EXPLORING THE NEXUS BETWEEN FOOD SECURITY AND CLIMATE CHANGE: THE CASE OF INDIGENOUS VEGETABLE PRODUCTION IN WEST AFRICA

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By

Colin Michael Minielly

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ABSTRACT

Climate change and food security are complex global issues that require multi-disciplinary approaches to resolve. A nexus exists between both disciplines, but little prior research has successfully bridged the divide. Climate data is usually coarse, outdated and challenging to acquire and work with, especially for farmers of West Africa. For impoverished nations, alleviating food insecurity, the inability to have access to safe and nutritious food year-round is a necessity. Accessing food is a significant challenge, as there exist many disconnects between farmers, marketers and consumers. If this disconnect can be bridged, new strategies can be undertaken to alleviate further stresses caused by food insecurity. Combining the struggles of the Benin Republic and Nigeria, the MicroVeg project set to create innovative strategies to help the farmers, across the entire food chain. MicroVeg established 102 research sites, and with a desire to continue scaling-up the project, a new approach was needed. Geographic information system (GIS) offered the solution, as large-scale visualization could be achieved. Through visualization tools, scaling-up could be achieved based on successes in the field. This technique also allowed for gaps and shortcomings of the research design to be identified, at the regional level.

To achieve the goals of the GIS database, a comprehensive dataset needed to be acquired. Many organizations collect data that is pertinent to a food security study, but no publicly known database has compiled all the necessary data. The GIS database combined factors such as precipitation, temperature, elevation, soil, and hydrology for the research area. The database was designed for farmers; thus, climate data had to be extremely high resolution. The Intergovernmental Panel on Climate Change (IPCC) and subsequent global climate models are very coarse datasets; although comparatively high in resolution, a regional climate model may still be too coarse in resolution for the farmers.

Once the necessary data was obtained, analysis using GIS techniques could proceed. Through the visualization, combination, and calculations of data, the potential capacity of each crop within the research project could be observed. These results can be used as communication and research tools.

Though controversial, climate change is going to have some effect on the agricultural systems of the world. Moreover, if a region is already facing food insecurity before any effects of climate

change, this can exacerbate the challenges to food security. Therefore, an assessment of how climate change effects may impact the region was undertaken. By adding climate estimates from IPCC to the visualization method, a model known as Scaling Agronomic Vegetable Innovations to Nurture Growth Sustainably, SAVINGS, was developed. Through the use of this model, researchers can develop a management strategy for the crops of interest. Additional benefits of the model are for farmers to understand the risk they may need to take to continue farming a specific crop, or by using a specific method.

SAVINGS was designed to be a dynamic model, with improvements being made as data becomes available. Associated with the SAVINGS model are a series of calculations and datasets, which have been combined into an online interactive database, known as WebGIS. By using these resources as communication and management tools the farmers of West Africa, not just the Benin Republic and Nigeria, have the potential to alleviate food insecurity within a lifespan.

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DEDICATION

This thesis is dedicated to any person, anywhere in the world, who has had a role in the creation of the document. I would also like to dedicate this thesis to my parents and grandma, who were instrumental to my success. Finally, I would like to dedicate this thesis and all of the outputs to the Sub Saharan countries of the Benin Republic and Nigeria. I hope that our work, as a team, can alleviate any stresses families, and/or individuals, are experiencing with regard to their local food insecurity.

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LIST OF EQUATIONS

LIST OF ABBREVIATIONS

AR4	Fourth Assessment Report
AR5	Fifth Assessment Report
CIA	Central Intelligence Agency
DEM	Digital Elevation Model
ESA	European Space Agency
ESRI	Environmental Systems Research Institute
FAO	Food and Agriculture Organization of the United Nations
GAC	Global Affairs Canada
GCM	Global Climate Model
GIS	Geographic Information System
GMTED2010	Global Multi-Resolution Terrain Elevation Data 2010
GTOPO30	Global 30 Arc-Second Elevation Mission
IDRC	International Development Research Centre
INuWaM	Integrated Nutrient Water Management
IPCC	Intergovernmental Panel on Climate Change
MicroVeg	Synergizing Fertilizer Micro-dosing and Indigenous Vegetable Production to Enhance Food and Economic Security of West African Farmers
NASA	National Aeronautics and Space Administration
NGO	Non-governmental Organizations
NOAA	National Oceanic and Atmospheric Administration
RCM	Regional Climate Model
RCP	Representative Concentration Pathways
RegCM3	Regional Climate Model Version 3
SAVINGS	Scaling Agronomic Vegetable Innovations to Nurture Growth Sustainably
SSA	Sub Saharan Africa
SRES	Special Report on Emissions and Scenarios
SSRL	Social Sciences Research Lab
STRM	Shuttle Radar Topography Mission
TRMM	Tropical Rainfall Measuring Mission
UIV	Underutilized Indigenous Vegetable
WGS 84	World Geodetic System 1984

WWF	World Wildlife Fund

1 INTRODUCTION

Climate change is a pressing global concern due to its implications for future life on Earth. As a result of intense research, long-term modeling of climate variables, such as temperature and precipitation, has become more common. Better modeling of these parameters means that they can now be used to develop more sophisticated climate change scenarios that have predictive value. It is understood that Africa, as a continent, may suffer more drastically from climate change than much of the world due to Africa's reliance on agriculture for livelihood combined with the severity of current droughts and famines on Africa. For Sub Saharan Africa (SSA) and other areas of the developing world, food security operates under both knowledge and financial constraints; even when there is a desire to improve agricultural technology and communicate these innovations widely, there is no financial or technological method to realize those desires.

The Food and Agriculture Organization (FAO) (2006) describes food security as "the stable access of individuals to sufficient quantities of safe and nutritious food." Per the FAO (2017) 22.7% of the human population in SSA are considered undernourished; a value that has increased by 1.9% from 2015 to 2016, but is lower than the 28.1% of undernourished reported in 2000. Low soil fertility and unreliable rainfall patterns make agricultural practices challenging for subsistence level farmers that comprise 90% of the population in SSA. One promising development innovation to improve agricultural productivity was fertilizer microdosing, a low technology method whereby fertilizer is directly placed in soil at reduced quantities that can simultaneously increase yields and profits for SSA smallholder farmers. Adams (2015) reviewed the current extent of literature surrounding microdosing throughout Africa and found that results from 126 microdosing research sites were published in peer-reviewed articles, from a wide variety of research projects that generally involved cereal crop production. Figure 1.1 shows the spatial distribution of these sites. Two areas of concentration for microdosing research are the highly undernourished areas of SSA and Zimbabwe. As reported by FAO in 2016, Zimbabwe had 44.7% of its population, or seven million people undernourished; an increase of 1.4% since 2001 (FAO 2017).

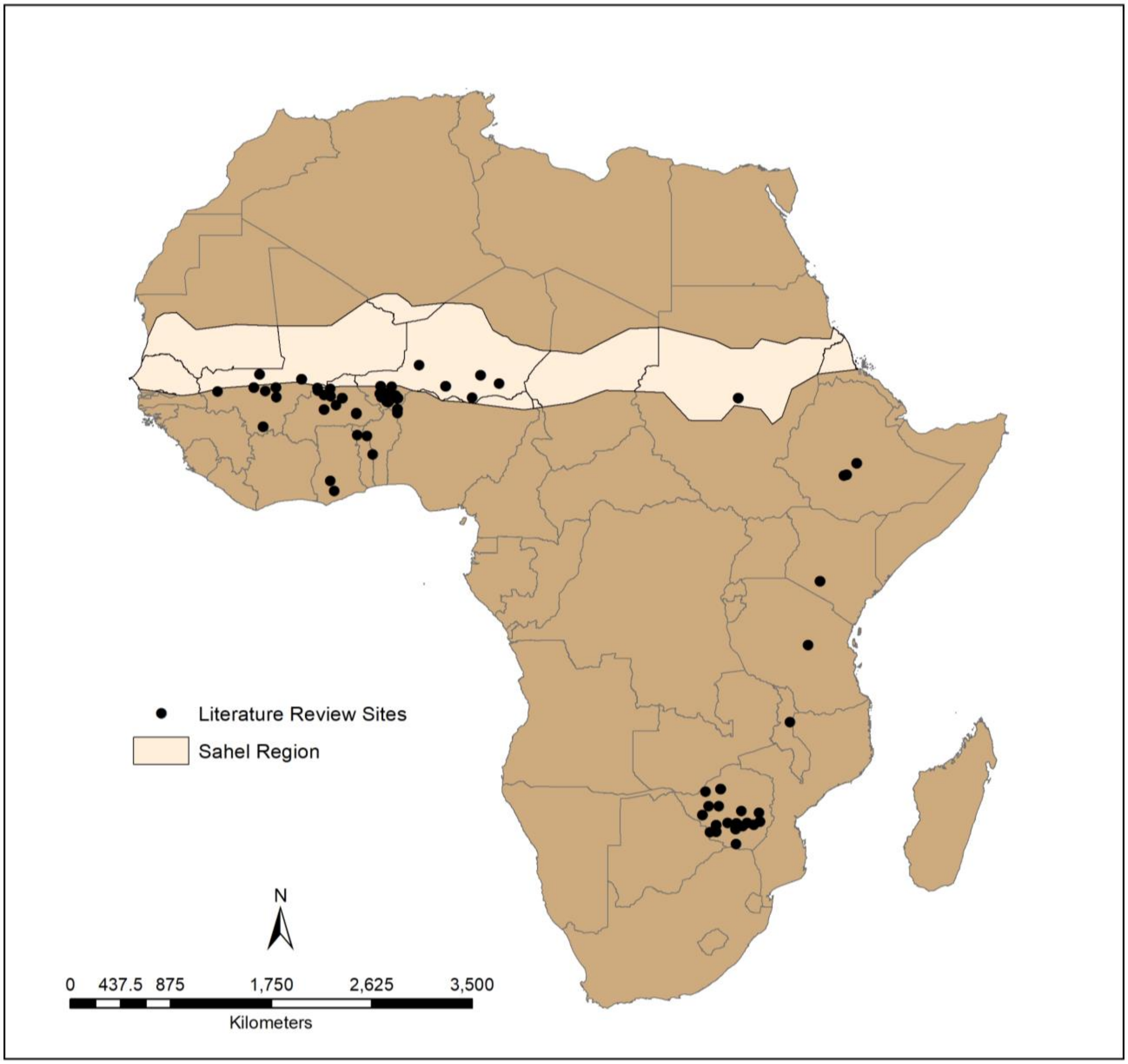

Figure 1.1 Microdosing research sites from peer-reviewed journal articles

These projects typically involve combining fertilizer microdosing with other agronomic practices such as rainwater capture in the Sahel and indigenous vegetable cultivation in more rainy climates. Fertilizer microdosing is a point-source fertilizer application technique that typically uses half of the recommended rate of broadcast fertilizer, while still producing comparable yields to the higher recommended application rates, due to improved nutrient and fertilizer use efficiencies (Adams et al. 2016).

Unlike the success of microdosing, climate change cannot be directly quantified and instead is analyzed via models. These models rely on complex, high-quality data that is ideally both recent and reliable. Many governmental and non-governmental institutions exist to model climate change. Globally, the most popular resource is the Inter-Governmental Panel on Climate Change (IPCC). The IPCC data outputs are essential determinants for global trends. Other models exist to describe regional, national, or local level issues affected by climate change. Climate change will not only have effects on surface materials but will also have a direct effect on ecological variables, including agricultural productivity. Indeed, the intersection between food production and climate change has been known for many years, but minimal research has been executed on this topic in developing nations.

For developing nations, such as those in SSA, food security research is often synonymous projects and financial aid lasting less than 5 years. However, there exists concern that this style of external aid does not have long-lasting effects on food security for a variety of reasons. Projects are often short-lived, only provide aid while resources are available, and are limited in the ability to scale up their innovations (Hartmann and Linn 2007). For development interventions to have long-term success, scaling-up becomes fundamental and needs to occur without reliance on extremal aid and resources. Conventional scaling-up approaches include developing a method, field research, and finally dissemination and widespread adoption of the technique.

The objective of the research in this thesis is to establish a model for understanding the nexus between the potential effects of climate change and food insecurity to the West African nations of the Benin Republic and Nigeria. The thesis is organized into two chapters, to achieve the above objectives. The first chapter constructs the foundations whereby the nexus can be examined. Compiling a portion of data from the Synergizing Fertilizer Micro-dosing and Indigenous Vegetable Production to Enhance Food and Economic Security of West African Farmers project (MicroVeg) a comprehensive Geographic Information System (GIS) database was created (Adebooye et al. 2018). This GIS database can then be used to establish a baseline for potential scaling-up to occur.. Three research sites (Ife, Ina, and Ogbomosho) had both agronomic and water management data, both of which were deemed essential values for the model. These three research sites became case studies. The second chapter develops a methodology for which climate change assessments can be made, in refernce to the long-term scalability of the UIVs. The methodology, supported by the case studies as thresholds, was then integrated into the GIS database. The two research chapters follow a literature review intended to illustrate the various types of models available for assessing climate change and the wealth of recent knowledge gained regarding food security. Finally, a chapter on discussions and conclusions is used to help understand the complex nexus and offer recommendations to the involved groups.

2 LITERATURE REVIEW

2.1 Food Security in Sub Saharan Africa Under a Changing Climate

2.1.1 Microdosing and Irrigation/Hydrology Management in the Sahel

The droughts of 2005 and 2010 are two recent severe droughts to hit SSA; the mechanisms responsible for these drought conditions are not well known (Agnew and Chappell 1999; Dike et al. 2015; FAO 2013). What is clear is that both of these droughts led to food scarcity within the region and that interventions to improve water use efficiencies and resilience to are necessary for SSA (Dike et al. 2015).

To mitigate drought and combat poor soil fertility, a University of Saskatchewan-led research team has developed a package of agronomic innovations for West African farmers since 2011. This initiative, Integrated Nutrient Water Management (INuWaM) was designed to find innovative means to increase crop yields without further degrading low fertility soils of the region. INuWaM research focused on four SSA countries: the Benin Republic, Burkina Faso, Mali, and Niger (IDRC 2016). Figure 2.1 illustrates where the research sites were within the intervention zone. The project focused on water management and microdosing, particularly the long-term effects on cereal crops. Yields of research sites improved on average by 116%, without modifications to water management techniques (Adams et al. 2016; IDRC 2016). By conserving fertilizer use and increasing yields, farmers could become more food secure, and SSA smallholder agriculture could become substantially more profitable.

