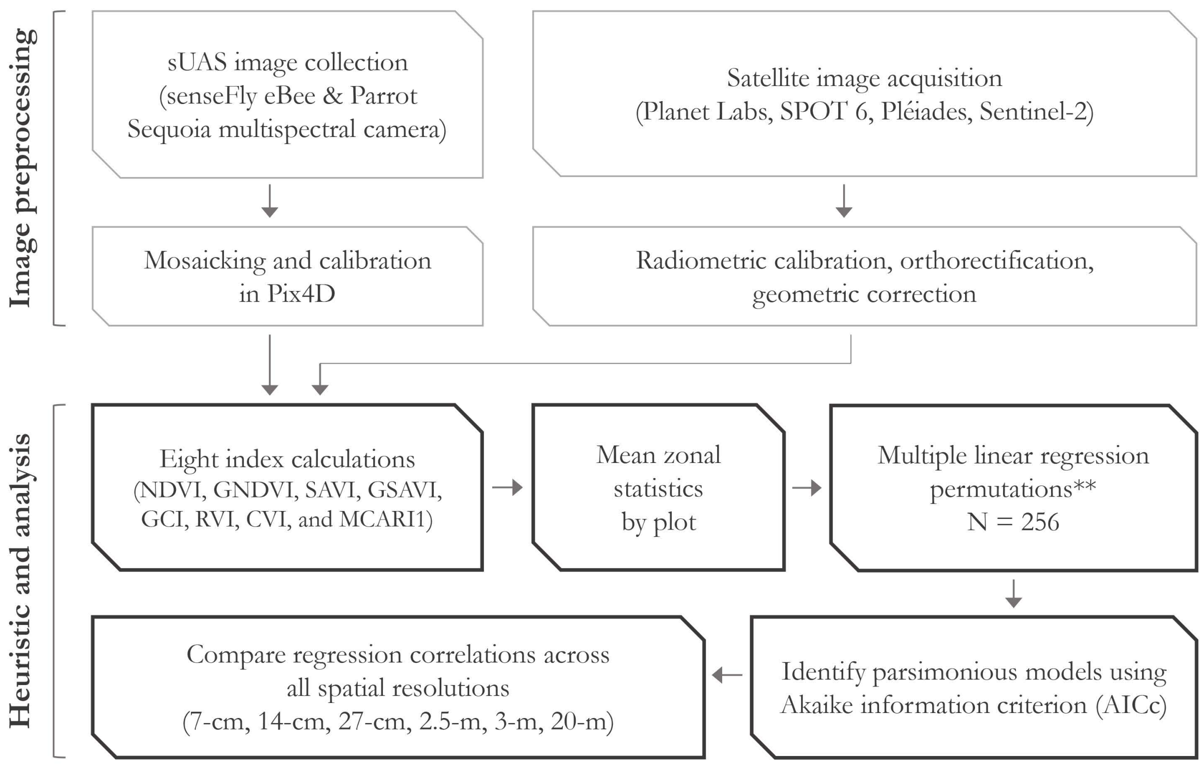

Figure 5.2. *Heuristic: multi-spatial resolution satellite and sUAS imagery for precision agriculture on smallholder farms in Malawi.*

The study took place on two trial farms in the central region district of Machinga in the villages of Ntubwi and Nyambi (Figure 5.3). The farms are approximately 0.084 hectares (ha) each, separated into 3 columns (referred to herein as replicates [R]) each containing 9 unique treatments (T). There are 27 total plots per farm, with 6 rows of monocrop maize in each plot; surrounding land cover was a complex mosaic of agriculture (e.g., groundnut, soybean, cassava, and finger millet), tree cover, shrubs, barren land, and housing structures. The Ntubwi farm is approximately 0.092 ha (918 square meters) with an average plot size of 34.0 square meters and the Nyambi farm is approximately 0.077 ha (769 square meters) with an average plot size of 28.5 square meters. These trial farms are under experimentation by a research group at Michigan State University in partnership with Africa RISING evaluating maize response to variable fertilizer treatments.

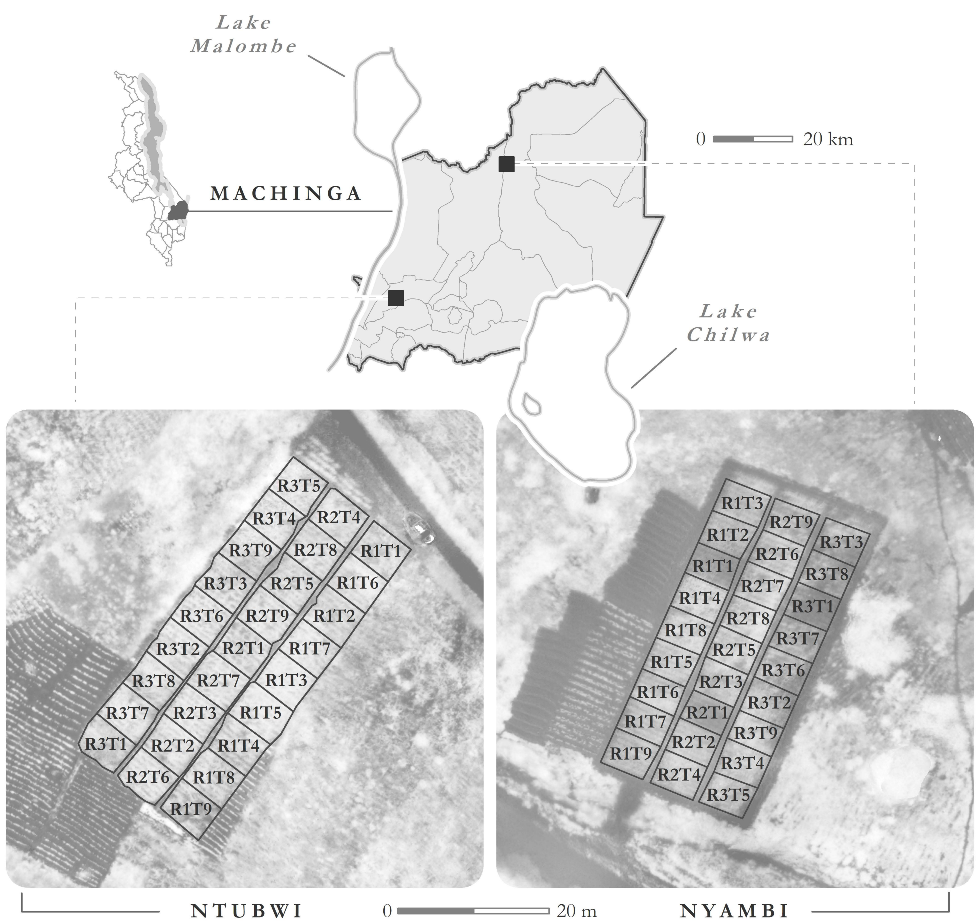

Figure 5.3. *Study area map of the trial farms in Ntubwi and Nyambi, Malawi, with plots of differing management strategies labeled.*

5.3.1 Problems of Clouds and Satellite Revisit Rates

One substantial challenge associated with precision agriculture using remote sensing satellites is the abundance of clouds during the crop production season. This is particularly problematic in

Malawi, where the unimodal rainy season introduces regular cloud cover. Persistent cloud cover, coupled with infrequent satellite image revisit rates, often results in few clear images available for farm observation. In the peak of the Malawi growing season, this may mean that only a handful of commercial satellite images free of clouds will be available. In the case presented here, for two farms in the central region of Malawi (Ntubwi and Nyambi) during peak growing season (February/March), only one clear image was available from Pléiades (January 28, 2018) and only one clear image was available from SPOT 6 (March 25, 2018). Cloud-free Planet images were available for both sites in close temporal proximity to our drone flights (February 17 at Nyambi and February 20 at Ntubwi); drone flights were conducted February 19–20, 2018. The regular revisit rate of national government satellites (e.g., Sentinel-2) minimizes this hurdle; however, the spatial resolution is insufficient for intra-farm precision agriculture in the Malawian smallholder context, where a 0.5-hectare farm may contain only 9 complete Sentinel-2 20-m pixels. To demonstrate and visualize the cloud-cover problem, we assembled NDVI calculations at the Nyambi trial farm from 5 global monitoring satellites—AVHRR, VIIRS, MODIS, Landsat 8, and Sentinel-2 (Figure 5.4). Each open circle on the time-series represents an image collection and/or image delivery. In the case of VIIRS and MODIS, composite images are delivered that 'smooth' out the effects of cloud cover. In the Sentinel-2 time-series, for example, the impact of clouds on the spectral signature is made apparent through frequent drops in NDVI. A clear advantage of sUAS technologies here is that imaging occurs below the cloud layer.

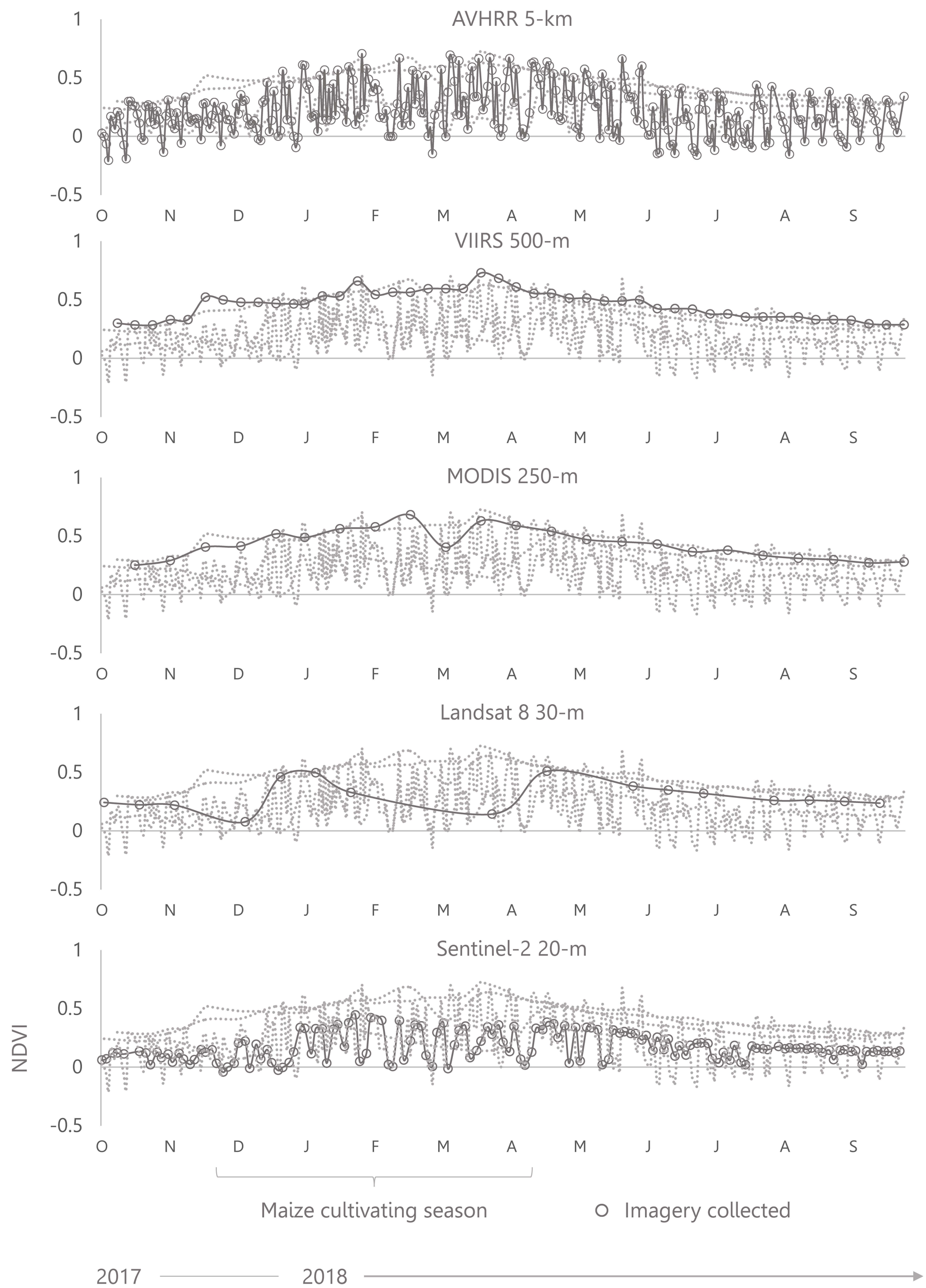

Figure 5.4. *Satellite image NDVI acquisition over the trial farm in Nyambi, Malawi.* Hollow circles indicate image collection or image delivery.