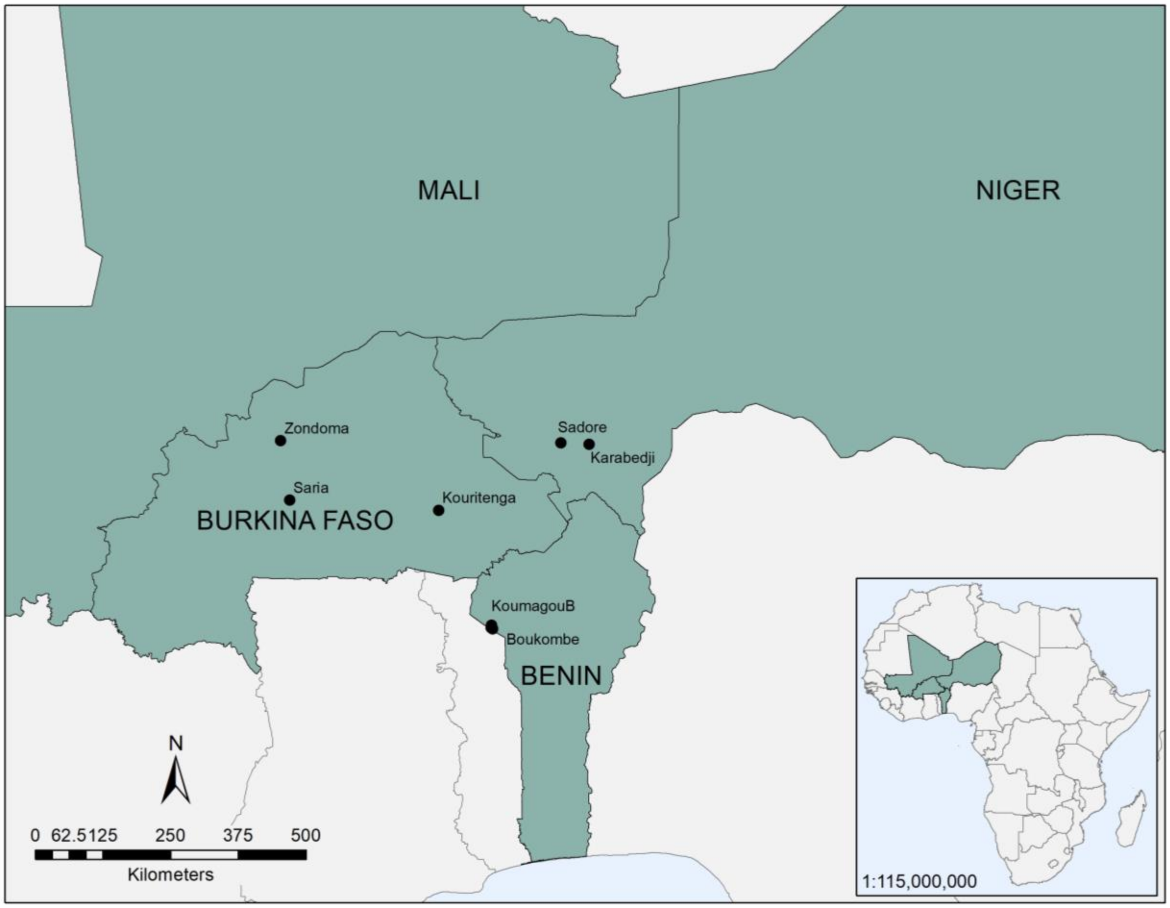

Figure 2.1 INuWaM research sites

Adoption of microdosing is, at heart, a shift in fertilizer application techniques that are consistent with modern nutrient stewardship practices. Standard cultural practices are to broadcast fertilizer, which is generally inefficient but more so when irrigating crops. Issues with this practice include limited access to fertilizer and excessive runoff, which both result in low yields and high input costs per unit exported. In contrast with traditional practices, microdosing is a low-tech precision agriculture technique that delivers a controlled amount of fertilizer at the base of each plant seed.

Microdosing also referred to as a reduced direct soil application, is not a new concept with research sites in West Africa, with some research sites having 30 years of results (Adams 2015; Minielly et al. 2015). Microdosing allows the user to increase yields while significantly reducing their input costs. Microdosing has the potential to triple the amount of harvest per plot compared to not applying mineral fertilization (Adams 2015). However, microdosing does increase the amount of labour needed, since each plant requires precise application of fertilizer. However, the return from fertilizer addition is still significant compared to local practices. Despite the potential of microdosing, the literature indicates that there is only a 5% adoption rate throughout the region due to a range of factors (Bacon et al. 2014; Adams 2015; Adams et al. 2016).

2.1.2 Indigenous Vegetable Production Using Microdosing

Synergizing Fertilizer Micro-dosing and Indigenous Vegetable Production to Enhance Food and Economic Security of West African Farmers, here on in referred to as MicroVeg, was funded to build on the successes of INuWaM. The shift in the project to focus on vegetables rather than cereal crops was due to a combination of nutritional (traditional vegetables are incredibly healthy) and financial (vegetables are much more profitable than cereal crops) reasons.

MicroVeg focused its efforts in the countries of the Benin Republic and Nigeria. This project has set up 102 research sites; many are less than 1ha (less than 100 m^2) in size. Figure 2.2 illustrates the distribution of the research sites within the Benin Republic and Nigeria. Also notable is how the research sites are concentrated in the southwestern corner of Nigeria and throughout the Benin Republic. In Nigeria, the easternmost site is near the Niger River but does not cross the river. The Niger River serves as a political divide, from stable to unstable governments.

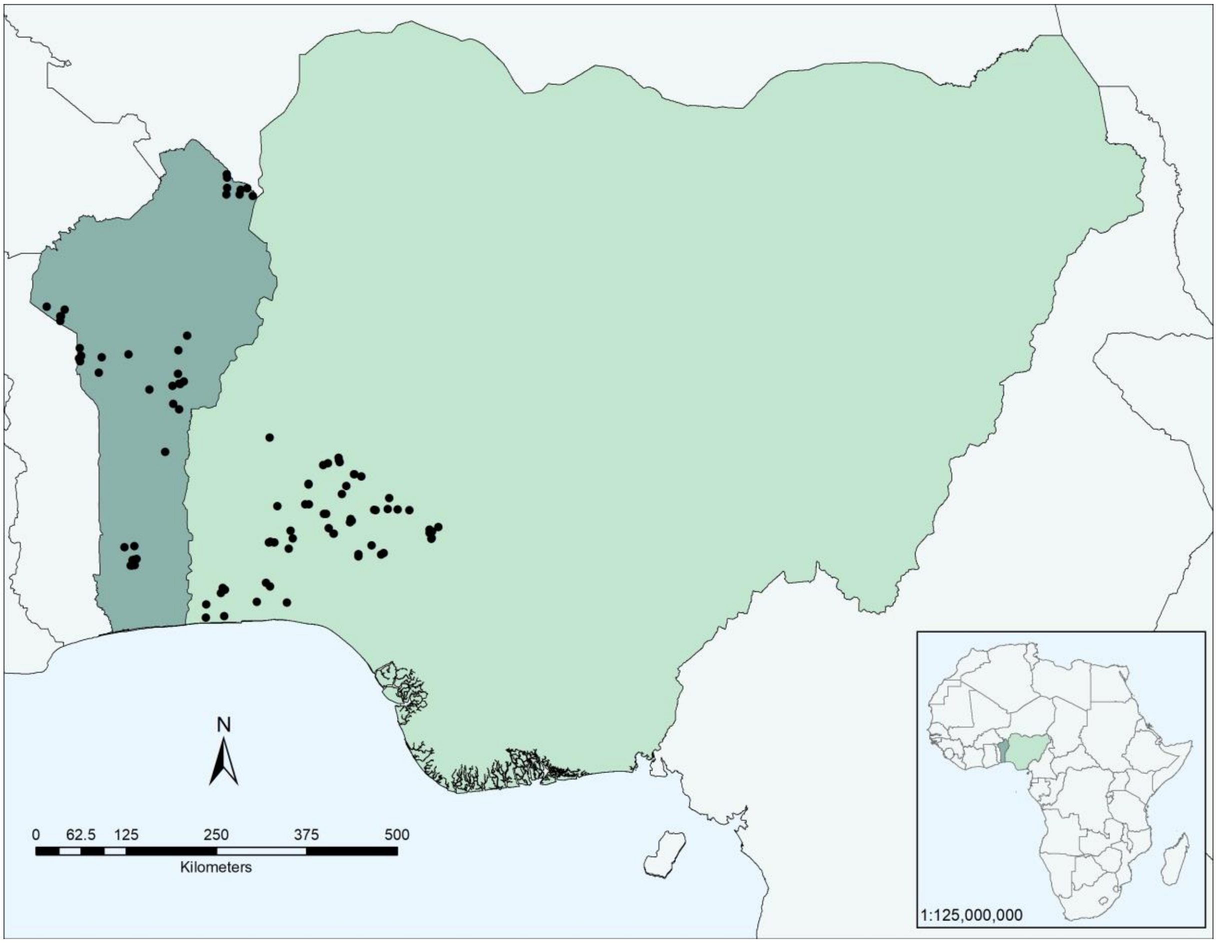

Figure 2.2 MicroVeg research sites

The MicroVeg project has focused on four indigenous leafy vegetables, also known as Under-utilized Indigenous Vegetables (UIVs). These UIVs are regularly produced using traditional methods, and they are commonly consumed throughout the Benin Republic and Nigeria but are referred to by different names. See Appendix A for a complete list. By focusing primarily on these crops, attempts are being made to improve regional food security, by using the local value chain as a starting point for intervention.

As a result of approaching food security via the entire value chain, MicroVeg has been addressing many large-scale issues outside of agronomy, including marketing and gender issues. By the end of the project, stakeholders will have access to multiple innovations and strategies to promote local food security.

2.1.3 Stresses to Food Security in Sub Saharan Africa

The population of both Benin Republic and Nigeria are expected to continue to rise over the next century and exacerbate the periodic food insecurity crises these countries currently experience. As of July 2017, the population was estimated to be 11,038,805 and 190,632,261, for the Benin Republic and Nigeria, respectively. With a growth rate of 2.71% and 2.43%, populations are expected to reach 23.9 million and 410.6 million, for the Benin Republic and Nigeria, respectively by 2050 (Central Intelligence Agency (CIA) 2018; The World Bank Group 2018).

Nigeria's percentage of the population, which is undernourished has decreased from 9.4 to 7.9, from 2001 to the 2014-2016 reporting year. Even with a decrease of 1.5%, total population growth has increased the total number undernourished to 14.3 million (2014-2016). During the same reporting period, Benin Republic dropped to 10.3%, or 1.1 million, from 22.6% of the population undernourished (FAO 2017). These numbers are low compared to the regional average of SSA, which is 21.3% (FAO 2017). By 2050, if the percentage of the undernourished population in SSA does not decrease, 92.5 million people would be classified as undernourished. Additionally, at the current rates, the Benin Republic and Nigeria could expect 16.6 million to be undernourished (The World Bank Group 2018).

2.1.4 The Significance of the MicroVeg Project to Food Security

Gender issues plague SSA, the Benin Republic and Nigeria are not exempt. With the joint efforts of INuWaM and MicroVeg, researchers were able to focus on women farmers that play a vital role in their families' food security. An objective of the project is to incrementally increase the households that are utilizing microdosing to reach 225,000 farmers in the Benin Republic and Nigeria (Akponikpe et al. 2016). Rapidly scaling-up agronomic practices require data management approaches capable of assessing where resource allocation can be most effective.

Although many graduate students have been involved in microdosing research throughout this project (IDRC 2015), each student's research has focused on isolating a limiting variable or developing a novel approach for their specific sites rather than pursuing the root causes of regional-scale agricultural limitations. Graduate students and scholars alike argue that climate, though typically outside the scope of research projects, plays a significant role in the determination of a project's success. Lobell (2008) attempted to illustrate globally how cropping systems may be affected under the IPCC (2007a) scenarios. However, little research on the intersection of food security and climate change has to date been conducted in SSA.

2.2 Global Climate Models (GCMs) and Food Security

Global Climate Models (GCMs) that represent data over a large area, usually globally or continentally, are useful for understanding large-scale changes. GCMs include variables such as annual precipitation, temperature, elevation, and greenhouse gas emissions. Satellites are the most common source for GCMs; often creating very low-resolution datasets. Satellites operate with specific objectives, such as measuring rainfall and are thus restricted to the variables they need. Some satellites involved with GCMs include Tropical Rainfall Measuring Mission (TRMM), for measuring rainfall, Global 30 Arc-Second Elevation Mission (GTOPO30), and Shuttle Radar Topography Mission (STRM) for elevation (U.S. Department of the Interior 1999; Fick and Hijmans 2017).

GCMs have been used extensively in academia, primarily to illustrate gross global geographic variations of climate variables. For an analysis of projected food production, Lobell et al. (2008) utilized 20 unique GCMs to limit uncertainties within models and establish a holistic view. The data used by Lobell et al. (2008) are models that was interpolated using the IPCC Fourth Assessment Report (AR4) (IPCC 2007b), using a process that requires strong statistical knowledge.

The resolution of global datasets had recently been improved from an older dataset which was 55.6 km^2 at the equator (Hijmans et al. 2005). Hijmans et al. (2005) noted that before their study the finest resolution global dataset contained cells representing 18.5 km^2 at the equator; with their dataset improving the situation to $1km^2$ at the equator. The coarse resolution of these databases creates problems when trying to incorporate multiple diverse datasets.

In this type of assessment, each cell is given one value based on the mean, or other statistical measures, and the cell represents uniformity. When data is presented in this manner, it is referred to as a raster. Depending on the resolution of the data, the results may represent a large area; therefore, essential characteristics may be oversimplified and specific points, such as a city, may not be captured via the model (Hijmans et al. 2005; Lobell et al. 2008).

2.2.1 Global Climate Models and Food Security

When reviewing literature, no comprehensive database exists that explicitly contains elements of both food security and climate change. Hijmans et al. (2012) created a complex online database, with the primary use being in biological sciences research since the focus of their project was understanding plant genetics. The climate data used in the database was monthly average data from the 1970 - 2000 climate normal and was last updated in 2009.

The Hijmans et al. (2005) database has isolated five decades of temperature and precipitation data from 1950 - 2000. The data has been interpolated from various sources in a hierarchical methodology to eliminate duplication (Hijmans et al. 2005). The authors note that many advantages exist to their “very high resolution” data interpolation, which is a reference to data spatially being presented at 30 arc seconds or approximately 1 km^2. Some of the advantages of Hijmans et al. (2005) include an increase in spatial resolution upwards of 400 times, incorporation of additional weather stations, and improved elevation data (Hijmans et al. 2005). Based on a comparison of several approaches, the authors interpolated the data as per a standard statistical practice; allowing for comparisons between datasets and variables to be made. The variable with the lowest resolution will limit the analysis, and thus set the limit on the resolution of any model built with this approach.

Upon reviewing many databases, it was concluded that Hijmans et al. (2012) database is the most comprehensive ecological model available to the public. This project will be using the climate variables, independent of other analyses available through the above resources, to assess the interpolated data so that inferences can be made for regions within the project’s borders.

Moreover, when combining data from multiple sources, no accepted standard protocol exists. Data in West Africa is sparse due to the above reasons. Therefore, GCMs are a reliable resource for reviewing available data in SSA (IPCC 2014; Attaway et al. 2016).

2.2.2 The Intergovernmental Panel on Climate Change

The IPCC serves as a proponent of multiple GCMs. One of the primary goals for the IPCC is to develop global awareness of several variables associated with climate change, including energy use, forestry and changes in temperature and precipitation regimes ((IPCC 2014)). Understanding the ethics, governance, and reasoning behind the model selection of the IPCC is outside of the scope of this literature review. However, IPCC reports serve as a basis for academics to communicate with the public and they facilitate knowledge transfer (IPCC 2007b, 2014).

A potential limitation of IPCC reports is the frequency of their release. Many recent scholarly articles have been published using the 2007 or older data when new data was available, including O'Brien and Leichenko 2000; Kumar and Parikh 2001; O'Brien et al. 2004; Attaway et al. 2016. The IPCC has been releasing its climate change scenarios approximately every five years since 1990. One of the most heavily sourced reports is the AR4, published in 2007 (IPCC 2007b). Even when new reports are released, publications still rely on the older data; this is especially apparent since the release of the Fifth Assessment Report (AR5) in 2014. Although based on AR4, Attaway et al. 2016, drew conclusions that are skewing the literature by distorting situations and using scenarios which are no longer relevant based upon the current IPCC model. The reliance on AR4 data further increases the challenges in comparing data from different years, scenarios, and models.

In AR4, IPCC used a family of scenarios that are structured with strict assumptions on how society will adapt or perform in the future. These AR4 scenarios are based on the Special Report on Emissions and Scenarios (SRES) methodology, a complimentary report to AR4 (Alcamo et al. 2000). When the IPCC released the AR5 in 2014, they revised their approach on how they published their findings.

First cited in 2009, Representative Concentration Pathways (RCPs) is the newest and most advanced approach to assessing climate change. Van Vuuren et al. (2011) describe this novel approach as being a collaboration of the entire scientific community. Additionally, they note that the IPCC requested that the RCPs be developed by the scientific community and not by the IPCC (van Vuuren et al. 2011). By using an RCP, the perspective changes and focuses not on "projections or predictions, but rather represent possible alternative ways in which the future may unfold" (van Vuuren et al. 2011).

This conceptual change to RCPs eliminates the strict assumptions that were in place in the SRES models and replaces those assumptions with an estimate of how greenhouse gas concentrations may affect the environment. The RCP scenarios assess the factors that would be responsible for an increase in solar radiation. By looking at these factors, the scientific community established four RCP scenarios, which were published as the key findings in the AR5 (van Vuuren et al. 2011; IPCC 2014). The four RCPs are: 2.6, 4.5, 6, and 8.5, the values each represent an increase in radiative forcing, commonly referred to as solar radiation, and recorded as Wm^{-2}. Radiative forcing is described as the energy in the earth system. Values greater than zero equate to a warming effect, while less than zero cools the earth (IPCC 2014).

Within literature, it is agreed upon that RCP 2.6 will equate to a global change in temperature of 2°C, by 2100. Using this notion, the United Nations drafted and signed The Paris Agreement. This agreement has goals to mitigate global temperatures so that temperatures do not increase by 2°C compared to pre-industrial temperatures (Climate Focus 2015). Tellingly, even without using the term RCP, the Paris Agreement has set targets in line with RCP 2.6. In comparison with RCP 2.6, it is widely accepted that RCP 8.5 represents a catastrophic societal failure. Regarding a spectrum, RCP 4.5 and 6.5 are intermediate scenarios.

2.2.3 IPCC Estimates and Food Security

IPCC estimates are not the only climate change scenarios, but they are the most widely cited source. For our purposes, we do not want to challenge the reliability of the AR5 (IPCC 2014) forecasts. Instead, we want to incorporate the broad estimates into a localized environment to see what implications arise when the GCM assumptions are utilized at a regional scale. The focus of this research will be to understand if two scenarios released in the AR5 (RCP 4.5 and 8.5) could be used to construct a high-resolution model of climate change over the MicroVeg region and further inform food security research.

2.3 Regional Climate Models

Regional-scale Climate Models (RCM) are complementary models to GCMs that exist to reduce the number of errors produced by other models. Literature suggests that RCMs are more data-intensive, compared to GCMs, and must have a boundary in which to operate (Larsen et al. 2013). After reviewing the estimates presented in the AR4 (IPCC 2007b), three known case studies (Abiodun et al., 2012; Dike et al., 2015; Kithiia and Dowling, 2010) have developed regionally-based models for countries that integrate climate change estimates. The Abiodun et al. (2012) study provided additional validation of IPCC's regional climate model, version 3 (RegCM3). This data was then used to show short-term effects (2030 - 2050) of climate change on reforestation in West Africa. Dike et al. (2015) focused on changes in temperature in Nigeria but considered all of Africa in their analyses throughout 2073 - 2098.

Reforestation has been one accepted method of mitigating climate change. Abiodun et al. (2012) created scenarios under eight different land cover patterns. The rationale behind their study was to validate earlier theories that local precipitation would increase, even under a warmer climate (Abiodun et al., 2012). The results of the study, however, remain inconclusive since the positive feedbacks of trees may offset the monsoons or affect total greenhouse gas emissions. For their study, Abiodun et al. (2012) used RegCM3 coupled with a global circulation model. This study further validated the RegCM3 model and additionally altered the boundaries of the model. This study did not provide any conclusive results. However, this study further illustrates a need to consider specific regions when trying to scale projects, as not all regions may respond similarly.

Dike et al. (2015) developed a regional climate model that divided the African continent into four regions. To forecast future climate, the researchers needed to understand the present climate better. While considering the current African climate, they found that a GCM was unable to account for tropical rainfall by comparing modelled and observed data. Indicating a "deficiency" within their model, and it was especially present for Western and Eastern regions of Africa. To verify the model, it was rerun for Nigeria and focused on five cities. The modelled data was still unable to describe the variations in precipitation cycles, caused by seasonal monsoons, for two of the five cities; therefore, misrepresenting the local climate. However, their RCM had better quality outputs than GCM (Dike et al., 2015). The resulting model was inconclusive and requires further validation.

The final case study using the AR4, targeted impacts that a small rise in sea-level could have on a coastal city in Kenya. Kithiia and Dowling (2010) developed an RCM for the coastal city of Mombasa, Kenya, currently 45 metres (147.6 feet) above sea level. The authors speculate that the city will be submerged with only a 30 cm increase in sea-level (Kithiia and Dowling 2010). Currently, IPCC models are indicating a minimum increase of sea level of 40 cm by the end of the century, and this sea level rise will not be consistent around the globe ((IPCC 2014)). The RCM was developed to give government officials a foundation to implement engineering precautions, in hopes of mitigating sea-level rise. The RCM also gives rise to a new, more collaborative approach to municipal development.

2.3.1 RCMs and Food Security

The criteria established by Larsen et al. (2013) for RCMs suggest that the MicroVeg project could benefit from using an RCM. MicroVeg has a boundary to operate within, with substantial regional variability within the landscape; an RCM may be able to capture the variability (Bacon et al. 2014; Adams 2015; Minielly et al. 2015). From this perspective, RCMs would have the necessary tools and resolution to create a food security database based upon the MicroVeg project.

By increasing resolutions, RCMs improve how data is disseminated. By focusing on a specific area, RCMs also can influence decisions and establish a dialogue with vulnerable groups. Giving RCMs more control of variables, but also necessitates the addition of more variables and higher resolutions, making these models more data intensive.

2.4 Application of Climate Models to Food Security

2.4.1 Predicting Regional Temperature and Precipitation with GCMs

Several GCMs exist (Hijmans et al. 2005; IPCC 2014; Dike et al. 2015; Fick and Hijmans 2017) that all have advantages or drawbacks, and limitations associated with data resolution and the years being reported (Hijmans et al. 2005; Lobell et al. 2008). Both GCMs and RCMs have positive attributes when attempting to model large-scale trends of West Africa. Running climate scenarios is essential to understanding the potential repercussions of climate-related actions. The basis for these scenarios needs to be the best available data. High-quality data does not exist explicitly for West Africa; therefore, global data is necessary. AR5 is the most reliable and highest resolution data available for West Africa. Each subsequent IPCC report improves resolution, yet even with these improvements, the resolution is today still 250 km^2. In an attempt to overcome these limitations Hijmans et al. (2005) developed a multivariable database. By using various statistical methods, Hijmans et al. (2005) obtained temperature and precipitation monthly, and annually for a 30 year period, known as a climate normal. The resolution of this global data set is 30 arc seconds, which is approximately 1km^2 at the equator. The Hijmans et al. (2005) dataset, which is available to the public, is the most comprehensive dataset for the MicroVeg, and West African, regions (fig. 2.3).

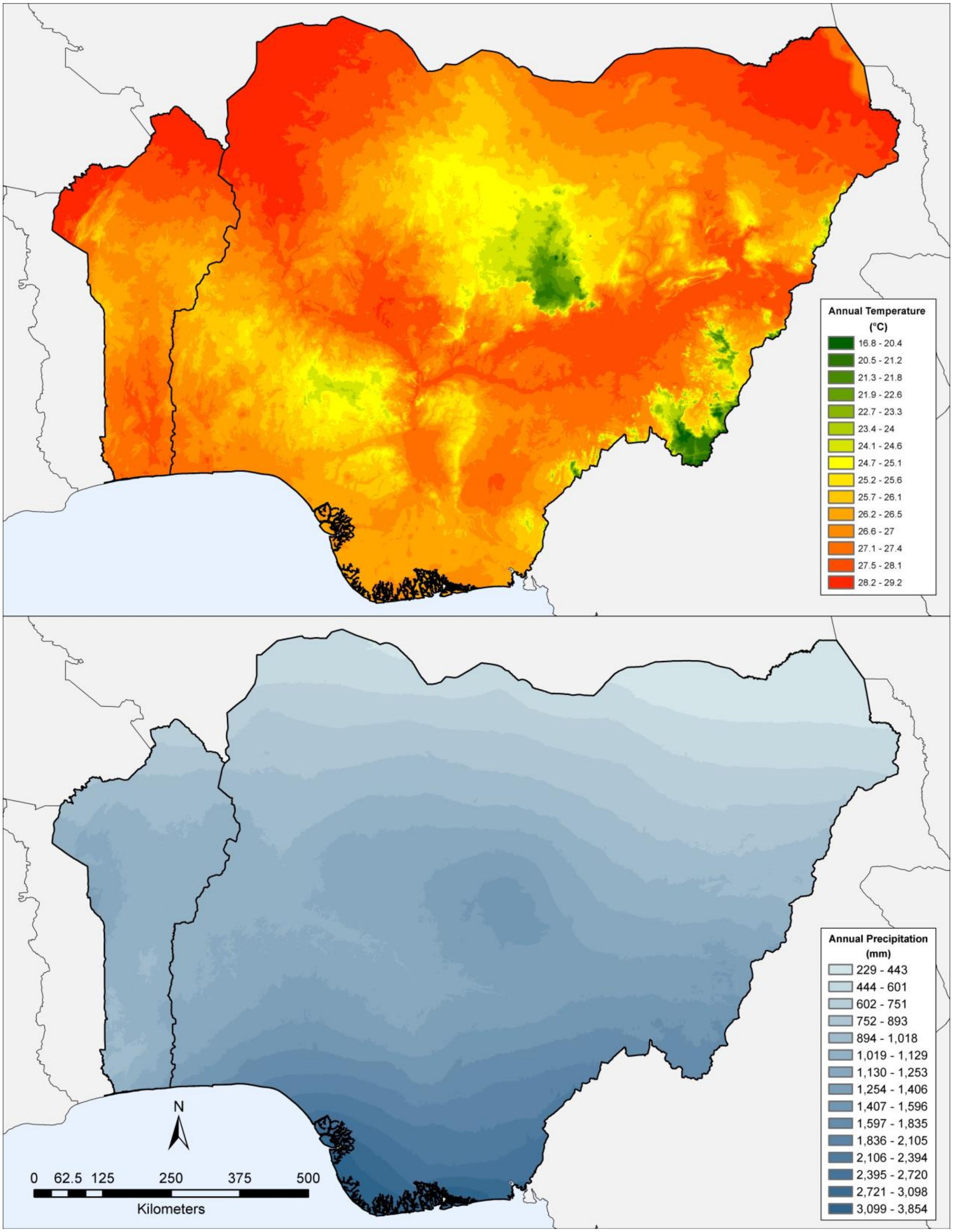

Figure 2-3 Climate normal (1970-2000) Top: mean annual temperature (°C). Bottom: total annual precipitation (mm)

2.4.2 Elements of Ecological Models

When creating a database, multiple factors play significant roles in the success of the model. Databases include only the variables that are pertinent to the project; eliminating potentially useful data at the expense of finer spatial resolution. Common climate variables include temperature, precipitation, elevation, greenhouse gases, and sea-level rise. For a food security model, soil and agronomic data also become essential variables.

2.4.2.1 Ecology

The primary goal of biological and ecological models is to suggest the ecological services that a site or landscape may provide. Included in these databases, are variables such as plant communities, soil quality and type, interactions with water and slope (Mclaughlan et al. 2010, p. 12). These ecological assessments are conducted on a fine scale and with a specific purpose. Landscape-level assessments usually fail to include fine details associated with specific plant communities. Therefore, the proposed model does not include ecological parameters. Instead, general ecological boundaries, referred to as ecoregions, have been used to help delineate large-scale trends within the research areas.

2.4.2.2 Ecoregions

The World Wildlife Fund (WWF) has created a high-resolution GIS-based ecoregion map of the world. This map has amalgamated several sources of ecological and climatic data into one comprehensive database (Olson et al. 2001). The ecoregions for Africa originated from White (1983), whereby the author identified characteristics pertinent to plant growth. After amalgamating data from various sources, Olson created a map that encompassed all the global ecoregions and improved the resolution of the ecoregion polygons by increasing the spatial extent from an average of 740,000 km^2 to 150,000 km^2. This new database, shows a four-fold increase in resolution, resulting in 867 global ecoregions (Olson et al. 2001). This work has been heavily cited, making it an ideal foundation upon which to develop a GIS model.