Every cloud free image over the Ntubwi and Nyambi trial farms that was available on the Apollo Mapping web service (Apollo Mapping 2018) was purchased and processed for dates as close to February 20th, 2018 as possible (the date of the sUAS image collection flights). Those satellites included SPOT 6 (March 25, 2018 for Ntubwi) and Pléiades (January 28, 2018 for Nyambi); however, the SPOT 6 image was collected after harvest had already taken place and was excluded from analysis, but is presented here to further demonstrate unexpected timing issues (Figure 5.5). Planet images were downloaded via the Planet API for February 17, 2018 (Nyambi) and February 20, 2018 (Ntubwi) (Planet Team 2017). Sentinel-2 images were acquired using Google Earth Engine (Gorelick et al. 2017) at both sites for February 20, 2018. Orthorectification and geometric corrections of the SPOT and Pléiades imagery were performed using the recommended parameters in the metadata from the imagery suppliers. The senseFly eBee drone flights at Ntubwi and Nyambi were conducted at flight heights ranging from 79-m to 303-m for spatial resolutions of 7-cm, 14-cm, and 27-cm. Image collection took place at peak overhead sun hours (between 1000 and 1400) to minimize shadow. Flight plans were prepared using eMotion and ground control points were set with a Topcon HIPER SR GPS base station, rover, and tripod. The drone images were mosaicked, radiometrically calibrated, geometrically corrected, and orthorectified using Pix4D (Pix4D SA 2017). Figures 5.5 and 5.6 show the range of imagery resolutions and collection dates for both sites using NDVI as an example.

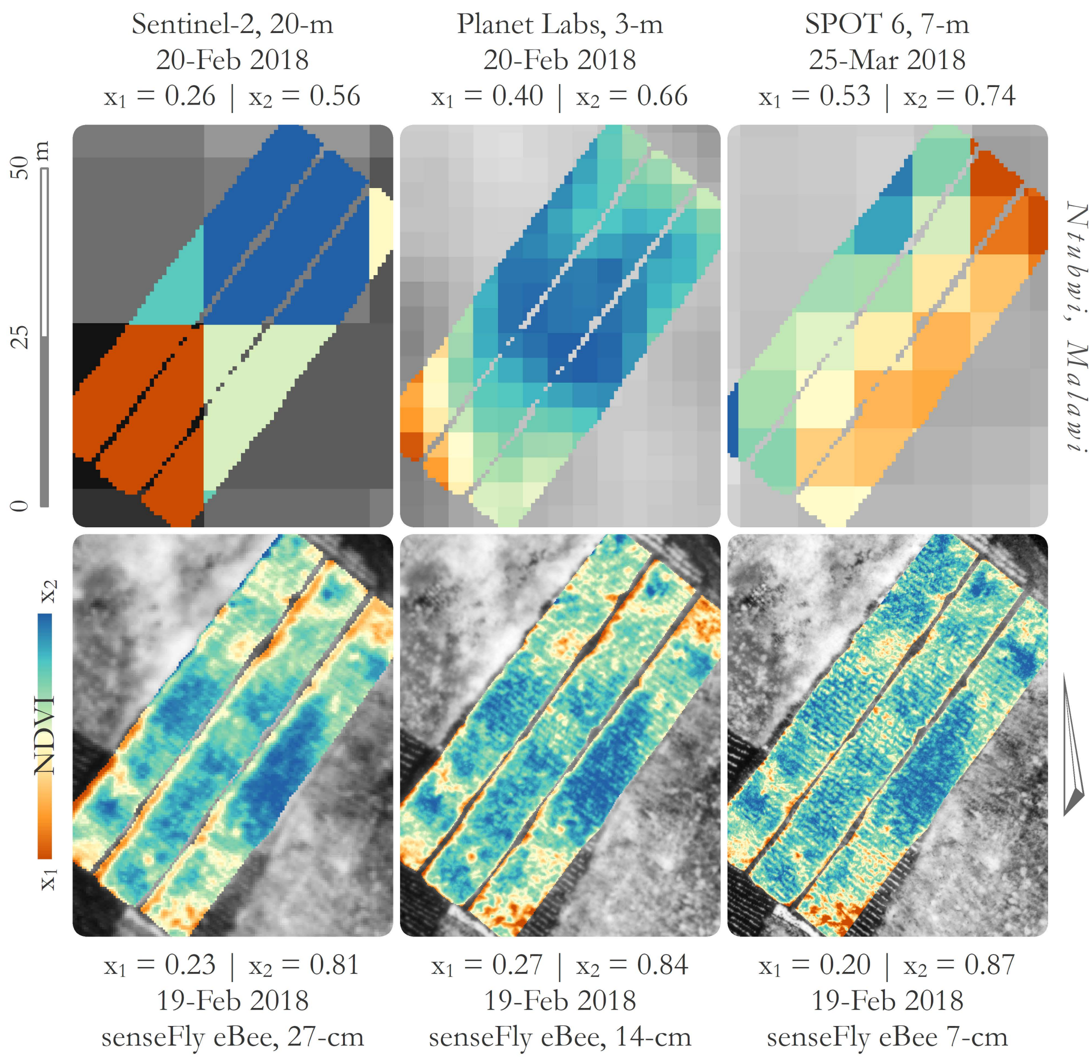

Figure 5.5. *NDVI of the trial farm in Ntubwi across spatial resolutions*. Note that min (x_1) and max (x_2) NDVI are unique to each map.

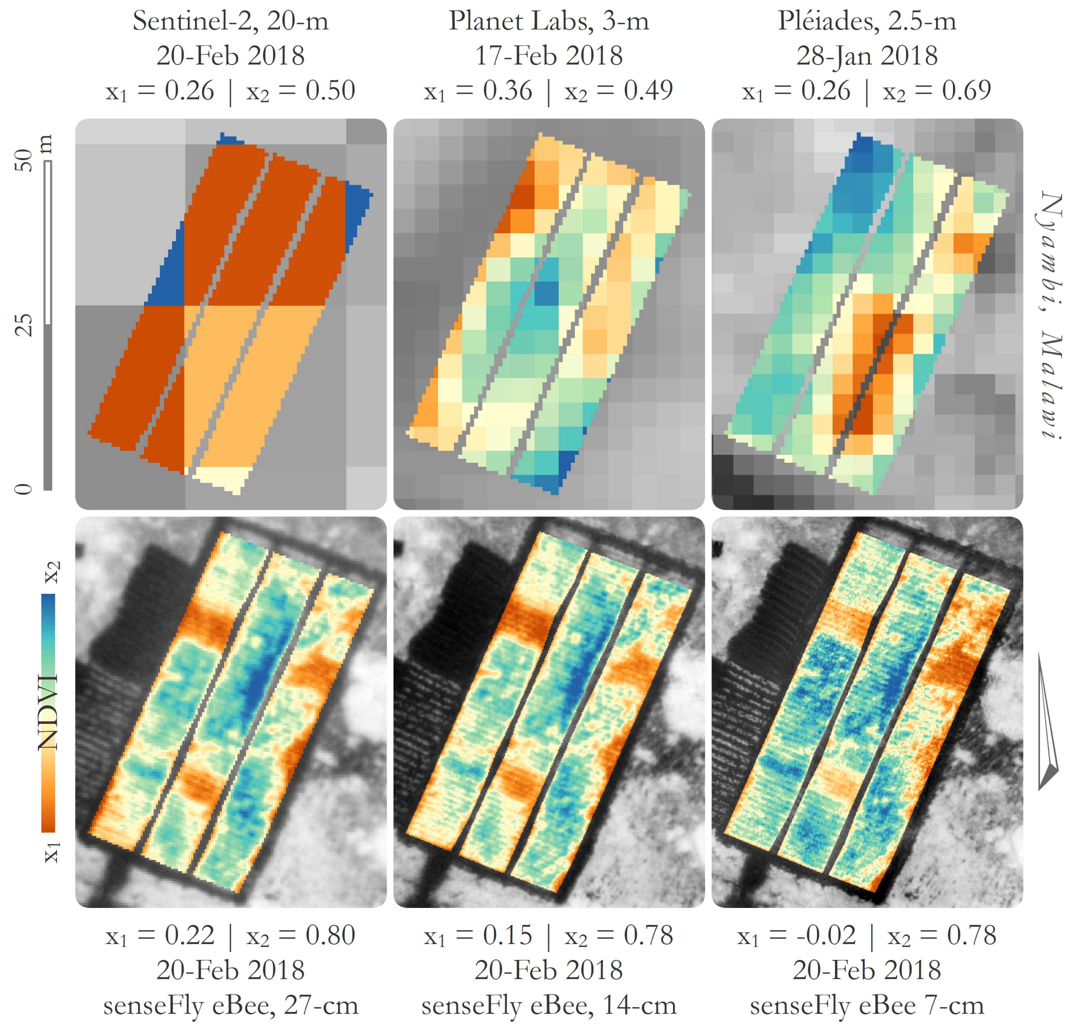

Figure 5.6. *NDVI of the trial farm in Nyambi across spatial resolutions.* Note that min (x_1) and max (x_2) NDVI are unique to each map.

5.3.2 Multispectral Indices and On-Farm Measurements

Using spectral bands consistent across all imaging platforms under study (i.e., green, red, and NIR), eight vegetation indices were selected to relate spectral signals with on-farm plant metrics (Table 5.1). Spectral wavelengths of each product are listed below Table 5.1. The indices selected included the normalized difference vegetation index (NDVI), green normalized difference vegetation index (GNDVI), soil adjusted vegetation index (SAVI), green soil adjusted vegetation index

(GSAVI), green chlorophyll index (GCI), ratio vegetation index (RVI), chlorophyll vegetation index (CVI), and modified chlorophyll absorption ratio index 1 (MCARI1) (Figure 5.7).