2.4.2.3 Topography

Various methods exist for how to acquire elevation data necessary for topographical mapping. The most accepted method for large-scale images is the use of satellites. Alternatively, drones can be used to capture elevation data at extremely high resolutions at local scales; covering large areas with drones is impractical and expensive. Resource limitations for countries, especially for West Africa, has led to no high-quality regional elevation maps of the research area. Therefore, to use topographical data, one is currently limited to satellite-based mission results of varying resolutions. Nonetheless, the topography data available publicly is becoming more refined. Three recent satellite missions have collected global topography data: GTOPO30, Global Multi-Resolution Terrain Elevation Data 2010 (GMTED2010), and STRM with highest available resolutions at 30, 7.5 and, one arc second (U.S. Department of the Interior 1996, 2015; Danielson and Gesch 2011). When satellite data is used for topography, the most common approach for published data is to assign the cells the average value obtained. STRM data is not user-friendly to download, and at a regional scale, the one arc second (or 30-metre cell size) is too fine of a resolution to visualize regional trends. Furthermore, the data is incomplete, as the satellite's orbit does not entirely cover the globe, leaving large swaths of land unmapped. GMTED2010 gives users more download options, and at these scales can illuminate hills and mountain regions. Although comparatively weak in resolution, GTOPO30 provides elevation data at $1km^2$, which is compatible with climate data obtained by Hijmans et al. (2005) (fig. 2.4).

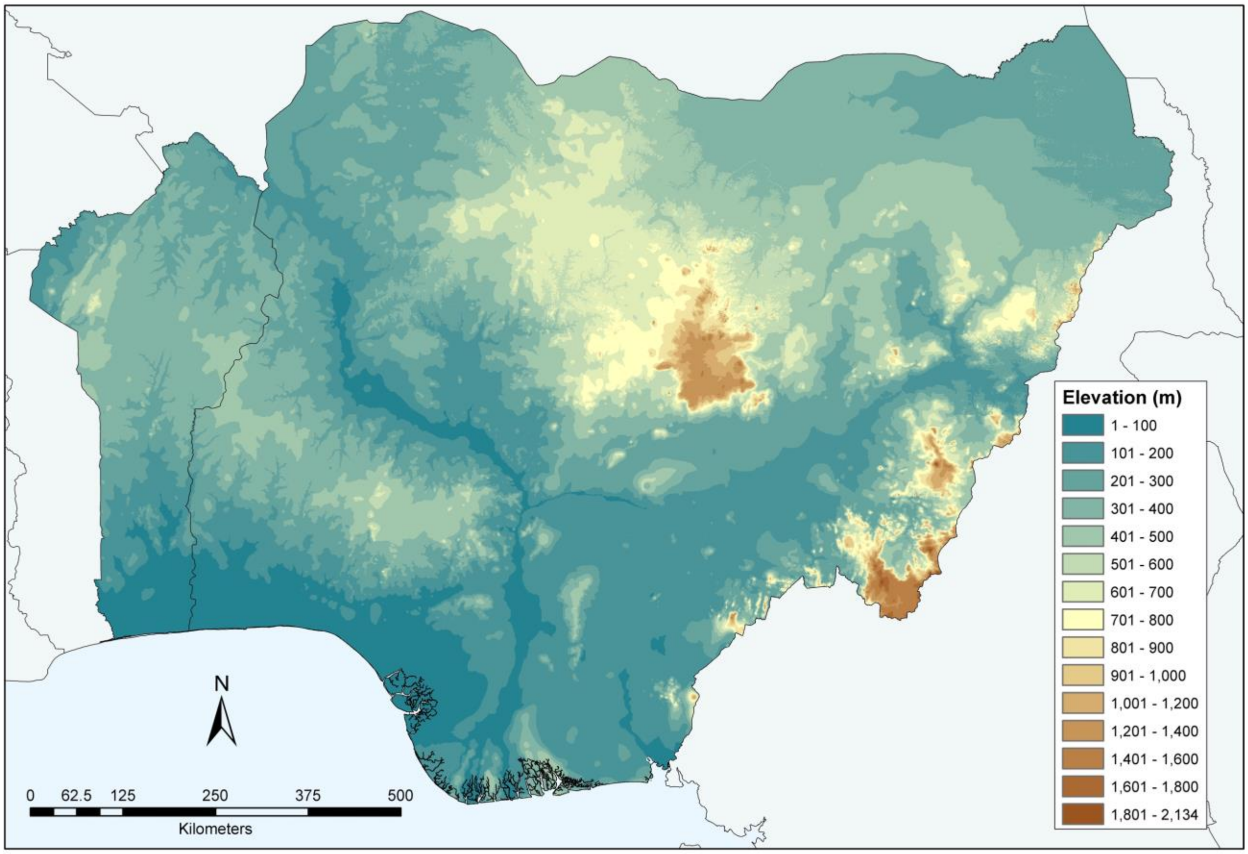

Figure 2.4 Topography of Benin and Nigeria as viewed from GTOPO30

As described earlier, the data with the lowest resolution will limit the model's resolution. Climatic variables within the model are at $1km^2$ resolution. The GMTED2010 data is 16 times finer compared to the climate data. To keep the resolution the same for both climate and climate topography the GTOPO30 data was used. At this resolution, the data is too coarse to see many variations in relief.

2.4.2.4 Sea Level

Sea level change is an essential variable for both climate change and food security since it can provide insights into zones where salinity (from saltwater impingement) could affect crops and areas likely to be flooded. IPCC (2014) does not indicate high confidence in their models, but rather in the fact that sea level rise will not be uniform, with estimates ranging from 0.26 to 0.82 meters. Sea level rise is forecasted to cause severe flooding and famine. Although sea level may become a vital West African issue, it was omitted from the model because the necessary data was not available. Additionally, the majority of West Africa is non-coastal, even though the largest cities in both Nigeria and the Benin Republic are coastal.

2.5 Scaling-Up

MicroVeg operated at the regional level, encompassing both Nigeria and the Benin Republic, with a novel knowledge dissemination approach. This project established a cooperative innovation platform where farmers and marketers directed the research, which aided in the adaptation and dissemination. For technique demonstration and refinement, research sites were still valuable resources. Adebooye et al. (2018) showed significant increases in adaptation and collaboration with the innovation platform approach when compared to other projects (Adams et al. 2016; IDRC 2016). To further improve the scaling-up capabilities of the MicroVeg suite of GIS tools were introduced. A strength of GIS is the ability to actively update and analyze data, for any region of any size. The amounts of available data only limit GIS systems.

3 SCALING UP RESEARCH USING GIS AND WEBGIS SPATIAL TOOLS: CASE STUDY OF MICROVEG PROJECT

3.1 Preface[1]

As of writing this thesis, the attached paper has been accepted for a special edition publication in Acta Horticulturae. Financial assistance, support and reviewing were provided by Derek Peak, Department of Soil Science and David Natcher, Department of Indigenous Land Management Institute, University of Saskatchewan, Saskatoon, Saskatchewan, Canada. Logistical support for the creation of the Web-based tools was provided by Winston (Weiping) Zeng and his team at the Social Sciences Research Lab (SSRL), University of Saskatchewan.

3.2 Abstract

Sustainable intensification of agriculture is a pressing issue for the countries of the Benin Republic and Nigeria. Akponikpe et al. (2016) and Adebooye et al. (2018) note that for the Benin Republic and Nigeria amaranth (*Amaranthus cruentus* L.), solanum (*Solanum macrocarpon* L.), fluted pumpkin (*Telfairia occidentalis* f. Hooke), and parsley (*Ocimum gratissimum* L.) were identified as important indigenous vegetables with the potential to enhance food and household security in West Africa. An international collaboration known as MicroVeg was established in 2015 to scale up the production and consumption of these nutritious vegetables. Traditional agronomic field research has a relatively small spatial footprint; by using a GIS, we expanded the reach of MicroVeg research to a regional scale. A GIS database allows for data to be visualized using a variety of methods and to create larger inference spaces. With GIS, we can use the data to infer areas which are similar to the characteristics of a site. GIS data were stored, analyzed, compared, and extrapolated to infer where scaling-up of the MicroVeg agronomic package is likely to be most successful. GIS has enabled this project to expand potential areas from several research sites with an approximate total area of 50 ha, to a possible extent exceeding 100,000 km^2 for each crop, independent of seasonal variation. As it is challenging to disseminate such information to audiences, we developed and implemented an

[1] Minielly, C., Peak, D., Natcher, D., and Zeng, W.W. 2018. Scaling Up Research Using GIS and WebGIS Spatial Tools: Case Study of the MicroVeg Project. Acta Hortic. **In Press**.

interactive, online, database (WebGIS) of agronomic trial data designed for use with minimal GIS knowledge. The results of this project will be necessary for policymakers and agronomists who are scaling-up vegetable production in the Benin Republic and Nigeria.

3.3 Introduction

Food security is a pressing issue facing humanity, especially in developing countries. The Food and Agriculture Organization (FAO) (2006) describes food security as "the stable access of individuals to sufficient quantities of safe and nutritious food." Food insecurities are attributed to a combination of social, economic, agricultural, and climatic components. Sub Saharan West Africa (SSA), is facing large-scale food security issues; it is the only region in the world where the per capita basis of food production is decreasing. In 2015, the "MicroVeg" project (IDRC 2015) was established to address food security issues in the Benin Republic and Nigeria via scaling-up production of indigenous vegetables (Akponikpe et al. 2016).

The MicroVeg project set a target to directly affect 255,000 food insecure households in rural the Benin Republic and Nigeria by 2018 (Akponikpe et al. 2016). To achieve this goal with limited time and resources, scaling-up needs to occur in many different aspects of the vegetable value chain. Current data suggests that scaling-up is occurring at an agronomic level due to an increase in yields, better water management, and an increase in the knowledge level. Scaling-up is also occurring due to market demands to the incorporation of vegetable extracts into fortification and value-added products (Adebooye et al. 2018).

These scaling-up successes have put a strain on MicroVeg's available resources; expansion of MicroVeg practices into additional areas will place further strain on non-governmental organizations (NGOs) and extension agents who are in the field consulting for and aiding farmers. Thus it is necessary to prioritize expansion in a data-driven manner. Understanding the factors that can facilitate or impede the scaling-up of the MicroVeg technology is necessary if the goal of reaching 255,000 farming households is to be reached. This understanding includes the spatial representation of where the adoption and scaling-up of MicroVeg may occur most successfully.

GIS is a computer-based technology that has become the standard tool for capturing, manipulating, analyzing, and visualizing geographically referenced information. GIS has become a mainstream tool for producing representations of data for many academic disciplines, governmental agencies, and commercial agricultural industries. GIS can be in a variety of forms, from static and dynamic maps to online interactive databases. The most commonly used GIS tools belong to a suite of tools known as ArcGIS (Environmental Systems Research Institute (ESRI), 2017). Today, examples of GIS tools can be found in almost every industry and city in the world. For example, both North America and Europe have well documented the use of GIS in cases ranging from forest fire management, flood mitigation, civic services, public health to precision agriculture. Using multiple research methods, organizations like the National Oceanic and Atmospheric Administration (NOAA), the National Aeronautics and Space Administration (NASA), and the European Space Agency (ESA) have produced GIS resources which are freely and readily available, for a range of topics such as climate, soil, and population. These organizations have been making correlations between economics and agriculture and food security and other multi-disciplinary research using GIS approaches.

Unlike North America and Europe, African nations have not invested many resources in GIS; thus, examples of African GIS projects are sparse. However, a few projects have been completed to illustrate the versatility and feasibility of GIS for African researchers. Examples include mapping Dengue Fever over the continent (Attaway et al. 2016), mapping potential impacts of climate to reforestation of West Africa (Abiodun et al. 2012), and establishing ecoregions and soil classification at a regional scale (Olson et al. 2001; Jones et al. 2013).

Some of the above examples rely on newer tools, such as the Predictive Analysis Tools (ESRI 2014), while other systems integrate computer sciences. To date, there is no accepted standard method for using GIS, especially when scaling-up projects. The objective of this paper is to describe how GIS can be used to infer potential areas in the Benin Republic and Nigeria where scaling-up of the MicroVeg agronomic package is likely to be most successful. Data from three research sites in the Benin Republic and Nigeria will be used as case studies.

3.4 **Methods**

3.4.1 Data Sources

This work builds on the work of Bacon *et al*. (2014) and Minielly *et al*. (2015). Datasets were managed and processed by ArcGIS 10.5 (ESRI 2017). Data came from various sources, in various formats, and varying resolutions. Table 3.1 outlines the data sources and formats. Data resolution may limit the modelled outputs. A raster with smaller cell size, or higher resolution, would increase the model's overall usability for the targeted audience, by giving a more localized perspective. The resolution of a raster is based on the data collection methodology; and is defined as a cell (ESRI 2016). Point data does not have any spatial attributes that would be limited to the database. In contrast, the resolution of polygon data is limited on how precise the inputted data is. For example, a city may have a simple polygon or be outlined precisely, depending on the data used or the purpose. Precipitation, temperature, and elevation are rasters with resolutions of 30 arc seconds which at the equator are approximately 1 km^2. Elevation data originated from the GTOPO30 satellite mission and had a cell size, or resolution, of 1km^2. (U.S. Department of the Interior 1996).

Table 3.1 Data sources and formats utilized in the MicroVeg project

Data type	Format	Data Source and Citation
Ecoregion	Polygon	Terrestrial Ecoregions of The World (Olson et al. 2001)
Temperature	Raster	Worldclim.org (Hijmans et al. 2005)
Precipitation	Raster	Worldclim.org (Hijmans et al. 2005)
Elevation	Raster/DEM	USGS (U.S. Department of the Interior 1996, 2015)
Political Boundary	Polygon	DIVA-GIS (Hijmans et al. 2012)
Lake and River	Polygon/polyline	DIVA-GIS (Hijmans et al. 2012)
Infrastructure	Polyline/point	DIVA-GIS (Hijmans et al. 2012)
Soils of Africa	Polygon	European Union Soil Atlas (Jones et al. 2013)
Airport	Point	Share Geo Open (Pope and Sietinsone 2017)

3.4.2 Seasonal Variability

Ojo and Olurotimi (2014) divided Nigeria's weather into two seasons: the wet season (March to October) and the dry season (November to February). Precipitation and temperature vary significantly between seasons. Figure 3.1 illustrates that precipitation varies more in intensity, whereas temperature varies more with latitude.

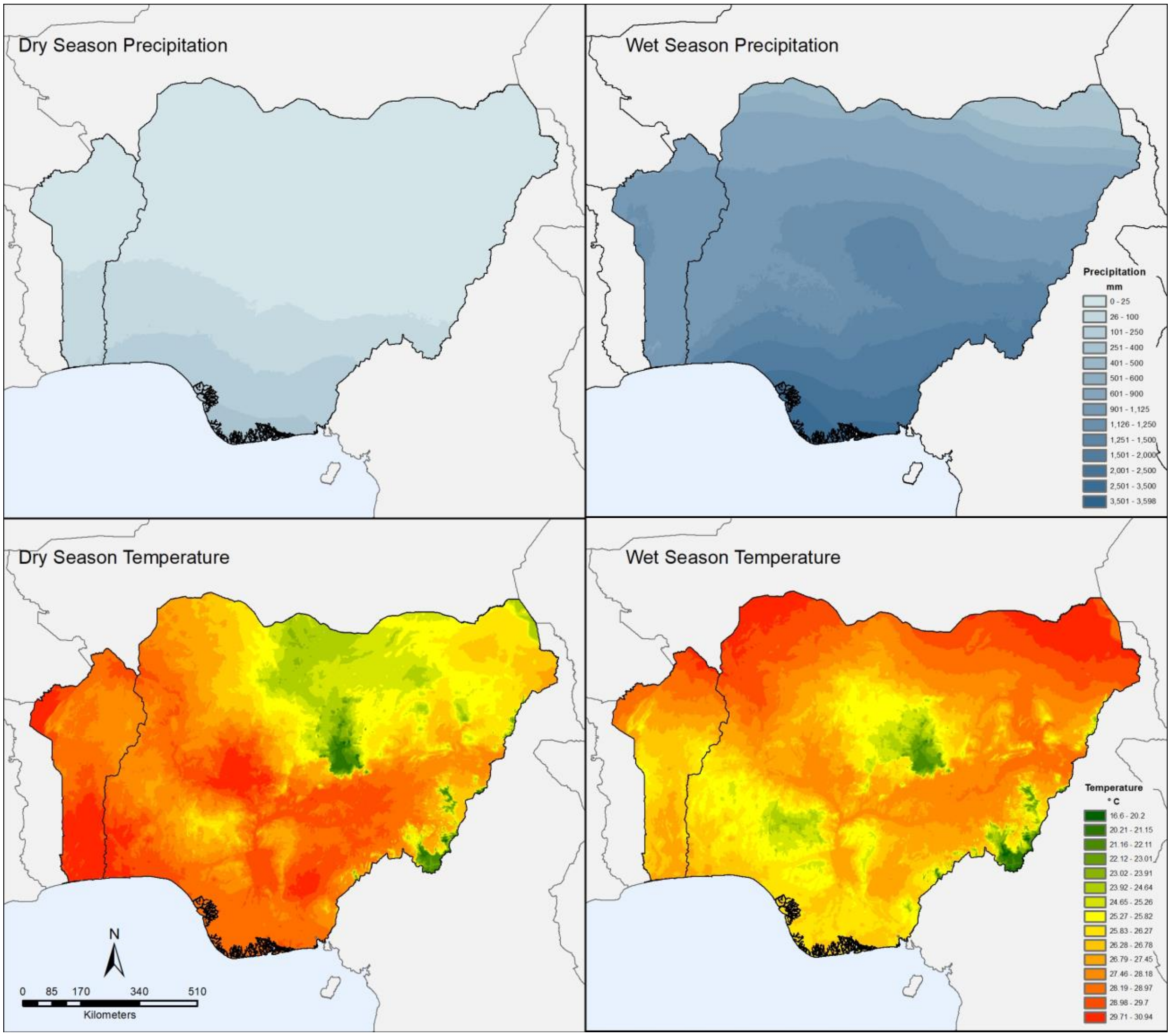

Figure 3.1 MicroVeg seasonal variability based on 1970-2000 climate normal of average precipitation and temperature

3.4.3 Site Criteria

Researchers in the project divided the Benin Republic and Nigeria into large agro-ecological areas. Colloquially, these agro-ecological zones, or ecoregions are referred to as forest, humid, and dry savanna, amongst other variations (Descroix et al. 2009; Scheiter and Higgins 2009; Ndehedehe et al. 2016; Adebooye et al. 2018). With the support of the World Wildlife Fund (WWF), Olson *et al*. (2001) created a global terrestrial ecoregion map. The ecoregion dataset served as a foundation for understanding differences among research sites in our project.

According to Olson *et al*. (2001), the Benin Republic and Nigeria contain a total of 15 unique ecoregions, within four biomes.

Referring to the regions defined by Adebooye et al. (2017), the 15 ecoregions were grouped into three ecoregions, using the biomes as a guide for the reclassification. The ecoregions were then assigned the appropriate name within the project. The mangroves biome was merged with the rainforest, as there was no data. To ensure consistent terminology and complete coverage of the region, the names assigned to the ecoregions are rainforest, savanna, and sudano savanna. Similar to the seasonal precipitation and temperature figures, figure 3.2 illustrates that the ecoregions are drier and become harsher the further north from the Gulf of Guinea they lay. The next ecoregions, in northward progression, are the Sahel and the Sahara Desert, which are both sparse ecologically.

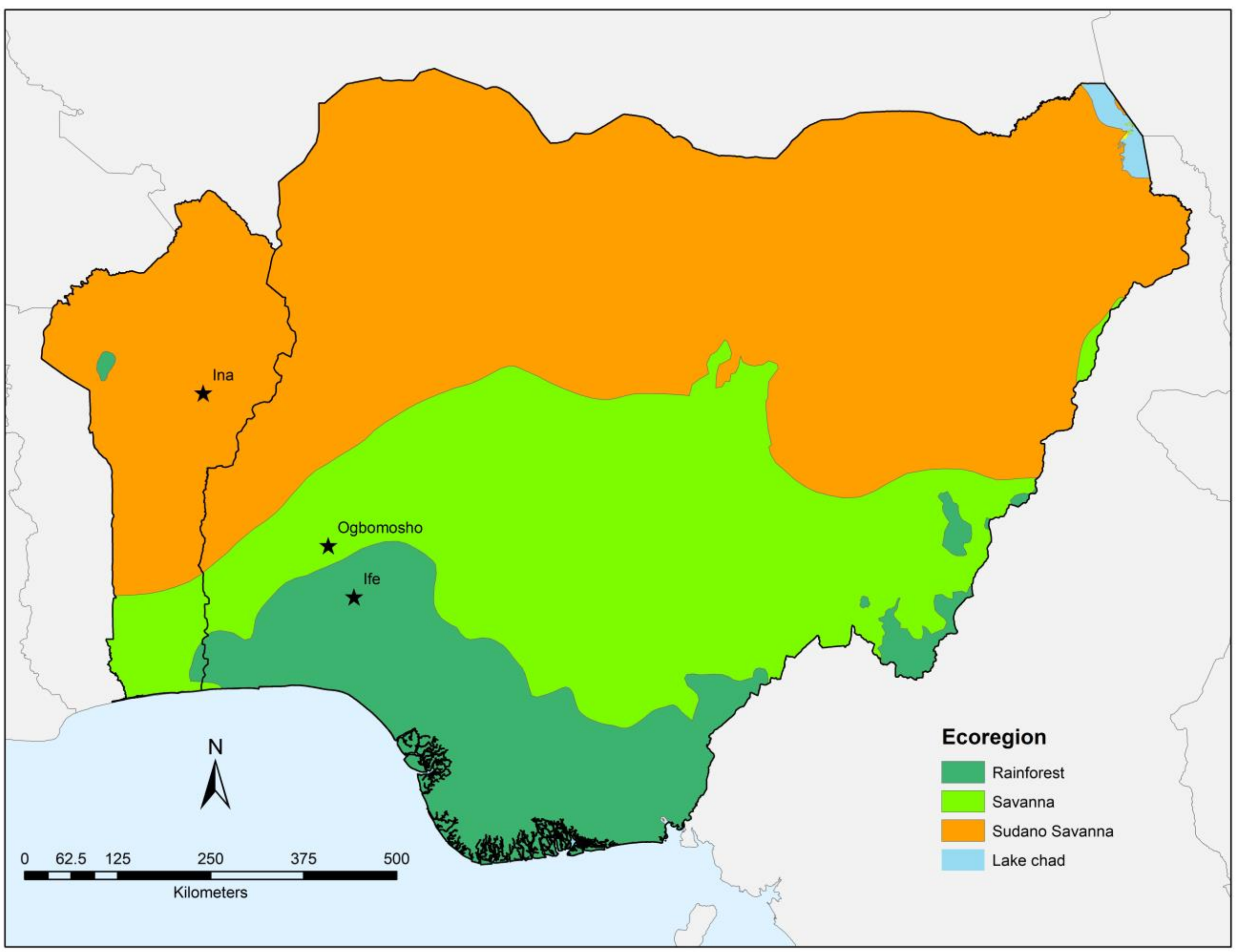

Figure 3.2 Ecoregions of Benin and Nigeria

3.4.4 MicroVeg Agronomic Data

Akponikpe *et al*. (2016) and Adebooye *et al*. (2017) conducted extensive agronomic trials at various sites. The trials consisted of comparisons amongst various factors including, but not limited to yield responses, fertilizer rates, fertilizer application techniques, and water management. Table 3.2 shows some key findings from three research sites, two in Nigeria (Ife Central and Ogbomosho South) and one in the Benin Republic (Ina).

Additionally, Akponikpe et al. (2016)researched water management at these three sites. Data collected from these sites show the UIVs grown in the particular ecoregion, the optimum fertilizer rates, expected yields, and additional crop-specific water requirements. Yield data was collected in the dry season, after 3 harvests (Akponikpe et al. 2016). Multiple harvest and planting cycles, especially for vegetables are possible in West Africa. These results are the foundation of the agronomic recommendations for the MicroVeg Project (Adebooye et al. 2018).

Table 3.2 Agronomic data for amaranth, solanum, fluted pumpkin, and parsley

Site Name	Ecoregion	Indigenous Vegetable	Optimum Fertilizer Rate (kg ha^{-1})	Optimum Yield (kg ha^{-1})	Crop Water requirement† (mm)
Ife	rainforest	amaranth	40	12,000	209
		solanum	40	5,500	157
		fluted pumpkin	40	7,633	174
Ogbomosho	savana	amaranth	40	11,667	430
		solanum	40	5,367	303
		parsley	40	12,550	544
Ina	sudano savana	amaranth	20	13,000	980
		solanum	40	33,000	980
		parsley	60	27,000	980

† Crop water requirement was recorded at the mid-season (Akponikpe et al. 2016)

3.4.5 Logic Model for GIS Development

A model for scaling-up was created to assimilate the various types of data, that originated from multiple organizations, see Table 3.1 for the complete list. The conceptual model shown in figure 3.3 describes how the assimilated data was converted, or transformed, into a geodatabase for use within the scaling-up model. Although a variety of datasets were obtained, the primary datasets used for the scaling-up model were ecological boundaries, precipitation, and temperature. The downloaded ecoregion dataset was stored as a polygon; while temperature and precipitation were stored as raster files. Having the three key datasets in different forms complicated the executability of the scaling-up model. The ecoregion data was converted into a raster that bore the same raster properties as precipitation and temperature. For the model and geodatabase to function, attributes such as the datum and projection needed to be set. The scaling-up model used the World Geodetic System 1984 (WGS 84) projection and datum. The spatial attributes of the rasters were also standardized. The chosen resolution, or cell size, was 0.0083333338, which equals approximately 1km^2, at the equator. Additionally, this resolution matches the first precipitation and temperature data (Hijmans et al. 2005).

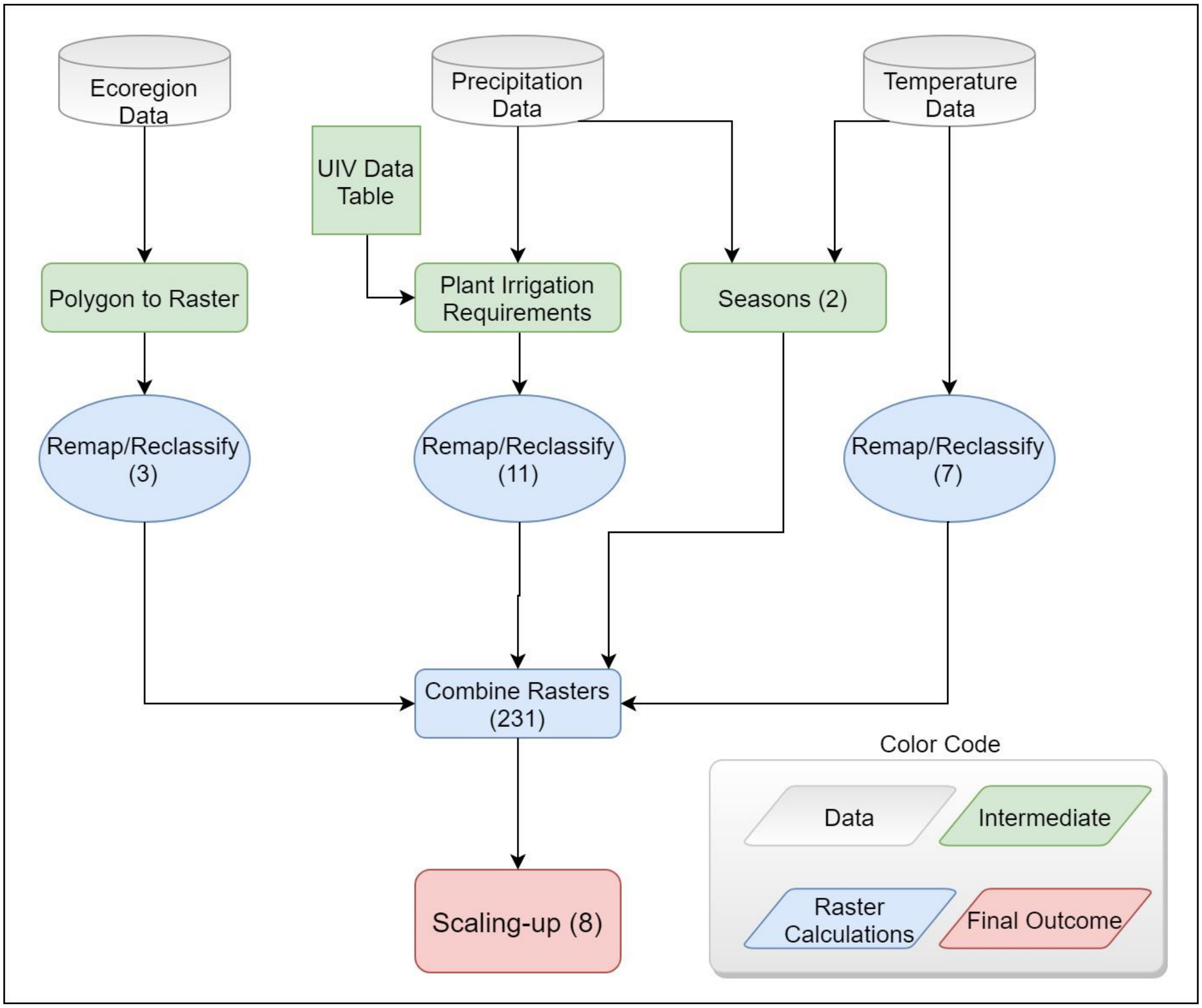

Figure 3.3 Flowchart of the process of scaling-up MicroVeg results

Seasonal variability is one of the most constraining variables affecting food security in SSA. For the scaling-up model, each season was analyzed independently. The research sites were used as a reference to obtain the average precipitation, and temperature values were extracted from ArcGIS and utilized as the scaling-up model's thresholds. Using ArcGIS, the precipitation and temperature data was reclassified into categories, instead of the absolute values. These categories are used to visualize the differences between the two seasons. The scaling-up model utilized the categorical data, and further refined it into smaller classes, using the "remap/reclassify" function within ArcGIS. The temperature data was reclassified into seven classes; precipitation was reclassified into 11 categories. For temperature, the remapped value of five represented the mean average value of all three research sites. Although not directly used, precipitation was the function of irrigation requirements less the precipitation value. The irrigation data was both plant and ecoregion-specific, achieved by using the agronomic data. The value shows how much of the total amount of supplemental water is needed to achieve optimal water supply. Based on the agronomic data, each research site had to be visualized differently on a map. Therefore, the model needed to retrieve the correct value from the model.