Index selection was informed using *a priori* knowledge of demonstrated relationships between crop status (e.g., crop chlorophyll and yield) and remote sensing spectral signals. The indices selected are among the most commonly used in precision agriculture contexts, and consideration was given to representation of both red- and green-based spectral indices, as well as two indices (CVI and MCARI1) that use both the green and red bands in their calculation (Table 5.1). NDVI is one of the most commonly used indices for evaluating healthy vegetation (Tucker 1979) and is ubiquitous across precision agriculture applications; however, NDVI is sensitive to high leaf area index (LAI). GNDVI was popularized by Gitelson and Merzlyak (1998) as a metric sensitive to chlorophyll content in leaves and has been used similarly to NDVI as a decision support metric in precision agriculture mapping tools (Zhang et al. 2010; Candiago et al. 2015); its calculation is the same as NDVI, but using the green band in place of red. SAVI is similar in formulation to NDVI, but uses an adjustment factor to minimize the effects of soil on the spectral signal (Huete 1988); this can be critical in areas where vegetation is sparse or where cropping arrangements (or crop types) allow visibility of the soil beneath the canopy. GSAVI follows the SAVI formula structure, but uses the green band in calculation instead of red; this index has shown to be effective for determining early in-season nitrogen requirements for corn (Sripada 2005). CVI and MCARI1 are both indices that use NIR, red, and green in combination. CVI was designed to estimate leaf chlorophyll at the canopy scale while minimizing the effects of LAI variation (Vincini et al. 2008). Conversely, MCARI1 has an increased sensitivity to leaf area while also suppressing the sensitivity to chlorophyll (Haboudane et al. 2004).

Index	Abbreviation	Equation
Normalized difference vegetation index	NDVI	(NIR – R)/(NIR + R)
Green normalized difference vegetation index	GNDVI	(NIR – G)/(NIR + G)
Soil adjusted vegetation index	SAVI	1.5 × [(NIR – R)/(NIR + R + 0.5)]
Green soil adjusted vegetation index	GSAVI	1.5 × [(NIR – G)/(NIR + G + 0.5)]
Green chlorophyll index	GCI	(NIR/G) – 1
Ratio vegetation index	RVI	NIR /R
Chlorophyll vegetation index	CVI	(NIR/G) × (R/G)
Modified chlorophyll absorption ratio index 1	MCARI1	1.2 × [2.5 × (NIR – R) – 1.3 × (NIR – G)]

Table 5.1. *Indices, abbreviations, and equations for each index under study*. Parrot Sequoia multispectral camera specifications: green 530–570 nm, red 640–680 nm, and NIR 770–810 nm. Planet surface reflectance multispectral specifications: green 500–590 nm, red 590–670 nm, and NIR 780–860 nm. Pléiades-1A multispectral specifications: green 490–610 nm, red 600–720 nm, and NIR 750–950 nm. Sentinel-2 MSI Level-1C multispectral specifications: green 560 nm, red 665 nm, and NIR 835 nm. NIR = near infrared; R = red; G = green.

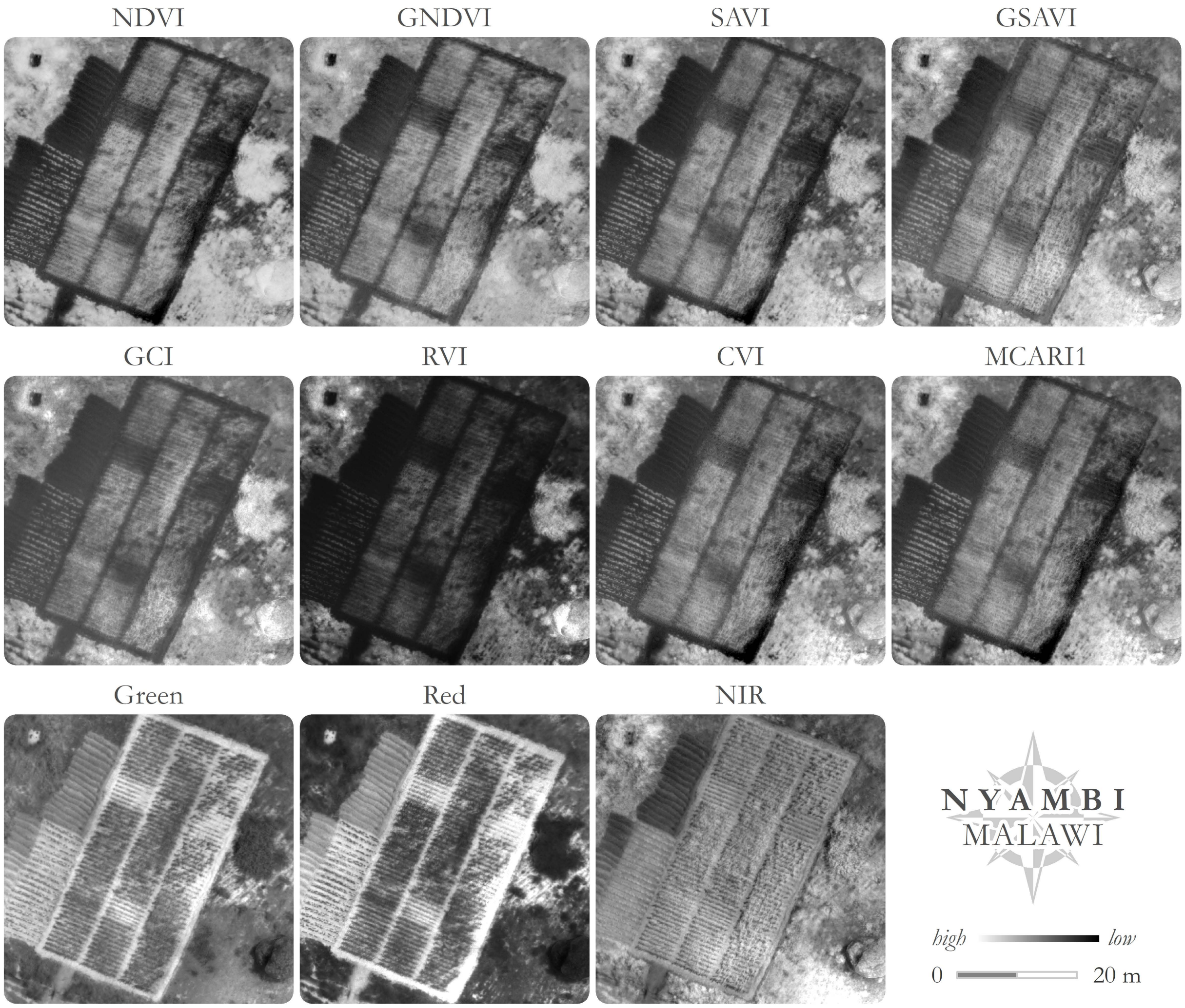

Figure 5.7. *Nyambi multispectral index panel, 7-cm spatial resolution.*

After computing index grids, mean zonal statistics were calculated for each plot to match the scale of the on-farm measurements. Satellite images were resampled down to 50-cm so that mean calculations of coarse resolution images were relative to the amount of each pixel contained within each plot; no soil or shadow masking was performed. To link the imagery with *in situ* measurements, we used a handheld SPAD (Soil-Plant Analyses Development) 502 Plus Chlorophyll Meter, which returns an index of relative chlorophyll content (calculated using the 650 nm and 940 nm spectral bands) (Spectrum Technologies, Inc., 2019) and can be used to estimate leaf nitrogen concentration in maize (Bullock and Anderson 1998). We collected the average SPAD reading from the center two rows of each plot. The rationale for selecting plants near the center of each plot was to minimize influence from neighboring plots that underwent different fertilizer treatments. Yield measurements were also collected for each plot (Table 5.2).

			T1	T2	T3	T4	T5	T6	T7	T8	T9
NTUBWI	**R1**	SPAD	33.2	54.7	55.7	51.9	56.6	53.5	56	52	54.1
		Yield	1426	2133	3494	1848	2966	1808	3433	3128	3880
	R2	SPAD	39.6	51.1	56.9	53.6	54.4	54	56	51.6	53
		Yield	2033	3169	2600	3067	2336	2986	2377	2397	3006
	R3	SPAD	42.3	53.1	53.3	51.5	54.6	54.6	56.5	55.5	50.9
		Yield	911	2113	3433	2275	3250	1727	4063	4834	2945
NYAMBI	**R1**	SPAD	24.6	36.8	38.9	43.8	35.7	41.6	39	49.9	34.2
		Yield	467	3129	3869	4514	3415	3153	1696	6067	2723
	R2	SPAD	25.9	36.3	39.9	45.8	46.7	44.9	49.5	48.2	43
		Yield	467	3105	3798	4347	6950	4228	9172	5876	2651
	R3	SPAD	25.5	42.7	46.4	46.6	54.2	53.9	50.8	58.2	47
		Yield	488	6616	5422	6019	6067	5876	5780	9482	6473

Table 5.2. *SPAD and yield measurements at the Ntubwi and Nyambi trial farms.* T = treatment; R = replicate.

5.3.3 Multiple Linear Regression Permutations

Hatfield and Prueger (2010) argue that using a collection of indices to quantify agricultural status can be more effective than selecting a single index. To correlate the remote sensing indices with crop status, we tested every possible multiple linear regression (MLR) permutation between the remote sensing indices selected (independent variables) and the on-farm measurements (SPAD and yield as dependent variables). A principal component analysis was also conducted, but no significant groupings emerged due to the inherent collinearity among the variables under study. In addition to multiple regression, tests were conducted using stepwise regression, partial least squares regression, and a classification and regression tree (CART) approach. Ultimately, we elected the multiple regression approach to maximize potential linear relationships while maintaining model parsimony. The following is the global MLR model:

$\hat{Y} = b_0 + b_1\text{NDVI} + b_2\text{GNDVI} + b_3\text{SAVI} + b_4\text{GSAVI} + b_5\text{GCI} + b_6\text{RVI} + b_7\text{CVI} + b_8\text{MCARI1}$,

where $\hat{Y}$ is SPAD or yield. To generate these permutations, we used the MuMIn package in R (Barton 2016), which produced 256 multiple linear regression equations per imagery spatial resolution. We then ranked the models according to the Akaike Information Criterion (AICc), which aims for a parsimonious balance of predictive power and model simplicity to adjust for model overfitting or underfitting (Akaike 1974). Additionally, the Bonferroni Correction (Bonferroni 1935) was applied to the multiple regression permutation p-values to adjust for model overfitting. The Bonferroni Correction method selected here involved simply multiplying each p-value by the number of permutations (N = 256), which was done using p.adjust in R. The top performing models from these tests are listed in Table 5.3.