By combining the remapped precipitation and temperature data to the ecoregion layers, the resulting data had 231 possible combinations. Each variable was classified using a different base ten value. Precipitation was a value in % multiplied by ten, with a max value of 1,000, and the temperature was a remapped value multiplied by 10, with a max value of 100.

Ecoregions were assigned a base ten value of one, with a max value of three. Even though ecoregions were assigned a value, the data was selected based on the ecoregion values, creating three separate layers. After clipping the appropriate crops and ecoregions together, the resulting data layers were combined into one map. The resulting data is a series of eight individual maps. Figure 3.4 shows the results of four out of the eight output maps, amaranth and solanum over both seasons.

3.5 Results and Discussion

By utilizing all the players within the value chain, MicroVeg focused on developing and implementing solutions to alleviate food insecurity. Each research site had specific goals; the three chosen research sites reported optimal water usage data and yield potentials of each UIV.

The scaling-up model used a series of steps to create figures that contained the computed inference space of each UIV within each season. Cells that are illuminated in the figure were calculated to resemble the conditions of the research site. The research sites used for scaling-up were Ina, Ogbomosho South, and Ife Central. The latter two sites were a generalization of a cluster of research sites.

Water availability was identified as the most limiting climatic variable. Using the optimal water usage, from the agronomic report, the model used a buffer of 10% for each UIV at each research site. This buffer is a theoretical value of the UIV's ability to tolerate additional water and/or short-term droughts, which may occur during the growing season. This buffer can be modified in the model, by selecting different classes of data. Table 3.3 describes the scaling-up potential, which suggests that the four UIVs can be expanded within country boundaries. The resulting maps from the model included each UIVs scaling-up potential in both seasons. Treating each season individually illustrates how crucial water availability is for certain UIVs.

In total, MicroVeg research sites have an approximate area of 50 ha. In Benin and Nigeria, farmers are growing UIVs on an average of less than 0.02 ha and on plots that are 6 m^2 (Adebooye et al. 2018). Each cell is assumed to be 1 km^2, the same as the inputted climate data. Based on the model, the scaling-up potential of each UIV exceeds 100,000 cells. Scaling-up potential does not imply that large Western-style commercial agriculture should occur, but rather that current farmers within the mapped areas should see results comparable to the research sites, as this is how the model has predicted the area. The dry season is expected to have a lower scaling-up potential compared to the wet season, but the UIV with the highest dry season potential is amaranth with 325,506 cells. Amaranth and solanum have the same potential for growth in the wet season, with 355,756 cells.

Table 3.3 Total potential area (in km^2) for scaling-up amaranth, solanum, parsley, and fluted pumpkin

	Amaranth		Fluted Pumpkin		Parsley		Solanum	
	Dry[1]	Wet[2]	Dry[1]	Wet[2]	Dry[1]	Wet[2]	Dry[1]	Wet[2]
Benin	76,812	73,456	-	16,113	76,812	57,343	76,812	73,456
Nigeria	248,694	282,300	120,557	207,515	115,674	82,649	179,158	282,300
Total	325,506	355,756	120,557	223,628	192,486	139,992	255,970	355,756

[1]Dry season - November to February.

[2]Wet season - March to October.

The potential for scaling-up was calculated based on the optimum water requirements of each UIV in the respected ecoregion. For the savanna and sudano savanna, this was interpreted as an irrigation requirement. Since the rainforest receives sufficient rainfall, no irrigation was needed. The results of the scaling-up analysis favour development during the wet season, but it is also clear that substantial expansion of UIV's can occur in the dry season. The results also suggest that even though the plants yield more when fertilizer is applied via microdosing, access to sufficient water will likely limit agriculture during the dry season.

In contrast, there is also a threshold where too much water, either within a period or over a season, is detrimental to vegetable production. The 10% buffer, from the optimal value, was used to be inclusive of areas that may have more access to water or slightly drier or wetter than the research site. Additional factors, such as limitations to accessing fertilizer or land, may need to be taken into consideration before proposing scaling-up at a specific location.

Due to local preference, not all UIVs were grown in all regions; this limits the predictive power of our scaling-up model for some crops. For example, at the scaling-up research sites, parsley was only grown in the sudano-savanna. Data for parsley was only available at the Ina research site.

The outputted values of the model represent the total count of cells. The total cell count for parsley was 192,486 and 139,992 for the dry and wet season, respectively. Restrictions in the model are the causation for a decreased scaling-up potential in the wet season.

The scaling-up potential for fluted pumpkin was also limited by the model, with the data being limited to the savanna and rainforest ecoregions. The potential scaling-up area for fluted pumpkin is 120,557 and 22,3628 cells, in the dry and wet season, respectively. This increase in potential growth can be attributed to Nigeria, where the area increased by 86,958 cells in the wet season compared to the dry season. The potential area for both seasons extends to the north and east portions of the Nigerian research sites. Because of geopolitical conflicts, these lands have not been explored within the project. Another scaling-up potential for fluted pumpkin comes from potential lands meeting the criteria during the wet season in the Benin Republic, which accounts for 16,113 cells (data is available online at www.microveg.ca).

Amaranth and solanum are popular UIVs within the Benin Republic and Nigeria, and their scaling-up potential is significantly more significant than either parsley or fluted pumpkin. During the dry season, potential growth for amaranth and solanum are, respectively 325,506 and 255,970 cells, or km^2. In the wet season, amaranth and solanum have the same potential growth, at 355,756. Figure 3.4 illustrates the estimated areas for scaling-up of amaranth and solanum for the dry season and wet season. Currently, the research sites are clustered in the south-west portion of Nigeria and the southern portion of the Benin Republic. Both amaranth and solanum have a high scaling-up potential in the central and eastern parts of Nigeria, which are outside the intervention zone of our project but important regions of Nigerian agricultural productivity. Our model also suggests a more northern expansion could occur with amaranth, suggesting that additional countries in sub-Saharan Africa may benefit from the adoption of MicroVeg practices for amaranth. Scaling-up of solanum might be most productive along the southern coast of Africa, where water is not as limiting.

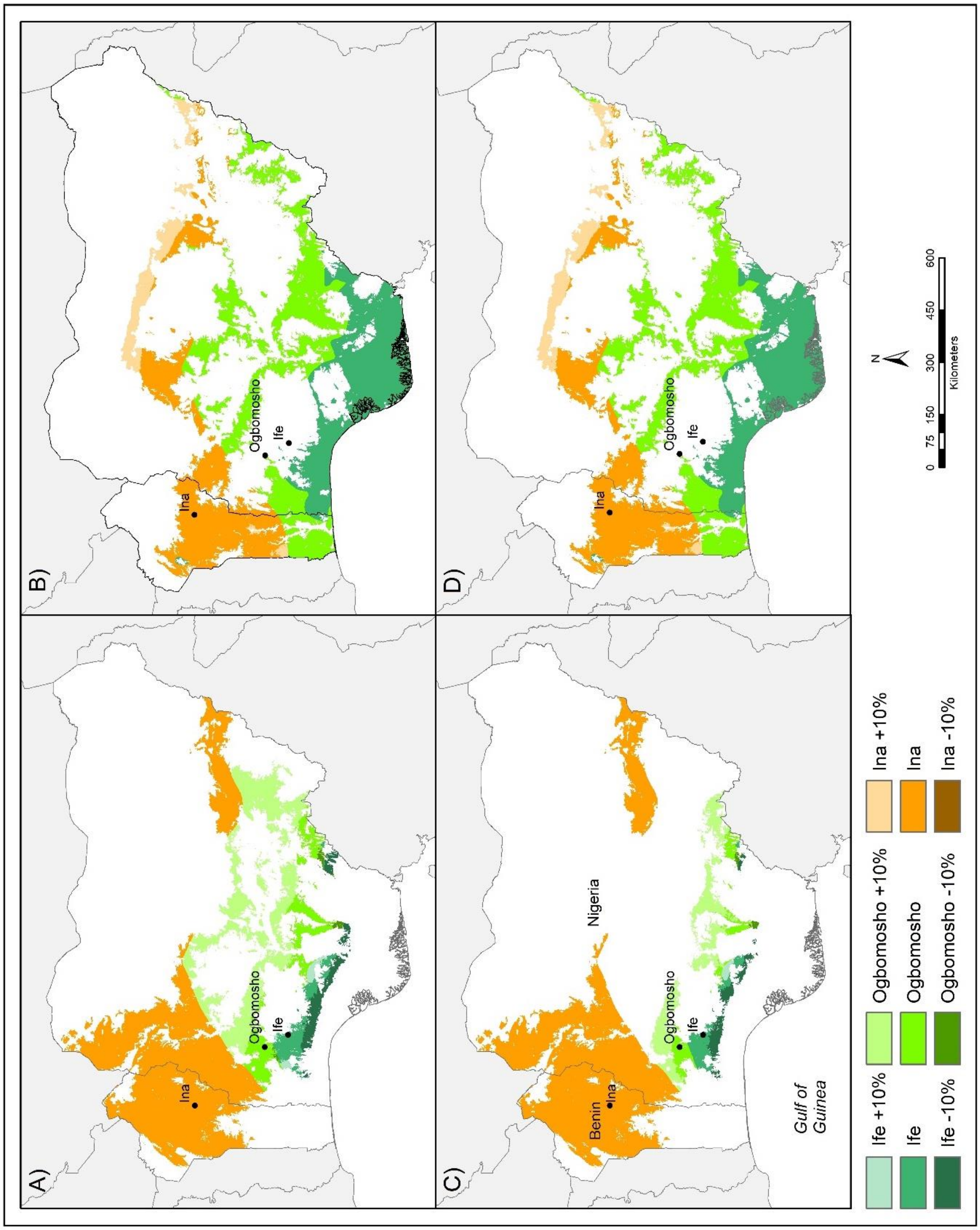

Figure 3.4 Scaling-up potential of amaranth (A and B) and solanum (C and D) for dry and wet seasons, respectively.

Elevation and soil type were considered as output variables for scaling-up but were omitted due to small variations in these factors. This is consistent with the work of Jones *et al*. (2013) who concluded, at a scale of 1: 3,000,000, the regions where our project's research occurred are relatively uniform. However, elevation and soil classification might also need to be taken into consideration in eastern Nigeria, where the sites may have different responses than the scaling-up research sites. Regionally, the soils vary considerably, and more information needs to be obtained to validate the relationship between soil classification, UIV yields, and effective water usage for eastern Nigeria. Elevation and slope are other variables that can be used to determine atmospheric limitations. A slope that is too steep can cause severe erosion and water degradation, which significantly increases the risk to farmers and would negate any progress in improving food security. The slope was omitted from our model because the data available at the time of analysis was too coarse. With a resolution of 1 km^2, this digital elevation model (DEM) did not show any variation within the region, except along the southeast Nigerian border. A finer resolution DEM may be able to improve the model. An acceptable satellite mission may be the STRM, which has a cell size of $30m^2$ (U.S. Department of the Interior 2015).

3.5.1 Disseminating Microveg with GIS

Scaling-up cannot be achieved without a means of disseminating necessary data to the various groups involved. A Web-based GIS database, WebGIS, was developed to help disseminate project data. The WebGIS database was developed with the help of the Social Sciences Research Laboratories (SSRL), University of Saskatchewan and is hosted at http://www.microveg.ca. Traditional GIS databases have many drawbacks, including file size, software requirements and literacy, high cost of software licensing, and reliable internet access to maintain the databases. Our WebGIS database overcomes all of these limitations. WebGIS databases are not new, but at the time of conception, this was the only known open-sourced database for a research project to combine several international data sources for a food security project. Our WebGIS combines 16 unique layers of GIS data into one interface. Together, these layers create an interactive tool for assistance in UIV production.

Our WebGIS database contains three unique interfaces: homepage, map database, and profit calculator. The homepage is a source of project information, resources, and printable maps.

The map interface uses ArcGIS Server and ArcGIS API for Javascript, to present multiple layers of data interactively, by allowing users to click and change information. Our map interface allows for various tools to be viewed, similar to ESRI's ArcGIS interface. An extensive list of options was created by Zeng *et al*. (2017). Upon clicking on a particular point, users are shown a detailed list of data, presented in a “data viewer.” This data viewer, figure 3.5, dynamically updates whenever the user changes the location.

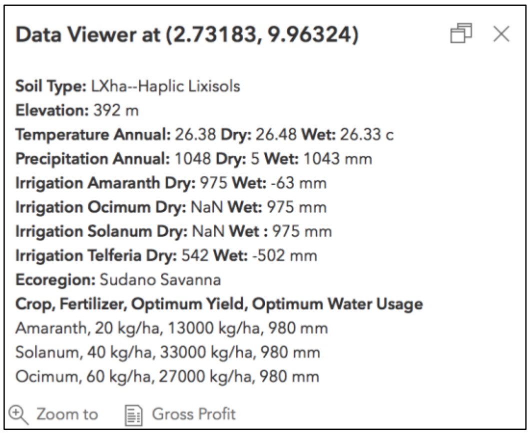

Figure 3.5 Sample View of the WebGIS data viewer

As an extension tool, we created a gross profit calculator as a way to utilize the data viewer for NGOs, extension agents, and farmers. This calculator allows farmers to compare their current practices with the MicroVeg agronomic approach. Associated with this tabular data, we implemented a Gross Profit Calculator, figure 3.6. This profit calculator allows for site-specific assessment of the fertilizer microdosing technique (Akponikpe et al. 2016). The Gross Profit Calculator allows farmers or NGOs to input their data to see how much potential gains they can receive by adopting the MicroVeg agronomic package.

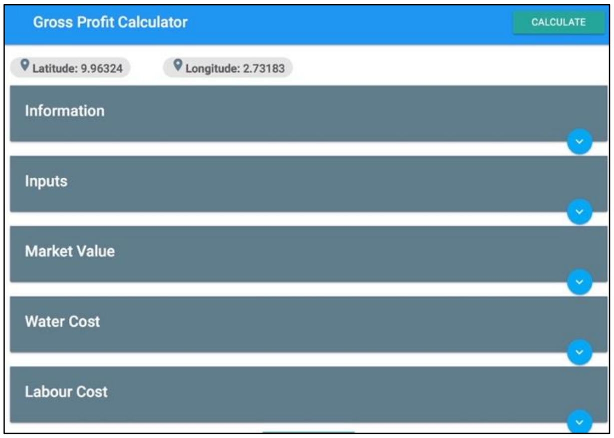

Figure 3.6 Screenshot of the gross profit calculator interface

3.6 Conclusion

Developing a GIS database with agronomic trial data was the primary objective of scaling-up within the MicroVeg agronomic package; however, the WebGIS database also facilitated our scaling-up process by making the results useful for a wider audience. Not a lot of scaling-up research focuses on dissemination approaches and reaching new users. Finding new lands to grow crops and applying the scaling-up approaches is an inevitable requirement of scaling-up, but it is typically not a data-driven process. We demonstrated that GIS provides a means to understand landscape level relationships for a development project and GIS can also serve as a medium for scaling-up discussions. As an example, the MicroVeg project focused their project on four UIVs in a targeted region of the Benin Republic and Nigeria due to constraints of time and resources. Based purely on climatic variables, however, each UIV has the potential to be grown in over 100,000 cells, and the most significant area is 355,756 cells (1 cell = 1km^2). To more readily share GIS results and disseminate our project's findings on the Web, our WebGIS system includes downloadable resources, a map interface, and a profit calculator. Both GIS and WebGIS programs are limited only by the available data and the knowledge of the users and GIS programmers. These results suggest that data-driven GIS approaches can be an essential tool to address food insecurity for farmers not only in Sub Saharan Africa but also worldwide.

3.7 Addendum

Grammatical changes, including the restructuring of some sections, and reformatting have occurred since the date of submission.

4 METHODOLOGY FOR CREATING 1KM^2 RESOLUTION MODEL FOR CLIMATE CHANGE IN WEST AFRICA BASED ON IPCC RPC 4.5 AND 8.5

4.1 Preface[2]

Climate change will continue to be a complex issue to both understand and mitigate. The complexity increases as we understand how food security and economics are connected to climate change. Tools for discussing and disseminating information are vital to alleviating hardships caused by climate change and food insecurities. Using GIS, the following manuscript developed a new set of tools for researchers in West Africa to understand, mitigate and plan for the uncertainties of climate change.

4.2 Abstract

Climate modelling is becoming more accessible due to improvements in the availability of data and conceptual approaches from organizations such as the IPCC; it is now feasible to integrate climate modelling with practical research questions including food insecurity in developing countries. Large-scale climate models, such as IPCC models, are not particularly useful to a farmer who is facing food insecurities at a local scale; instead, the development of a fine-resolution climate model would provide more useful data and information to farmers. These fine-resolution climate models are not common throughout Africa due to a lack of investment and training. By using pre-existing agronomic and climatic data, we developed a fine-resolution model that relies on globally acquired data. The objective of this paper is to describe the newly conceptualized model. The outputs of this model are available for multiple disciplines to assess the likely outcomes of crop development under a changing climate. Furthermore, the model should be utilized as a means to disseminate climate and crop data, and as a multi-disciplinary communication tool to improve land management strategies.

[2] Manuscript will be submitted to an academic journal (TBD) for publishing during thesis review process. Coauthors include D. Peak (provided financial assistance, and feedback), O. C. Adebooye (Principal Investigator of MicroVeg project, Nigeria research team), P.B. Irenikatche Akponikpe (Principal Investigator of MicroVeg project, the Benin Republic research team).

4.3 **Introduction**

Climate modelling is becoming a common research practice, but at the continental scale, Africa has significant portions which are not mapped using high-resolution methodologies. Some countries, however, have invested in technologies that make such mapping possible. Sub-Saharan Africa, including the Benin Republic and Nigeria, is one of the regions for which high-resolution climate data does not exist.

To obtain high-resolution climate data for SSA, the use of a GCM is imperative. GCMs are large-scaled, coarse models used to model global trends. One of the most prominent proponents of GCMs is the IPCC. The first IPCC report was published in 1990, and since then both the available data and the resolutions continue to improve, by decreasing the cell size, which the model assesses. The most recent report by the IPCC was the AR5. In this report Representative Concentration Pathways (RCPs) were used to illustrate probable futures. This report created four RCPs: RCP 2.6, 4.5, 6 and 8.5.

A countless number of models exist, which model various food security elements, but none illustrate the importance of the IPCC scenarios. Literature has noted the potential importance of RCP 2.6, 4.5 and 8.5 regarding both climate factors and food production. RCP 2.6 is the driving force behind large-scale intergovernmental agreements (Paris Agreement); RCP 8.5 would represent a catastrophic societal failure; RCP 4.5 is a key intermittent model. RCP 4.5 is also suggested to be our current societies most likely scenario (IPCC 2014; Adeniyi 2016)

High-resolution climate models exist, known as RCMs. These models operate under strict spatial rules and operate at a significantly higher spatial resolution compared to CGMs (Larsen et al. 2013). RCMs can be useful tools for creating a food security model under climate change but become more data-intensive the broader the spatial extent, and the resolution of data used.

Primarily because of data availability, most published models use GCMs. However, for a food security study, using an RCM would prove more useful because of the finer details available in the data. Currently, no RCM exists over the region of the Benin Republic and Nigeria. Therefore, the objective of this paper is to create a methodology for a high-resolution climate model that resembles an RCM using globally acquired data. The model will predict climate until the end of the 21st century and hopefully will help in understanding if a temporal trend is occurring. The goal of the paper is for the outputted model to serve as a communication tool to help alleviate food insecurity for SSA.

4.4 Methods

The literature on how climate models, whether GCM or RCM, are developed is sparse; particularly when it comes to the methodologies used. Additionally, no literature was found which bridges GCMs and RCMs as complementary entities in the SSA region. To evaluate the effects on time and climate change scenario on the region, we required that the model be versatile and easy to run multiple times with variation in input parameters. ArcGIS was the primary tool used for data management and manipulation. However, to ensure that the inputs and parameters of the model were consistent between each iteration, scripts using Python 2.7 were created. The package of python scripts is known as Scaling Agronomic Vegetable Innovations to Nurture Growth Sustainably model (SAVINGS); the full script is available in APPENDIX B.

SAVINGS is a continuation of Scaling-up model proposed by Minielly et al. (2018). SAVINGS was designed to be executed externally from ArcGIS to optimize computer processing power. However, subsets of the model can be executed within ArcGIS, via the python window. All calculations and data creation utilized the python scripts, ensuring replicability. Development of the tools and scripts was run within ArcGIS then replicated in python. Figure 4.1 shows how SAVINGS is structured and organized.

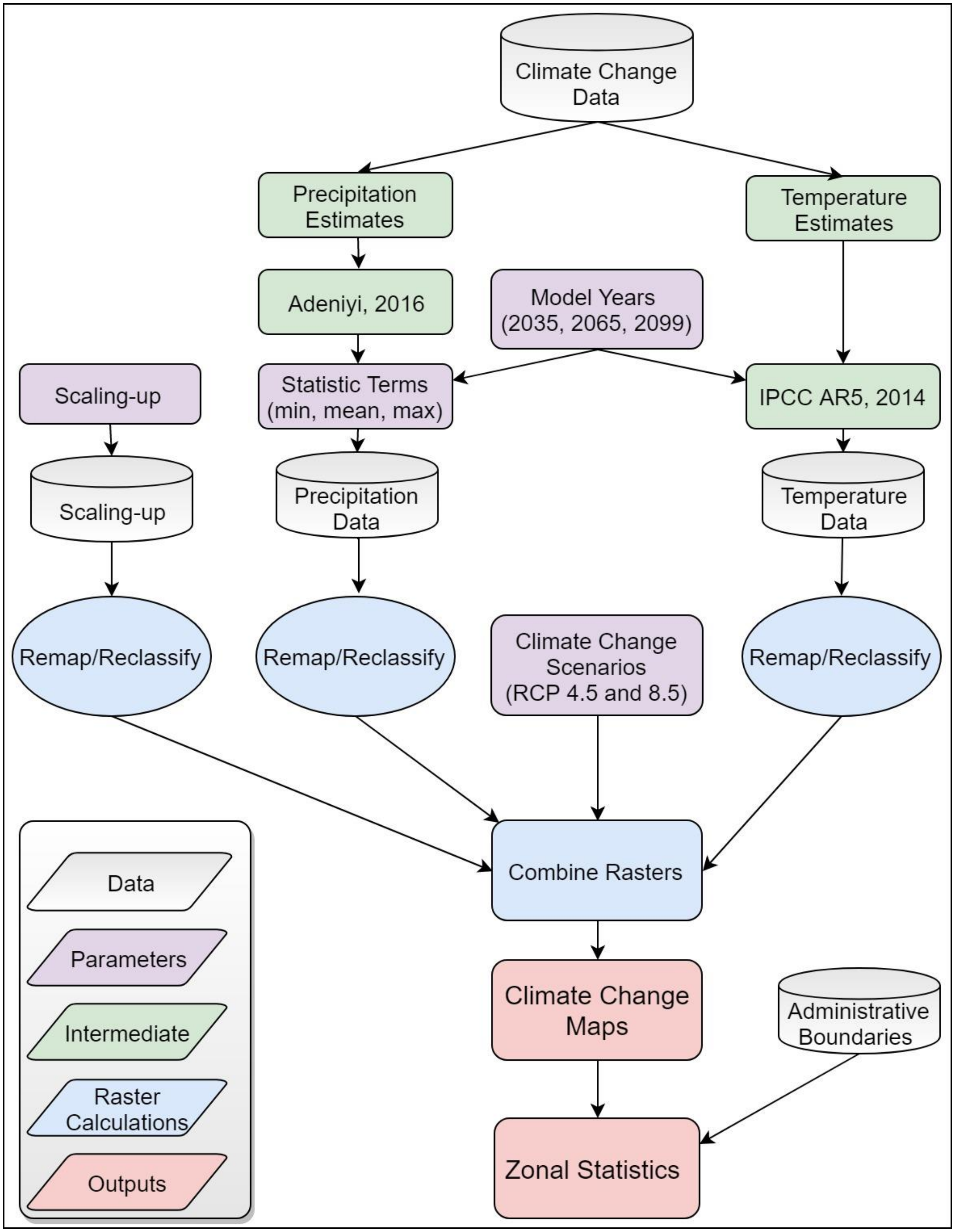

Figure 4.1 Simplified methodology for climate research

Determining the parameters was the first step in running the SAVINGS model. As a parameter, scaling-up refers to the input and output data from Minielly et al. (2018). Table 4.1 summarizes the parameters used in the scaling-up model originally published in Minielly et al. (2018). This model was built on agronomic data provided by (Akponikpe et al. 2016). Both the water and temperature needs are plant and research site specific. The next parameter to determine was the years for which to run the model. The scaling-up model was built on climate data from the year 2000; SAVINGS added the years 2035, 2065, and 2099. For the end of the 21st century the year 2099 is used. The chosen years were also reporting years for IPCC (2014) and Adeniyi (2016), though additional years could be used. The final parameter to determine, prior to running the model, is the climate change scenarios to be used; we used IPCC (2014) RCP 4.5 and 8.5, based on data availability.

Table 4.1 Parameters used for SAVINGS model.

Site Name	UIV	Water Needed mm	Temperature °C
	amaranth	209	26.3
Ife	solanum	157	26.3
	fluted pumpkin	174	26.3
	amaranth	430	26.5
Ogbomosho	solanum	303	26.5
	fluted pumpkin	544	26.5
	amaranth	980	26.5
Ina	solanum	980	26.5
	fluted pumpkin	980	26.5

The second step to executing SAVINGS is preparing the data. Outputs of the scaling-up model, described by Minielly et al. (2018) served as the foundation for the SAVINGS model. Precipitation, temperature, ecoregions, and MicroVeg agronomic data were all used in SAVINGS. Data that pertained to climate change, precipitation, and temperature, originated from two sources, Adeniyi (2016) and IPCC (2014).

Adeniyi (2016) analyzed projected precipitation rates over West Africa for the years 2035, 2065 and 2099. The published data makes projections for both RCP 4.5 and RCP 8.5. To run their model, Adeniyi (2016) delineated the region into five regions, which were not synonymous with the ecoregion layers. This inconsistency, shown in figure 4.1 as an intermediate step, required additional processing to occur before the data could be incorporated into SAVINGS. Figure 4.1 also illustrates that Adeniyi (2016) also contained statistical data as a parameter. The analysis of the precipitation data yielded multiple statistical parameters, and it was determined that the minimum, maximum, and mean values would be run within SAVINGS.

With medium confidence, IPCC (2014) published projections for temperature. The values presented by IPCC (2014) are global estimates but are the highest calibre of data available for SSA. The temperature had an intermediate step, in figure 4.1, which included populating tabular data from the IPCC reports into a structure that was readable by SAVINGS.

After the intermediate steps were completed, the data from IPCC (2014) and Adeniyi (2016) data were converted from their respected reports into datasets to be used by SAVINGS, shown in figure 4.1 as grey cylindrical data sections. Included in the data section is administrative boundaries, which allows for statistics to be run based on a polygon. For this assessment, we used the third level of administrative boundaries.