5.4 Results and Discussion

The first test consisted of single linear regressions of all indices under study. One example of the single variable linear regressions is presented here in Figure 5.8 to illustrate the relationships between proximal farm measurements and spectral signals derived from the sUAS images. This example is from the senseFly eBee/Parrot Sequoia multispectral camera at a spatial resolution of 27-cm at Nyambi. The index with the highest R^2 in this particular case is GSAVI ($R^2 = 0.607$), followed by GNDVI ($R^2 = 0.554$), GCI ($R^2 = 0.510$), and SAVI ($R^2 = 0.489$). Contrary to popular use, NDVI does not rank among the top four, but ranks fifth with an R^2 of 0.423. Interestingly, the green band is in each of the top three index calculations. This evidence is consistent with other studies that have found green-band indices critical for accurately predicting crop health (Gitelson 1998; Shanahan 2001; Sripada 2005). Overall, these R^2 values fall below those produced with the

MLR models, echoing the argument from Hatfield and Prueger (2010) that a multivariable approach to predicting farm yields from remote sensing spectral indices is the optimal route. Given these findings and the abundance of literature reiterating the value of a broader range of spectral indices, precision agriculture and sUAS developers would benefit from diversifying their marketed indices and integrate green-based indices alongside NDVI. The 27-cm spatial resolution GSAVI image at Nyambi is mapped in Figure 5.9, scaled to the plot level, and compared to the on-farm measurements of SPAD and yield.

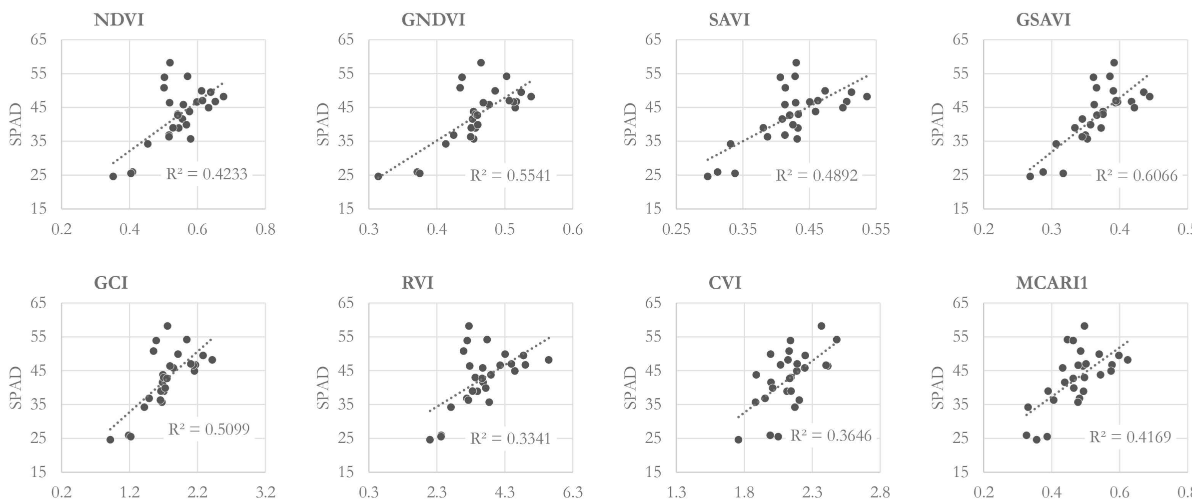

Figure 5.8. *Example single variable linear regressions—SPAD and spectral indices.* Nyambi, senseFly eBee Parrot Sequoia 27-cm spatial resolution.

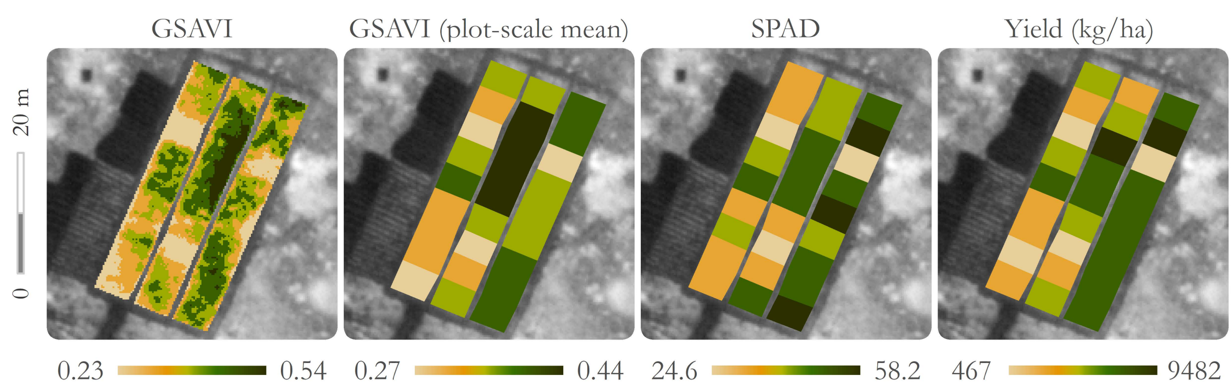

Figure 5.9. *GSAVI 27-cm spatial resolution grid at Nyambi, scaled to the plot level and compared to on-farm measurements of SPAD and yield.*

The second test consisted of all possible MLR permutations of the indices under study. From the collection of multiple regression permutations, we filtered the top performing models across all of the imaging platforms and compared spatial resolutions with their correlative strength (Table 5.3). Each regression model presented has a *p*-value less than 0.05. Multiple linear regression models are only presented if the single variable model was outperformed. At Ntubwi, the highest R^2 (0.553) for SPAD (single variable linear regression) was at a spatial resolution of 14-cm with GNDVI. The highest R^2 (0.790) overall for SPAD was at a spatial resolution of 14-cm in a multiple linear regression with CVI, GNDVI, NDVI, and RVI. Single variable regressions for SPAD at a 7-cm spatial resolution at Ntubwi did not perform well, with the top performing model returning an R^2 of 0.196 using RVI. The highest R^2 (0.349) for yield at Ntubwi was at a spatial resolution of 14-cm using CVI; 0.27-cm spatial resolution ranked second (R^2 = 0.302) with GSAVI, and there was no statistically significant relationship between yield and spectral indices at a 7-cm spatial resolution at this site ($p > 0.05$). Somewhat surprisingly, the top performing MLR at 7-cm spatial resolution for SPAD at Ntubwi returned a high R^2 of 0.750; however, this MLR equation required 7 out of the 8 selected indices. At Ntubwi, neither Sentinel-2 nor Planet returned significant relationships with SPAD or yield.

At Nyambi the highest R^2 (0.607) for SPAD (single variable linear regression) was at a spatial resolution of 27-cm with GSAVI. The highest R^2 (0.720) overall for SPAD was at a spatial resolution of 27-cm in a multiple linear regression with GNDVI, MCARI1, and RVI. Single variable regressions for SPAD at a 7-cm spatial resolution at Nyambi also did not perform well, with the top performing model returning an R^2 of 0.283 using GNDVI. In contrast to Ntubwi, there was no significant MLR model for SPAD at Nyambi at the 7-cm spatial resolution. At Nyambi, Planet (3-m spatial resolution) GSAVI emerged as statistically significant ($p < 0.05$), but with an

R^2 of only 0.165. At Nyambi, neither Sentinel-2 nor Pléiades returned statistically significant relationships with SPAD. At Nyambi, there were more statistically significant relationships between spectral indices and yield than at Ntubwi. The highest R^2 (0.637) for yield (single variable linear regression) at Nyambi was at a spatial resolution of 27-cm using GSAVI. The top performing model overall was at a 27-cm spatial resolution using MLR with CVI and MCARI1 (R^2 = 0.677). Planet and Sentinel-2 emerged with statistically significant relationships to yield at Nyambi (p < 0.05), but both with R^2 < 0.2. The results of these tests are plotted in Figure 5.10.

Site	Var.	Res. (m)	R^2	p-value	Regression equation
NTUBWI	SPAD	0.07	0.196	0.021	S = 37.3 + 2.5(RVI)
		0.14	0.553	8.7E-6	S = -19.4 + 112.6(GNDVI)
		0.27	0.495	4.3E-5	S = -1.4 + 94(GNDVI)
		0.07	0.750	0.033*	S = 491.3 – 76.2(CVI) + 202.7(GCI) – 2314(GNDVI) + 1715.2(GSAVI) – 1010.6(MCARI1) + 939(NDVI) – 64.9(RVI)
		0.14	0.790	8.7E-5*	S = -252.3 – 48(CVI) + 1498.6(GNDVI) – 622.8(NDVI) – 7.7(RVI)
		0.27	0.580	0.008*	S = -31.3 + 179.8(GNDVI) – 4.3(RVI)
	Yield	0.14	0.349	0.001	Y = -4694.2 + 1820.5(CVI)
		0.27	0.302	0.003	Y = -3599.7 + 16880.1(GSAVI)
NYAMBI	SPAD	0.07	0.283	0.004	S = 3.8 + 74.6(GNDVI)
		0.14	0.476	6.9E-5	S = 7.9 + 71.6(NDVI)
		0.27	0.607	1.7E-6	S = -16.2 + 160.1(GSAVI)
		3	0.165	0.035	S = -61.1 + 288.5(GSAVI)
		0.14	0.546	0.020*	S = 31.3 – 128(GSAVI) + 176(MCARI1)
		0.27	0.720	3.8E-4*	S = -50.8 + 235.6(GNDVI) + 69.2(MCARI1) – 13(RVI)
	Yield	0.07	0.226	0.012	Y = -5068.4 + 18407.3(GNDVI)
		0.14	0.464	9.1E-5	Y = -4944.7 + 19526(NDVI)
		0.27	0.637	6.1E-7	Y = -12112.7 + 45275.7(GSAVI)
		3	0.157	0.041	Y = -17753.2 + 69123.8(SAVI)
		20	0.147	0.049	Y = -2103.8 + 31495(MCARI1)
		0.27	0.677	3.2E-4*	Y = -18049.5 + 6263.3(CVI) + 19556.8(MCARI1)

Table 5.3. *Top performing single and multiple linear regression models as ranked by AICc.* *Bonferroni correction applied. S = SPAD; Y = yield.

The primary objective of this research was to quantify the effective spatial resolutions for conducting precision agriculture on smallholder farms in Malawi. Based on the weak correlations drawn from the satellite imagery, the abundance of cloud cover, and infrequent satellite revisit rates, it is clear that sUAS are the optimal platforms for evaluating intra-farm variability. Figure 5.10 includes all single variable linear regressions ($p < 0.05$) and the top performing multiple linear regressions. Illustrated in this figure is a substantial drop in the statistical relationship between spectral index and on-farm measurements at the satellite scale. While the satellite spatial resolutions ranged from 2.5-m to 20-m, Pléiades, Planet, and Sentinel-2 all fell below an R^2 of 0.2. The relationship at the sUAS scale varied substantially depending on the index and spatial resolution, generally ranging between R^2 values of 0.2 to 0.6, with some instances nearing zero, while MLR models reached upwards of approximately 0.8. The second and fourth scatterplots show the regression model R^2 values at the drone scale (7–27-cm). This visualization demonstrates that the relationship between crop status and spectral signals varies substantially even at fine scales.

Emergently clear is that the 14-cm and 27-cm spatial resolutions are more effective than 7-cm for relating spectral indices with proximal farm measurements. Interestingly, resampling from 7-cm to 14-cm and 27-cm did not produce an increased correlation—there was minimal distinguishable change. The tests here were performed on the imagery as collected; however, it may be the case that soil and shadow extraction will improve the correlation at the 7-cm spatial resolution. However, for a generalizable methodology, it may not be more effective than imaging at a plant-scale spatial resolution. In this regard, one hypothesis is that a spatial resolution close to the plant dimensions is the optimal spatial resolution for spectral imaging.

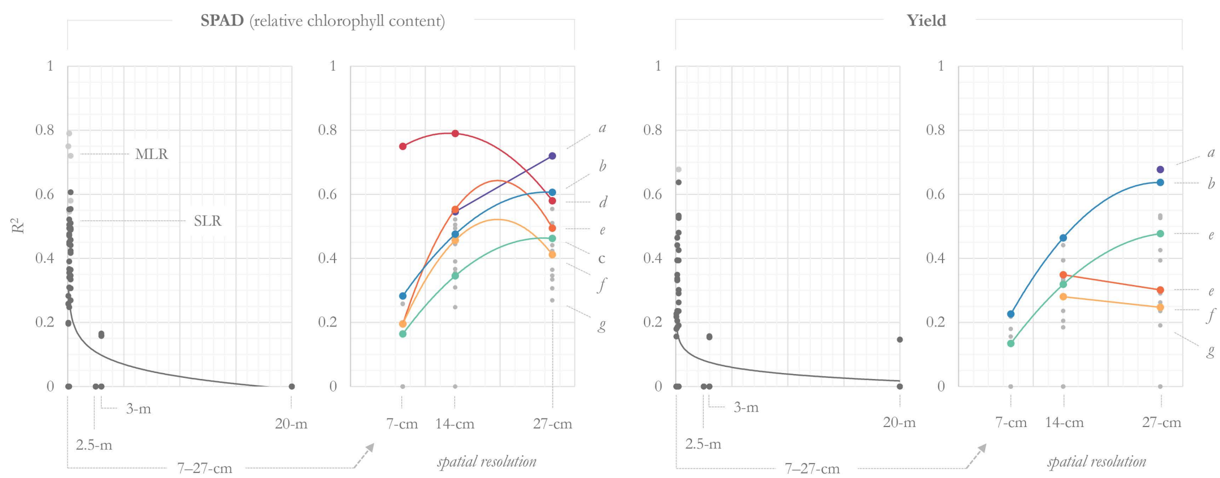

Figure 5.10. *Comparing linear regression correlations of spectral indices and on-farm measurements across spatial resolutions.* (a) Nyambi top performing multiple linear regressions (depicted in purple), (b) Nyambi max single variable linear regressions (depicted in blue), (c) Ntubwi top performing multiple linear regressions (depicted in red), (d) Ntubwi max single variable linear regressions (depicted in green), (e) Nyambi mean single variable linear regressions (depicted in orange), (f) Ntwubi max single variable linear regressions, and (g) all single variable linear regressions (depicted in gray). Left panel: SPAD; right panel: yield.

5.5 Conclusions

We evaluated a range of spatial resolutions of multispectral images over two trial farms in the central region of Malawi—Nyambi and Ntubwi in the district of Machinga. Single and multiple linear regressions were performed for all possible permutations of the indices selected. We found that the correlation between on-farm measurements and remote sensing spectral signals decreases substantially at 2.5-m, 3-m, and 20-m spatial resolutions. For precision agriculture, the problems of clouds and satellite revisit rates are hurdles that have not yet been overcome with satellite imagery for the smallholder farming context. For larger fields, coarser spatial resolutions may be adequate, but they were insufficient for the size of the field experimented in this study. Interestingly, we found that the top performing yield models were associated with the 14-cm and 27-cm spatial resolution imagery, rather than the 7-cm spatial resolution. We suspect that this is due to soils and shadows in the fine resolution imagery, and possibly a fractal problem where more pixels results in a greater number of pixels containing mixed soil and shadow. One hypothesis in this regard is that initial image collection at the resolution of the plant dimensions might be the most effective. In this case, 14–27-cm is closer to the maize plant size than 7-cm. We also found that GNDVI and GSAVI were consistent indices for relating spectral images to proximal farm measurements. These findings suggest that green-band indices are critical to test when monitoring crop production via sUAS. Outcomes of this research are consistent with other studies that have found that considering a broad range of indices may be more effective for evaluating plant status and farm productivity than selecting a single index; however, the specific set of indices appropriate for a given farm may vary.[8]

[8] This paper is made possible by the support of the American People provided to the Feed the Future Innovation Lab for Sustainable Intensification through the United States Agency for International Development (USAID). The contents are the sole responsibility of the authors and do not necessarily reflect the views of USAID or the United States Government. Program activities are funded by USAID under Cooperative Agreement No. AID-OAA-L-14-00006. The authors wish to thank the American Society for Photogrammetry and Remote Sensing and those affiliated with the Robert N. Colwell Memorial Fellowship for their support. The authors also wish to thank Africa RISING for collaboration in on-farm research activities, as well as the Global Change Learning Lab in Sub-Saharan Africa at Michigan State University for their involvement. Additional gratitude is extended to Planet's Education and Research Program for supplying access to their imagery archive.

CONCLUSIONS

6.1 Overall Contributions

The scientific community is largely in agreement that global environmental changes are occurring and that innovative crop system solutions are needed to increase food production and ensure a sustainable future. To address this need, the research conducted in this dissertation paired geospatial analytics with extensive interdisciplinary collaboration from plant and soil scientists. The three primary scales under analysis here included the continental, country, and farm scales.

Nature-Based Agricultural Solutions: Scaling Perennial Grains Across Africa (Study 1)—At the continental scale, government satellite-based imaging platforms (e.g., NASA MODIS) were used to evaluate agricultural productivity and elucidate the spatial organization of maize, pigeonpea, and sorghum suitability across Africa. Study 1 introduced a methodology for characterizing levels of crop suitability, showing unique agroecological zones that these crops occupy, and discussed the need for up-to-date crop climate-suitability mapping. One key finding from this study was that sorghum suitability occupies a unique agroecological niche in Africa. Due to its low rainfall requirements, sorghum is biophysically suited to persist in the Sahel region, the Horn of Africa (including portions of Kenya and Tanzania), northwestern Africa, and southern Africa, where pigeonpea and maize conditions are suboptimal. Another important outcome is that the optimal area for pigeonpea cultivation across Africa complements the niche for maize. Products from this study included: (a) high spatial resolution maps showing the fundamental climate niche for maize, pigeonpea, and sorghum across Africa at a 1-km spatial resolution; (b) high spatial resolution maps of Africa showing the intersection of marginal maize and optimal pigeonpea or sorghum at a 1-km spatial resolution.

A Multiscalar Approach to Mapping Marginal Agricultural Land: Smallholder Agriculture in Malawi (Study 2)—At the country scale, national government satellites were used to evaluate agricultural productivity and crop niche in Malawi to identify areas of marginal production and marginal maize biophysical constraints. To enhance geographical communication and support policy decisions, Study 2 contributed a heuristic for generating crop productivity map outputs that are relative to government boundary and agroecological zone delineations. Further, this study offered a commentary on reclaiming marginal lands for agricultural improvement by redesigning the ways these areas are represented through pixel categorization and cartography. A key outcome of this research was illuminating a clear spatial organization of the factors driving marginal maize production in Malawi. For example, in the southern region of Malawi, rainfall variability is a primary factor limiting agricultural production; in the central region of Malawi, temperature is a dominant factor limiting agricultural production. Products from this study included: (a) agricultural land-use map of Malawi that minimizes errors of commission; (b) heuristic for classifying agricultural productivity relative to spatial scales of observation; (c) map of marginal maize agricultural land in Malawi depicting measured agricultural productivity and suboptimal biophysical conditions.

Scaling Agricultural Innovations: Pigeonpea in Malawi (Study 3)—To communicate areas of focus for extension efforts regarding integration of pigeonpea into maize-based cropping systems, Study 3 identified and classified suitability with respect to soil as a primary driver of marginal production. This study also demonstrated that pigeonpea has extensive scaling potential across Malawi and that the crop is not limited geographically by biophysical constraints. Products from this study included: (a) pigeonpea climate suitability map of Malawi; (b) maps comparing the spatial organization of pigeonpea production and yields for 2005 and 2012; (c) map of the intersection of marginal maize agricultural land and optimal pigeonpea conditions, highlighting areas where pigeonpea integration would likely have beneficial outcomes.

Multi-Spatial Resolution Satellite and sUAS Imagery for Precision Agriculture on Smallholder Farms in Malawi (Study 4)—At the farm scale, a small unmanned aerial system (sUAS) was used to quantify the relationship between remotely-sensed spectral indices and proximal crop-leaf measurements. In Study 4, a methodology was devised for testing the linear relationship between on-farm measurements and spectral signals at multiple spatial resolutions. This study offers a framework for evaluating combinations of spectral indices in relation to on-farm productivity. Of note was that 14-cm and 27-cm spatial resolution images were more strongly correlated with proximal crop measurements than the 7-cm spatial resolution. One hypothesis here is that initial imaging at the plant scale is the most effective resolution because of how soil and crop shadows are integrated in the spectral signal. Additionally, it was observed that green-band indices (i.e., GNDVI and GSAVI) were consistently among the strongest correlative indices with both crop yield and crop chlorophyll. Products from this study included: (a) chart depicting the cost/km^2 for remote sensing imagery, and a chart illustrating problems of satellite revisit rates and clouds for a smallholder farm in Malawi; (b) maps comparing varying remote sensing imagery spatial resolutions at a smallholder farm in Malawi, as well as maps of a collection of spectral indices; (c) multiple linear regression models quantifying the correlation between remote sensing spectral signals across spatial resolutions and proximal farm measurements of crop chlorophyll and crop yield.

6.2 Future Research

6.2.1 Web-Based GIS for Near Real-Time Crop Niche Mapping

Remote sensing-based characterizations of crop suitability are regularly harnessed to visualize the spatial distribution of crop suitability and production potential. Conventionally, such mapping efforts occur at singular time intervals, include variable collections of crops, and are often presented with ambiguous suitability classifications. Even the most widely used land and crop suitability maps are subject to diminishing relevance over time, particularly in the face of global land and climate change. At present, the most notable crop suitability maps are the Global Agro-Ecological Zones (GAEZ) distributed by the Food and Agriculture Organization of the United Nations (Fischer et al. 2012). While these products are immensely valuable, they are not produced at regular or frequent intervals.

Acquisition and preprocessing of large-scale time-series satellite imagery is often time-consuming and an arduous management task, requiring expensive computational hardware, software licenses, and storage structures capable of processing and moving large volumes of data. Recently, however, cloud-based alternatives are offering increased efficiency for large-scale geospatial computing. Web-based geographic information science (GIS) has the potential to transform the crop niche mapping paradigm, bringing series of static maps to a dynamic form complete with interactive geovisualizations and temporal continuity. Google Earth Engine (GEE) is one platform offering planetary-scale geospatial data and analytical tools on the cloud (Gorelick et al. 2017). With platforms such as GEE, crop suitability maps can and should be produced at the same rate climate and land data are procured. Leveraging cloud-based technology can improve the accessibility of global climate information for crop niche mapping, granting more geographic decision power to agronomy academics, government stakeholders, and policymakers to effectively scale agricultural improvement and ultimately illuminate what crops can grow where.

Interactive Mapping for Geographic Communication—A valuable byproduct of web-based GIS is interactive mapping that can be queried for information at the pixel scale. Over the last several decades, the dominant platform for academic geographers to communicate geospatial science has been largely through journal publication. This has meant that a large proportion of map-based geographic science has been delivered at the scale of a printable page. Even with fine spatial resolution imagery, scaling a figure down for print on standard letter-size paper will result in data loss from resampling. With advancements in cloud-computing and server-side geoprocessing, data can be retrieved and analyzed at unprecedented scales and speeds. An obvious advantage here is that with web-based GIS delivery tools, stakeholders can pan, zoom, and query information as they need. Given these considerations, all models developed in this dissertation will be replicated using Google Earth Engine to offer temporally continuous and interactive geospatial crop information.

6.2.2 Crop Modeling and Return on Investment from Variable-Rate Technology

Remote sensing instruments and derivative models offer data that are synergistic with modern cropping system models (e.g., temperature, precipitation, and solar radiation). With increasingly fine-resolution data (both temporal and spatial), future precision agriculture may be conducted across geographies at intra-farm scales of analysis, particularly in areas where such data have previously been unavailable. Global satellite coverage of agriculture exists in myriad forms as demonstrated here; however, there are substantial barriers in retrieving climate and crop information at local scales due to problems of clouds, imaging spatial resolutions, and satellite revisit rates (Mulla 2013). To this end, remote sensing scientists are pairing optical imagery with synthetic aperture radar (SAR) (such as the sensors onboard Sentinel-1) to address problems of clouds and better estimate agricultural productivity on the ground during rainy seasons (e.g., Campos-Taberner et al. 2017). Downscaling global climate data to the farm scale is one avenue for achieving finer spatial resolution climate information; however, there is some contention regarding the accuracy of climate downscaling and large errors emerging due to crop model sensitivity (Atkinson 2013; Lobell 2013b).

Despite present hurdles, the potential for precision agriculture to take place at the farm scale using global satellite systems may become one of the frontiers of future agricultural improvement science. In this case, variable-rate technology applications will benefit from the use of crop modeling software to predict yield outcomes from soil amendments, particularly when local scale climate information becomes available and crop system models such as APSIM (Agricultural Production Systems sIMulator) integrate remote sensing-based metrics into their algorithms (Holzworth 2014). This dissertation addressed multi-spatial and multi-temporal remote sensing imagery, pixel and time-series agricultural productivity classifications, and variable rate technology. Research evaluating crop yield predictions and the return on investment from variable-rate technology applications will prove valuable in the future (Figure 6.1).

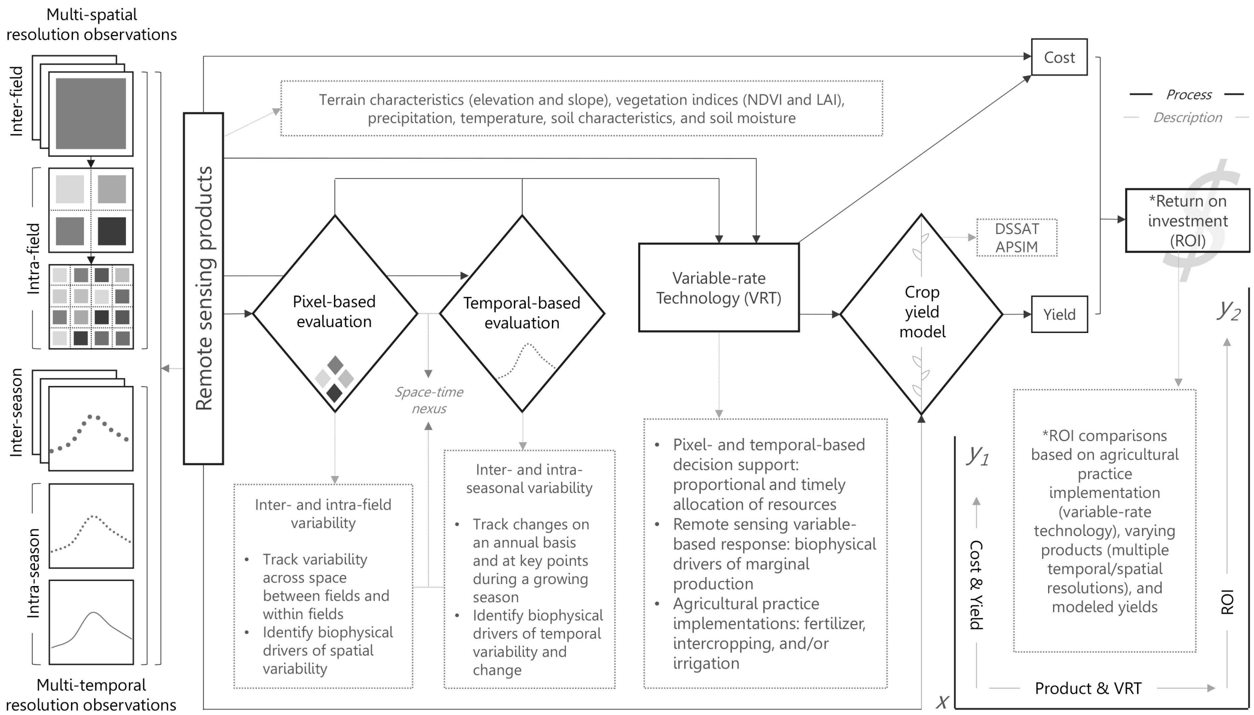

Figure 6.1. *Linking present and future research goals.* Integrated remote sensing, variable-rate technology, crop model yield predictions, and potential return on investment from intra-farm amendments.

6.2.3 Crop Biodiversity, Nutrition, and Land Equivalence Ratios

Three of the United Nations Sustainable Development Goals are to increase agricultural production, eliminate hunger, and end malnutrition (United Nations 2018). The potential for pigeonpea to enhance maize productivity and rehabilitate soils on Malawi smallholder farms was discussed at length in this dissertation, but also of importance is that introducing crop biodiversity supports household nutrient diversity (Jones et al. 2014; Luckett et al. 2015). Considering intersecting areas of maize and pigeonpea suitability, crop nutritional value (e.g., calories, protein, and vitamins), and crop arrangements, it is possible to map the scaling potential of crop systems through the lens of nutrition. Since yield is a primary metric of farm productivity, the land equivalent ratio (LER) can be used to evaluate the tradeoffs between yield (and calories) and nutritional properties for different spatial arrangements of maize and pigeonpea on a farm (Mead and Willey 1980; TerAvest

2019). Therefore, LER may be used as selection criteria for crop arrangement, then nutritional indices calculated and mapped based on crop suitability. Comparing maps such as these with food insecurity indicators and measures of agricultural productivity may provide substantial insight for extension efforts working toward food security, nutrition, sustainable agriculture, and environmental conservation.

6.2.4 Crop Differentiation and Further Evaluation of Spectral Indices Using sUAS

There are two studies planned to follow this dissertation that will further utilize imagery collected via sUAS in Malawi. The first is a land-use classification analysis of the smallholder agriculture environment. Since land-use is mixed at a local-scale, national government satellites (e.g., MODIS) are largely insufficient for land classification at local scales where mixing is high and subtle thresholds determine categorization (Li et al. 2017b). MODIS land-use/land-cover is 500-m spatial resolution and, as demonstrated in Study 4, this problem is not completely solved with finer spatial resolution national government satellites; there were zero complete Sentinel-2 (20-m spatial resolution) pixels within the trial farms. With broad categories of land-use classifications a challenge (e.g., agriculture or shrubland), differentiating between crop types within agricultural land-use classifications is even more of a challenge. At 7–27-cm spatial resolution, distinguishing between unique spectral signals from different crops is feasible (Park and Park 2015; Pajares 2015). Using our field data collection on crop type, coupled with RGB image interpretation, both supervised and unsupervised classification models will be tested. SVM (support vector machine) algorithms and CART (classification and regression trees) will also be evaluated for classification accuracy. Similarly to Study 4, a range of spatial resolutions will be tested (7-cm, 14-cm, and 27-cm) and a comprehensive collection of spectral indices will be used to classify each pixel. The next study planned will follow the heuristic described in Study 4, but will include a more exhaustive collection of all spectral indices currently used in precision agriculture at one spatial resolution and with a substantial sampling size for relating crop chlorophyll.

6.3 Closing Remarks

First, increasing agricultural production to meet population demand and ensure a sustainable future is a multiscalar problem; agricultural innovation will not be successful unless the appropriate scales of analysis are addressed. Decisions at the farm-scale cannot be made using a global-scale lens; every farm within a 1-km spatial resolution pixel is simply not the same. Prescribing solutions to an individual farm based on mixed-pixel data ignores the ecological fallacy problem. In some cases, coarse spatial resolution imagery will suffice (e.g., precipitation or temperature), but an area with multiple marginal farms surrounded by substantial tree cover could be classified as highly productive and thus be completely missed by innovation targeting. Awareness of the modifiable areal unit problem can help in this regard, normalizing by agroecological zone so that farms are evaluated relative to similar environments.

Second, the future of crop suitability mapping should consider a framework that can deliver maps with greater frequency. As global changes continue to occur at a rapid pace, current crop climate-suitability maps are needed as regularly as possible. With satellite climate data being delivered to the public at increasing rates, crop climate-suitability models can be automated to ingest these data and generate continuously updateable geospatial products.

Third, intra-farm precision agriculture in the smallholder context is in need of fine-resolution remote sensing imagery that can penetrate the cloud layer and provide data at high revisit rates. Perhaps more beneficial, however, is continued sUAS development that makes unmanned aerial vehicles more affordable and able to cover larger spatial extents. It must also be noted here that the most effective spectral index for any given farm or crop may vary; it is suggested here that crop chlorophyll and spectral index correlation tests be performed so that recommendations are made using the most appropriate index. Furthermore, crop system yield models that integrate remote sensing-based spectral indices as input data and more readily handle raster structure processing will greatly advance intra-farm precision agriculture and crop yield mapping in the future.

In conclusion, this dissertation has shown that multiple scales of analysis are required for integrating remote sensing with precision agriculture. Agricultural extension efforts using a geographic or remote sensing-based approach would benefit greatly from considering multiple scales of analysis. Finally, it is critical that the resolution of the geographical conclusions drawn match the resolution of the selected data, and that the scale of analysis matches the scale of the objective.

APPENDIX

Mixed-method Land Characterizations: Remote Sensing and Survey Data

While remote sensing data and geospatial models can be prepared entirely in a lab, unique insights often emerge from qualitative data collection in the field. To this end, integrative quantitative-qualitative models can offer a representation of reality that unifies geospatial data and human experiences (Yeager and Steiger 2012; Cheong et al. 2012). Aside from information collected from preplanned survey instruments, interfacing with people and pixels often unveils critical information that may be absent in the literature or not readily apparent through data mining.

In July of 2015, a field survey of farming areas across Malawi was conducted. Thirty-three extension planning areas (EPA) were visited and a total of 200 sites were surveyed. Interviews were held with farmers and EPA officers to inquire about cropping systems and the primary factors limiting crop production. Crop presence and the biophysical/social factors limiting production at each of the 200 survey sites are listed in Table A.1 (each survey site represents an area of approximately one square kilometer). Soil quality (e.g., soil degradation, lack of fertilizer, or soil type) was the dominant response (approximately 75 percent of respondents) for factors limiting production; the frequency of this response was expected given the volume of literature addressing this problem in Malawi. Throughout the interview process, there was an unexpectedly frequent response that erratic rainfall patterns and changes in the start of the rainy season were dominant factors, or one of the major factors, contributing to marginal production. Many EPA officers reported that the total amount of rainfall each year was consistent; however, the seasonal patterns and start date were changing and unpredictable. These experiences are consistent with published research (Tadross et al. 2009; Vizy et al. 2015; Sutcliffe et al. 2016), but the research regarding this topic in Malawi is scant. The model devised in Study 2 initially only considered rainfall amount in characterizing areas of marginal precipitation. However, given the abundance of marginal rainfall responses, we found it necessary to evaluate rainfall variability in addition to rainfall amount. Had these interview data not been integrated, a major limiting factor of marginal agricultural production could have been vastly underestimated or entirely missed. Though not a focus of this survey, we also discovered a common association of high productivity farms and the presence of a leguminous tree known as *Feidherbia albida*, which may also require more future attention.

Longitude	Latitude	Crop presence	Production limitations
33.7858	-13.7283	maize, groundnuts, soya, beans, tobacco	soil degradation
33.8504	-13.6828	maize, groundnuts, Irish potatoes, tomatoes	soil degradation, temperature (cold)
33.8226	-13.6648	maize, groundnuts, Irish potatoes, tomatoes	soil degradation
33.7951	-13.7463	maize, groundnuts, banana; guava and citrus across stream	soil degradation
33.62	-13.9909	maize, groundnuts soya, beans, tobacco	rainfall pattern, soil degradation
33.5923	-14.0181	maize, groundnuts, soya, tobacco	soil degradation
33.6017	-14.0543	tobacco	none
33.6388	-14.0723	maize, groundnuts, tobacco	soil degradation
33.6758	-14.0722	maize, groundnuts, tobacco	soil degradation, rainfall pattern
33.5741	-14.1538	maize, groundnuts, soya	rainfall pattern
33.6668	-14.1716	maize, groundnuts, beans, tobacco	soil degradation
33.6761	-14.1807	tobacco	soil degradation
33.7036	-14.0721	maize, groundnuts	none
33.9436	-13.8724	maize	soil degradation, monocropping, no fertilizer, management
33.9436	-13.8814	maize	soil degradation, erosion
33.9159	-13.8815	maize, groundnuts	rainfall pattern
33.8698	-13.945	non-agriculture	N/A
34.1117	-14.1971	maize, groundnuts, soya, beans	soil degradation, rainfall pattern
34.084	-14.2063	maize, groundnuts, soya, beans	soil degradation
34.0841	-14.2334	maize, groundnuts, soya, beans, sweet/Irish potato	rainfall pattern
34.0935	-14.2605	maize, groundnuts, soya, beans	rainfall pattern

Table A.1. *Field survey data—crop systems and biophysical factors limiting production.*

Table A.1 (cont'd)

34.0378	-14.2336	maize, groundnuts, soya, beans, cassava	soil degradation, erosion
34.5949	-14.3842	maize, groundnuts, pigeonpea, cowpea, cotton	rainfall pattern
34.5948	-14.3752	maize, cowpea	rainfall pattern, soil degradation
34.5858	-14.4114	maize, groundnuts, pigeonpea, cowpea	rainfall pattern
34.641	-14.3477	non-agriculture	N/A
34.6316	-14.3388	maize, tobacco, cotton	rainfall pattern
34.691	-14.8354	maize, groundnuts, soya, beans, tobacco, pigeonpea, cowpea, sweet potato, cabbage	rainfall pattern
34.7281	-14.8261	maize, groundnuts, soya, tobacco, sweet potato, millet	soil degradation, rainfall pattern, management
34.7371	-14.7899	maize, groundnuts, soya, sweet potato	topography
34.6909	-14.8174	maize, millet	management
34.6348	-14.7726	maize, beans, sugar cane, cabbage, lettuce, tomato	temperature, erosion
34.6626	-14.7543	maize, groundnuts, soya, beans, tobacco, millet, sorghum	management
34.7368	-14.7537	maize, groundnuts, soya, tobacco, cassava, sweet potato	soil degradation
34.6901	-14.7089	maize, groundnuts, beans, tobacco, cowpea, bananas, papaya	soil degradation, erosion
34.6619	-14.673	maize, tobacco, sweet potato, banana, pumpkin	management, soil degradation, erosion
34.634	-14.6551	maize, groundnuts, soya, beans, tobacco, millet	soil degradation, erosion
34.6524	-14.6459	maize, soya, tobacco, millet, banana, pumpkin	soil degradation
34.5965	-14.6101	maize, groundnuts, beans, tobacco, cowpea, millet, sweet potato	rainfall pattern
34.5779	-14.6103	maize, groundnuts, beans, tobacco, cowpea, millet, sweet potato	erosion
34.6259	-14.8178	maize, groundnuts, beans, cowpea, Irish potato, millet	soil degradation, erosion, cold temperature
33.5164	-13.1774	maize, groundnuts, soya, beans, tobacco, sweet potato, cassava; tomato, mustard greens, onion	soil degradation, rainfall pattern, pests/diseases, temperature (cold/hot)

Table A.1 (cont'd)

33.498	-13.1955	maize, groundnuts, soya, beans, tobacco, sweet potato, cassava; irrigation - tomato, mustard greens, onion, bananas	soil degradation, rainfall pattern, pests/diseases, temperature (cold/hot)
33.4704	-13.2317	maize, groundnuts, soya, beans, tobacco, sweet potato	soil degradation
33.4427	-13.2408	maize, groundnuts, soya, beans, tobacco, sweet potato, sugar cane, rice	soil degradation, rainfall patterns
33.4426	-13.2047	maize, groundnuts, soya, beans, tobacco, sweet potato, sugar cane	soil degradation, rainfall pattern, pests/disease
33.452	-13.277	maize, groundnuts, soya, beans, tobacco, sweet potato, sugar cane, Irish potato, mustard greens, rape, banana	waterlogging, soil degradation
33.4335	-13.277	maize, groundnuts, soya, beans, tobacco, tomato, banana	waterlogging, soil degradation
33.5708	-12.7342	maize, groundnuts, soya, beans, tobacco, sweet potato, cassava	soil degradation, rainfall pattern
33.5707	-12.698	maize, groundnuts, soya, beans, tobacco, cowpea, sweet potato, cassava	rainfall pattern
33.5523	-12.6981	maize, groundnuts, soya, beans, tobacco, cowpea, sweet potato, cassava	rainfall pattern
33.5338	-12.6891	maize, groundnuts, soya, beans, tobacco, cowpea, sweet potato, cassava	rainfall pattern, soil degradation
33.6168	-12.707	maize, groundnuts, soya, beans, tobacco, cowpea, cassava	soil type, rainfall pattern, soil degradation
33.6537	-12.734	maize, groundnuts, soya, beans, tobacco, cowpea, cassava	rainfall pattern, soil degradation
33.6813	-12.734	maize, groundnuts, soya, tobacco, cowpea	rainfall pattern, soil degradation
33.5984	-12.7432	maize, groundnuts, soya, beans, tobacco, cowpea	rainfall pattern, soil degradation
33.4607	-12.9786	maize, groundnuts, soya, beans, cassava, sweet potato, cotton, paprika	soil degradation, rainfall pattern
33.4791	-12.9876	maize, groundnuts, soya, beans, cassava, sweet potato, cotton, paprika	rainfall pattern, soil degradation

Table A.1 (cont'd)

33.4422	-12.9605	maize, groundnuts, soya, beans, tobacco	soil degradation
33.4699	-12.9605	maize, groundnuts, soya, beans, cassava	soil degradation
33.5066	-12.8971	maize, groundnuts, soya, beans tobacco, cassava, sweet potato, cowpea	rainfall pattern, soil degradation, erosion
33.4973	-12.87	maize, groundnuts, soya, beans, tobacco	rainfall pattern, soil degradation
33.5807	-13.0507	maize, bananas, other/unknown	none
33.5899	-13.0326	maize, other/unknown	none
35.3758	-15.4347	maize, groundnuts, pigeonpea, sorghum, banana, mango, cassava	soil degradation
35.357	-15.4168	maize, pigeonpea, sorghum, soya, sugar cane, cassava, banana	soil fertility, rainfall pattern
35.3854	-15.4526	maize, pigeonpea, sorghum, groundnuts, soya, mango, oranges, tangerines, lemons, papaya, guava	soil fertility
35.5438	-15.4599	maize, pigeonpea, rice, sorghum, cotton	none
35.5625	-15.4687	maize, pigeonpea, sorghum, rice, lablab	waterlogging
35.5626	-15.4778	maize, pigeonpea, sorghum, rice, lablab	soil fertility
35.4135	-15.4704	maize, pigeonpea, groundnuts, cassava, lablab, mango, soya	soil fertility
35.0319	-15.5104	maize, pigeonpea	soil degradation, rainfall pattern, labor
35.013	-15.4834	maize, pigeonpea, cowpea	soil fertility, rainfall pattern, labor
35.0128	-15.4563	maize, pigeonpea, sorghum, sweet potato, banana	soil fertility
35.0035	-15.4655	maize, sorghum, pigeonpea, okra	soil degradation, rainfall pattern
34.9851	-15.4837	maize, sugar cane, sweet potato, rice, mango	rainfall pattern
34.957	-15.4659	maize, pigeonpea, groundnuts, sorghum, cowpea, sweet potato	rainfall pattern, soil fertility
34.9659	-15.4297	maize, sorghum, cotton	management, labor, rainfall pattern
34.9753	-15.4296	maize, sorghum, cotton	rainfall pattern, soil degradation, temperature

Table A.1 (cont'd)

35.3806	-15.8502	maize, soya, sorghum, groundnuts, sunflower, pigeonpea	rainfall, soil degradation
35.3896	-15.814	maize, soya, sorghum, groundnuts, sunflower, pigeonpea	rainfall, soil degradation
35.3613	-15.7872	maize, pigeonpea, chickpea, sunflower, millet, sorghum	rainfall, soil degradation
35.3425	-15.7783	maize, pigeonpea, sorghum, sunflower, eggplant	rainfall, soil degradation
35.3048	-15.7426	maize, sorghum, tomato, pigeonpea, sunflower	soil degradation, rainfall
35.333	-15.7604	maize, pigeonpea, eggplant, mango, pumpkin	rainfall, rainfall pattern, soil degradation, management
35.3424	-15.7693	maize, pigeonpea, sorghum, rice, tomato	rainfall pattern, rainfall
34.9794	-15.8633	maize, pigeonpea, pumpkin	rainfall pattern, soil degradation
34.961	-15.8905	maize bananas, sugar cane, beans	rainfall pattern, soil degradation
34.9425	-15.9088	maize, beans, cassava, okra	rainfall pattern, soil fertility
34.9333	-15.9179	maize, banana, cassava	rainfall pattern, soil degradation
34.952	-15.9268	maize, beans, rape	rainfall pattern, soil degradation
34.9507	-15.7912	maize, pigeonpea, mango	rainfall pattern, soil degradation
34.9414	-15.7913	maize, pigeonpea, cassava, sweet potato	rainfall pattern, soil degradation
34.9321	-15.7914	maize, pigeonpea, cassava, sweet potato	rainfall pattern, soil degradation
34.9137	-15.8187	maize, pigeonpea, cassava, mangoes	rainfall pattern, soil degradation
35.2891	-16.0048	maize, pigeonpea, cowpea, sorghum, sweet potato, cassava	rainfall pattern, flooding, soil degradation
35.2705	-16.014	maize, pigeonpea, sugar cane, banana, mango	rainfall pattern, soil degradation
35.2799	-16.0229	maize, pigeonpea, cassava, sorghum, cowpea	rainfall pattern, soil degradation
35.2051	-16.0147	maize, pigeonpea, banana, sorghum, cowpea, cassava	rainfall pattern, soil degradation
35.1767	-15.9788	maize, pigeonpea, cowpea, sorghum, cabbage, banana	land suitability, rainfall pattern, soil degradation
35.13	-15.9793	non-agriculture	N/A
35.1487	-15.9791	non-agriculture	N/A

Table A.1 (cont'd)

34.0482	-12.362	maize, cassava, rice	soil suitability, soil degradation, rainfall pattern
34.0667	-12.3801	maize, cassava, rice, sweet potato, banana	rainfall pattern
34.0852	-12.3981	rice, sugar cane, cassava, banana, some maize	flooding, soil fertility
34.076	-12.3981	maize, cassava, rice	rainfall pattern, soil fertility
34.1037	-12.4342	maize, cassava, rice, beans, sweet potato, tomato, banana	rainfall pattern, none
34.0946	-12.4432	maize, cassava, rice, sweet potato	rainfall pattern
34.113	-12.4612	maize, bananas, some cassava	soil suitability, rainfall pattern
34.104	-12.4974	non-agriculture	N/A
34.141	-12.5515	sugar cane	none
34.1502	-12.5515	sugar cane	none
34.1504	-12.5786	non-agriculture	N/A
34.1504	-12.5877	non-agriculture	N/A
33.0366	-13.7476	non-agriculture	N/A
33.0366	-13.7566	maize, tobacco, bananas	none
33.0551	-13.6572	maize, groundnuts, tobacco	soil degradation, soil fertility
33.0459	-13.6662	maize, tobacco, banana, mango, groundnuts, soya, beans	land suitability, soil degradation
33.0921	-13.6662	maize, groundnuts, tobacco, soya, beans	soil degradation
33.0829	-13.6933	maize, tobacco, papaya, mango, soya	soil degradation
33.1384	-13.6933	maize, tobacco, sunflower, groundnuts, beans, soya	land degradation
33.0274	-13.6843	maize, tobacco, sunflower, groundnuts, soya	soil degradation, rainfall pattern
32.9904	-13.7114	maize, tobacco, bananas, mango, soya, beans, groundnuts, sunflower	soil degradation, rainfall pattern
32.9719	-13.7205	maize, groundnuts, sunflower, soya, tobacco, beans	rainfall pattern
32.9996	-13.5125	maize, sweet potato, sugar cane	rainfall pattern, soil degradation
32.9996	-13.4854	maize, groundnuts, tobacco, mangoes, soya	tree cover, rainfall, soil fertility
33.0089	-13.4492	maize, groundnuts, tobacco, mango, sunflower, soya	management
32.9719	-13.3859	maize, cassava, soya	soil degradation, soil type

Table A.1 (cont'd)

32.9349	-13.612	maize, tobacco, sugar cane, beans, soya, mango, banana, cassava, sweet potato	soil degradation, rainfall pattern
32.8979	-13.6391	maize, tobacco, groundnuts, soya	soil degradation, rainfall pattern
35.4272	-14.1964	maize, groundnuts, beans, banana, mango	soil fertility, rainfall pattern
35.418	-14.2056	maize, groundnuts, beans, banana, mango	soil fertility, rainfall pattern
35.4088	-14.2056	maize, groundnuts, beans, banana, mango, cassava, pigeonpea	soil fertility
35.4087	-14.1966	maize, groundnuts, beans, banana, mango, cassava, pigeonpea	soil fertility
35.4091	-14.2327	maize, cassava, banana, mango	soil fertility
35.3815	-14.2511	maize, beans, mango	soil fertility
35.4003	-14.278	maize, banana, mango, beans	soil fertility
35.4006	-14.3051	maize, beans, banana, mango	soil fertility
35.3663	-14.5675	maize, cotton, pigeonpea, tobacco, banana	rainfall pattern, flood, soil fertility
35.3845	-14.5402	maize, pigeonpea, cotton	rainfall pattern, soil fertility
35.3751	-14.5222	maize, rice, beans, shallots, tomato, banana, mango, potato	waterlogging
34.2238	-10.3992	maize, cassava, rice, banana, sweet potato, tomato, tobacco, mango, sugar cane, groundnuts, vegetables	rainfall pattern
34.2056	-10.4355	maize, cassava, groundnuts, sweet potato, cotton, tobacco, mango, banana	rainfall pattern, soil fertility
34.1875	-10.4627	maize, cassava, groundnuts, sweet potato, banana, mango, guava, rice, tobacco, sugar cane, pigeonpea, soya, beans	rainfall pattern, soil fertility
34.1326	-10.4448	maize, cassava, groundnuts	soil degradation
34.1052	-10.4539	maize, cassava, groundnuts, pigeonpea, mango	none
34.1875	-10.4808	rice, maize, banana, mango	none
34.0519	-10.8882	maize, beans, mango, banana, cassava, soya, tobacco	land suitability, soil degradation, rainfall pattern
34.0337	-10.9153	maize, beans, soya, mango, banana, cassava, tobacco	washaway, land suitability, soil degradation
34.0154	-10.9244	maize, beans, soya, mango, banana, cassava, tobacco	soil degradation

Table A.1 (cont'd)

33.9971	-10.9155	maize, beans, soya, mango, banana, cassava, tobacco, groundnuts	soil fertility, rainfall pattern
33.988	-10.9245	maize, beans, soya, mango, banana, cassava, tobacco, groundnuts	soil fertility
33.9788	-10.9336	maize, beans, soya, mango, banana, cassava, tobacco, groundnuts	soil fertility, washaway
33.9606	-10.9608	maize, beans, soya, mango, banana, cassava, tobacco, groundnuts, sweet potato	soil fertility, soil degradation
33.9607	-10.9698	maize, beans, soya, mango, banana, cassava, tobacco, groundnuts, sweet potato	soil fertility, soil degradation
33.9515	-10.9699	maize, beans, soya, mango, banana, cassava, tobacco, groundnuts, sweet potato	soil degradation
33.9424	-10.997	maize, other/unknown	none
33.8973	-11.1961	non-agriculture	rainfall patterns
33.8881	-11.1961	maize, banana, mango, vegetables	management
33.8972	-11.1599	sugar cane, banana, sweet potato, vegetables	minimal, washaway
33.9061	-11.0695	maize, banana, tomato, sugar cane, vegetables	floods, rainfall pattern
33.9519	-11.0784	maize, soya, beans, tobacco	rainfall pattern
33.9518	-11.0693	non-agriculture	N/A
33.9242	-11.0332	maize, soya, tobacco, beans, vegetables, sugar cane, sweet potato	floods, unimproved varieties
33.4937	-10.8534	maize, groundnuts, cassava, sweet potato, soya, beans, tobacco	rainfall pattern
33.5028	-10.8262	maize, groundnuts, cassava, sweet potato, soya, beans, tobacco	soil fertility
33.4936	-10.8172	maize, groundnuts, cassava, sweet potato, soya, beans, tobacco	none, rainfall pattern
33.5302	-10.8171	maize, groundnuts, cassava, sweet potato, soya, beans, tobacco, banana, mango	rainfall pattern
33.5394	-10.799	maize, groundnuts, cassava, sweet potato, soya, beans, tobacco, banana, mango	flood, washaway, waterlogging

Table A.1 (cont'd)

33.6227	-11.2963	maize, soya, mango, sweet potato, beans	rainfall pattern
33.6228	-11.3234	maize, groundnuts, beans	rainfall pattern
33.632	-11.3324	maize, beans, groundnuts, soya	soil type (sandy)
33.6595	-11.3685	maize, beans, groundnuts, soya	soil fertility, soil type
33.6412	-11.3776	maize, soya, groundnuts, cowpea, beans, cassava, sweet potato	soil fertility, rainfall
33.6412	-11.3686	maize, soya, groundnuts, cowpea, beans, cassava, sweet potato	soil fertility
33.3938	-11.4323	maize, tobacco, groundnuts, soya	soil fertility, soil degradation, management, income
33.403	-11.4142	maize, tobacco, groundnuts, soya	soil fertility, soil degradation, management, income
33.3938	-11.369	maize, groundnuts, tobacco, soya	soil fertility, soil degradation, management, income
33.412	-11.3419	maize, groundnuts, tobacco, soya	rainfall patterns, soil fertility
33.4307	-11.5318	maize, groundnuts	rainfall pattern, soil fertility, management
33.4215	-11.5137	maize, tobacco, groundnuts	soil degradation
33.4031	-11.4956	maize, groundnuts, soya, tobacco	rainfall pattern, management, soil degradation
33.4496	-11.9206	maize, soya, groundnuts, cassava, sweet potato, beans	soil degradation, soil type
33.468	-11.9206	maize, cassava, soya, sweet potato, groundnuts, beans, cowpea	soil fertility, soil type
33.4863	-11.9115	maize, cassava, sweet potato, soya, groundnuts, beans, cowpea	soil type (sandy), soil fertility
33.468	-11.8934	maize, cassava, sweet potato, soya, beans, banana, mango, cowpea	soil fertility
33.4496	-11.9025	maize, cassava, sweet potato, soya, beans, cowpea	soil type, soil fertility
33.4404	-11.8935	maize, cassava, sweet potato, soya, beans, cowpea	soil fertility
33.468	-11.9386	maize, cassava, sweet potato, soya, beans, cabbage, tomato, cowpea	rainfall amount
33.4313	-11.9206	maize, groundnuts, soya, millet, beans, cowpea	soil fertility, soil type
33.4221	-11.9387	maize, groundnuts, soya, millet, beans, cowpea	soil type, soil fertility
33.4592	-12.1376	maize, beans, vegetables, banana, guava, potato, sunflower, beans, paprika, sugar cane	soil fertility, management (access), rainfall amount

Table A.1 (cont'd)

33.3949	-12.1467	maize, tobacco, cassava, soya, groundnuts, beans	soil fertility
33.4132	-12.1105	maize, soya, beans, paprika, groundnuts, sugar cane, tomatoes, tobacco	rainfall amount
33.4684	-12.1557	maize, bananas, mango, tobacco, sugar cane, vegetables, soya, groundnuts, sunflower, ground bean, Irish potato, cassava, tomato, millet	soil fertility, rainfall patterns
33.6622	-12.4718	maize, beans, soya, groundnuts, cassava, millet, sugar cane, banana, vegetables	rainfall pattern
33.6898	-12.4717	maize, tobacco, beans, soya, sweet potato, cassava, sunflower, Irish potato, banana, sugar cane, vegetable	rainfall pattern, soil degradation
33.7082	-12.4626	maize, beans, sweet potato, cassava, tobacco, groundnuts, soya, millet, banana, vegetables, sugar cane	rainfall pattern, land suitability
33.6439	-12.4899	maize, tobacco, soya, beans, pigeonpea, cassava, sweet potato, sugar cane, banana, Irish potato	rainfall pattern, soil degradation
33.6663	-13.9818	maize, other/unknown	none

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