The next step in figure 4.1 is to run a series of raster calculations, illustrated as blue ellipses. A raster calculation, in its purest form, is a mathematical formula executed upon a specific cell, or pixel, in a dataset. The first raster calculation required, converting Adeniyi (2016) data from a polygon to a raster. After taking the precipitation and temperature data from Minielly et al. (2018), the respected climate change data was added to create the data for the model. Once the data was combined, via the SAVINGS model, the data was remapped and reclassified as needed to illustrate the areas of concern. Remapping the data allowed for discrete numbers to be turned into classes of data. The classes were defined by using the agronomic data from Minielly et al. (2018). The classes for precipitation ranged from 10 – 100, increasing by 10. Precipitation values represent the percentage of rainfall based on the case study site of that ecoregion and determined by equation 4.1. Water needed to be was derived from the agronomic data. SAVINGS ran this calculation for each UIV and each season.

Equation 4.1 Function to determine the amount of irrigation required for each case UIV. Data originally reported in (Akponikpe et al. 2016). Values recorded as percentages

$$Value = \frac{water\ needed - precipiation}{water\ needed} * 100$$

Classes for temperature ranged from 1 - 7, increasing by one. The ideal temperature range for the UIVs, as determined by the agronomic data, is 24 - 26°C, this range was remapped to class 5. Ecoregion data was remapped by Minielly et al. (2018), the classes used range from 1,000 – 3,000 increasing by 1,000. All the remap values were then reclassified based on UIV and season. Data that was not within the accepted range was automatically set as null. By setting the data to null removes all other classes of data, only leaving the accepted classes.

The fourth step of SAVINGS is to combine all the parameters. The reclassified values for temperature and precipitation were used and combined with appropriate ecoregion and agronomic data. Additionally, the climate change scenarios, RCP 4.5 and 8.5, are introduced into the outputted data. To allow for the climate change scenarios to be used, data is extracted from tabular versions of precipitation and temperature. SAVINGS differentiates between the climate scenarios. This process selects the correct precipitation, temperature, ecoregions, and UIV in accordance to the RCP and time series. This combine function outputted 144 unique maps. These output maps, step five, show how each UIV may respond to a climate scenario at a specific time and during a specific season. Included in the output maps are statistical values for mean, minimum and maximum. Only mean values are used, reducing the number of outputs to 48 maps.

The final step of the model was to run zonal statistics. By overlaying the administrative boundaries at the commune and state boundaries for the Benin Republic and Nigeria, respectively, SAVINGS extracted the number of cells contained within the administrative boundaries. By using the data from the combining step, each UIV, climate change year, and climate scenario are present. The resulting data is saved as a table and can be viewed and manipulated within various software programs.

4.5 Results

The maps that resulted from the SAVINGS model use data from the three research sites and a +/-10% buffer of the sites to create an inference space, that resembles the outputs from Minielly et al. (2018). Thus, the areas illustrated are regions where scaling-up most likely will succeed, strictly based on the climatic variables of the research sites. By using research data, SAVINGS extrapolated data into 2100. Using the current agronomic data, from 2015, the estimates from 2035 onward become less confident, as illustrated by a decrease in mapped areas. Areas outside of the range can still grow the UIVs at the discretion of farmers. However, this land is not favourable for Scaling-up as is not expected to be as profitable and may incur additional costs such as fertilizer, labour, and water.

By combing the input constants, SAVINGS outputted 144 maps based on three statistical terms, four UIVs, two seasons, two climate change scenarios, and three years. Each of the input variables is viewable within GIS software. Ecoregion and agronomic data were crucial variables for understanding the output maps. The agronomic data was used to determine the optimal growing conditions based upon respective scaling-up research site. Each scaling-up research site was contained within a different ecoregion (Adebooye et al. 2018).

By using a case study approach, the resulting data represents the most likely outcome for scaling-up to occur until 2100 at each of the research sites. By using the scaling-up research sites directly, each output map would contain a maximum of three values, each value corresponding to the respective site for the ecoregion. By applying a 10% variation to each research site, this creates a larger inference space. Water is the most limiting resource for these crops to grow; therefore, 10% buffer was added or subtracted from the remapped precipitation values. The buffer is a parameter within the model that can be modified. For example, the average remapped precipitation value for Ife was 50, adding the inference area allowed us to view 40 and 60 classes. This larger inference space represents a buffer for the optimal growing conditions of each UIV, allowing for more realistic estimates.

By assessing each UIV independently from season and RCP, the research years show a decreasing trend in arable land, suited to sustain each UIV. By using the tabular data created during the zonal statistics, the trend for amaranth, as an example, can be viewed under any combination of season, years or RCP. The tabular data, also allows for specific regions to be reviewed, at all three administrative boundaries, as described by Hijmans et al. (2012).

SAVINGS operated at a resolution of 30 arc seconds, and in literature, this equates to 1km^2, at the equator. The output from zonal statistics considers the total cells within a polygon. These cells, which represent 1 km^2, will be referred to as the scaling-up potential. By viewing the zonal statistic tables at the country level, table 4.2 and 4.3 illustrate how each UIV responded to the SAVINGS model.

Table 4.2 Climate change scenarios for Benin Republic research for amaranth, parsley, solanum, and fluted pumpkin, shown values represent cells (km^2)

		RCP 4.5				RCP8.5			
		2000†	2035	2065	2099	2000†	2035	2065	2099
Amaranth	Wet	73,456	20,443	206	10	73,456	20,443	3	-
	Dry	76,812	14,063	-	-	76,812	14,063	-	-
Parsley	Wet	57,343	18,764	134	6	57,343	18,764	-	-
	Dry	76,812	-	-	-	76,812	13	-	-
Solanum	Wet	73,456	20,443	206	10	73,456	20,443	3	-
	Dry	76,812	14,063	-	0	76,812	14,063	-	-
Fluted Pumpkin	Wet	16,113	1,679	72	4	16,113	1,679	3	-
	Dry	-	-	-	-	-	-	-	-

†The year 2000 represents the current maximum extent for scaling-up. Derived from the 1970-2000 climate normal. Originally published in Minielly et al. (2018)

Table 4.3 Climate Change scenarios for Nigeria research for amaranth, parsley, solanum, and fluted pumpkin, shown values represent cells (km^2)

		RCP 4.5				RCP8.5			
		2000[†]	2035	2065	2099	2000[†]	2035	2065	2099
Amaranth	Wet	282,300	232,684	87,819	50,040	282,300	232,903	40,315	7,018
	Dry	248,694	172,692	152,074	166,775	248,694	172,955	172,263	76,531
Parsley	Wet	82,649	63,404	24,973	11,764	82,649	63,623	9,065	34
	Dry	115,674	-	-	-	115,674	-	-	-
Solanum	Wet	282,300	232,684	87,819	50,040	282,300	232,903	40,315	7,018
	Dry	179,158	144,767	130,995	151,809	179,158	143,861	161,203	70,495
Fluted Pumpkin	Wet	207,515	169,280	62,846	38,276	207,515	169,280	31,250	6,984
	Dry	120,557	72,639	41,948	27,429	120,557	72,374	21,698	6,550

[†]The year 2000 represents the current maximum extent for scaling-up. Derived from the 1970-2000 climate normal. Published initially in Minielly et al. (2018).

The scaling-up potential of MicroVeg agronomic recommendations for the Benin Republic, across all UIVs, was significantly lower than compared to Nigeria, based on the total number of cells within MicroVeg, Benin Republics scaling-up potential was 20 and 26% of the MicroVeg total, for the wet and dry season respectively. When tables 4.3 and 4.4 are compared to each other, SAVINGS predicts that by 2035, the Benin Republic will only contribute to 8 and 7%, wet and dry season respectively, of the regions scaling-up potential. This decrease is modelled to be the same for RCP 4.5 and 8.5.

After 2035, the scaling-up potential for the Benin Republic becomes negligible, based solely on cell count. For the Benin Republic, SAVINGS predicts that under RCP 4.5, in 2065 the wet season will have 618 cells, or 618 km^2, which are acceptable for growing the UIVs; while 2099 will have 30 cells. The scaling-up the potential for the Benin Republic in the dry season is modelled to be zero cells, after 2035. Under RCP 8.5 the total cell count for the Benin Republic decreases to zero after 2035 regardless of season, except 2065 where the modelled cell count is six.

SAVINGS is showing a preference for Scaling-up to occur in Nigeria. SAVINGS shows that Nigeria will be affected by climate change. Since Nigeria is more abundant in the area, more climate variability allows for the modelled output to move through the country. Nonetheless, Table 4.3 shows how the total cell count decreases over time. Summing all UIVs per season, current potential for Nigeria is 854,764 and 664,083 cells, for wet and dry season respectively. RCP 4.5 is expected to yield a milder climate by 2100, compared to RCP 8.5. The total scaling-up area under RCP 4.5 is modelled to decrease to 18% of the current scaling-up potential by 2099. The same scenario for RCP 8.5 is modelled to see a decrease to 2% of the current scaling-up potential.

In contrast, the dry season is modelled to decrease to 52 and 23% of the current potential, for RCP 4.5 and 8.5 respectively. For RCP 4.5, there is a slight increase in total cells from 2065 to 2099. The UIVs that are responsible for the shift are amaranth, solanum, and fluted pumpkin. The net changes in cell counts are 14,701, 20,814, -14,519, respectively from 2065 to 2099.

Total cell count, or total land, is expected to decrease by 2099. SAVINGS shows that each UIV will decrease at a different rate. Overall, the scaling-up potential in the wet season will decrease faster than the dry season. This decrease might be attributed to an excess in precipitation rather than a shortage (Adeniyi 2016). The decrease in 2099 for the wet season is modelled to be 150,150 (-86%) and 21,054 (-98%) cells for RCP 4.5 and 8.5, respectively. For the dry season, the decrease is modelled to be 34,6013 (-61%) and 15,3576 (-83%) for RCP 4.5 and 8.5, respectively.

SAVINGS does not only predict a decrease in total land area but suggests that the land that is meeting the criteria will move. As an example figures 4.2-4.5 belong to a series of maps outputs for amaranth. Each panel represents a year within the seasonal and climate modelled scenario. Amaranth was chosen as an example UIV, as it is abundant between both countries and widely consumed. The colours in this figure indicate three classes for each research site: the research site, +/- 10% precipitation. Each figure in the series shows the years 2000, 2035, 2065 and 2099. The year 2000 is the modelled output from Minielly et al. (2018). Figures 4.2 and 4.3 show the scaling-up potential for amaranth under RCP 4.5 for the dry season and wet season respectively. Figures 4.4 and 4.5 show how RCP 8.5 will impact amaranth differently for both the wet and dry seasons, respectively.

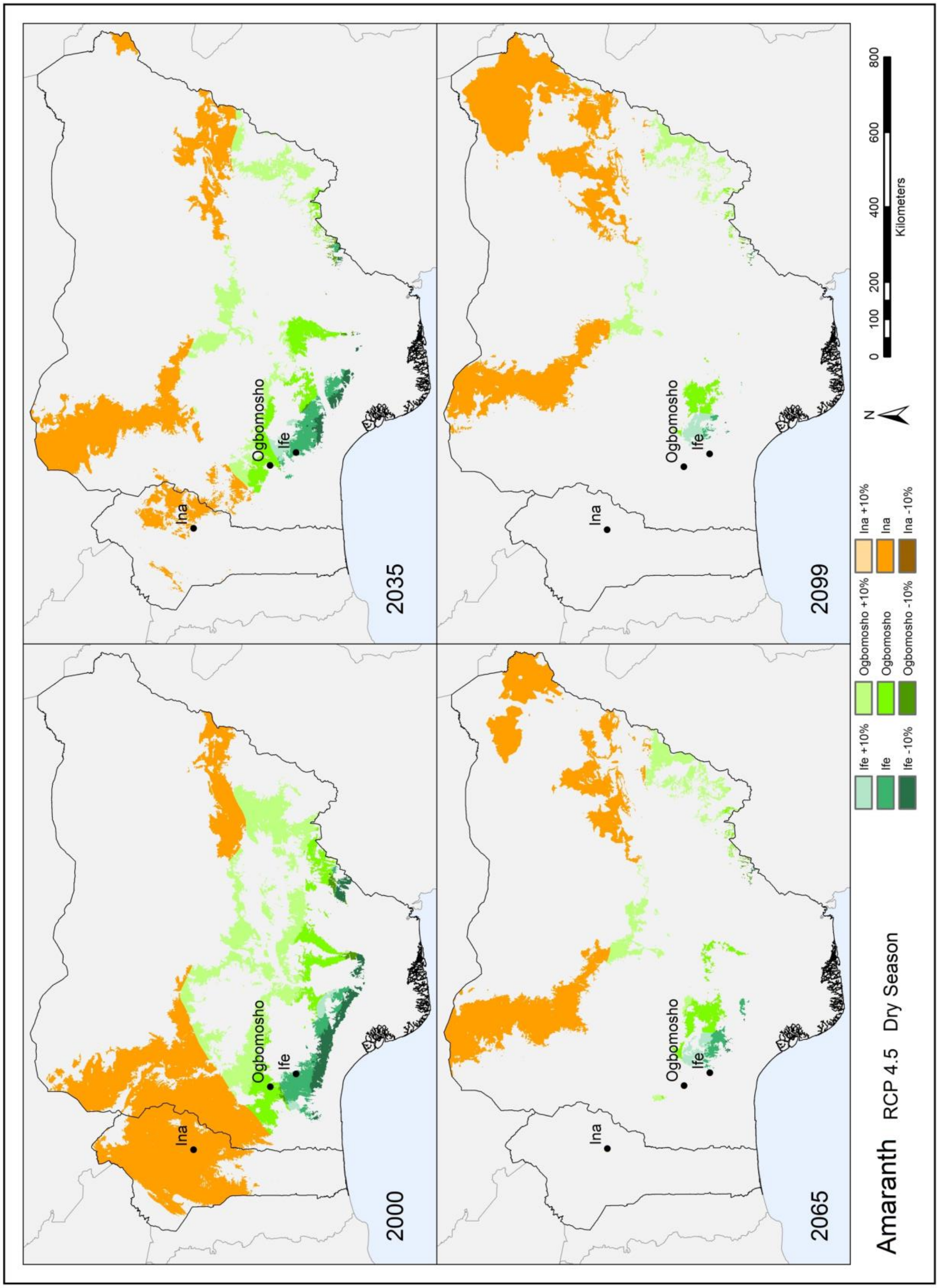

Figure 4.2 Dry season scaling-up potential of amaranth RCP 4.5

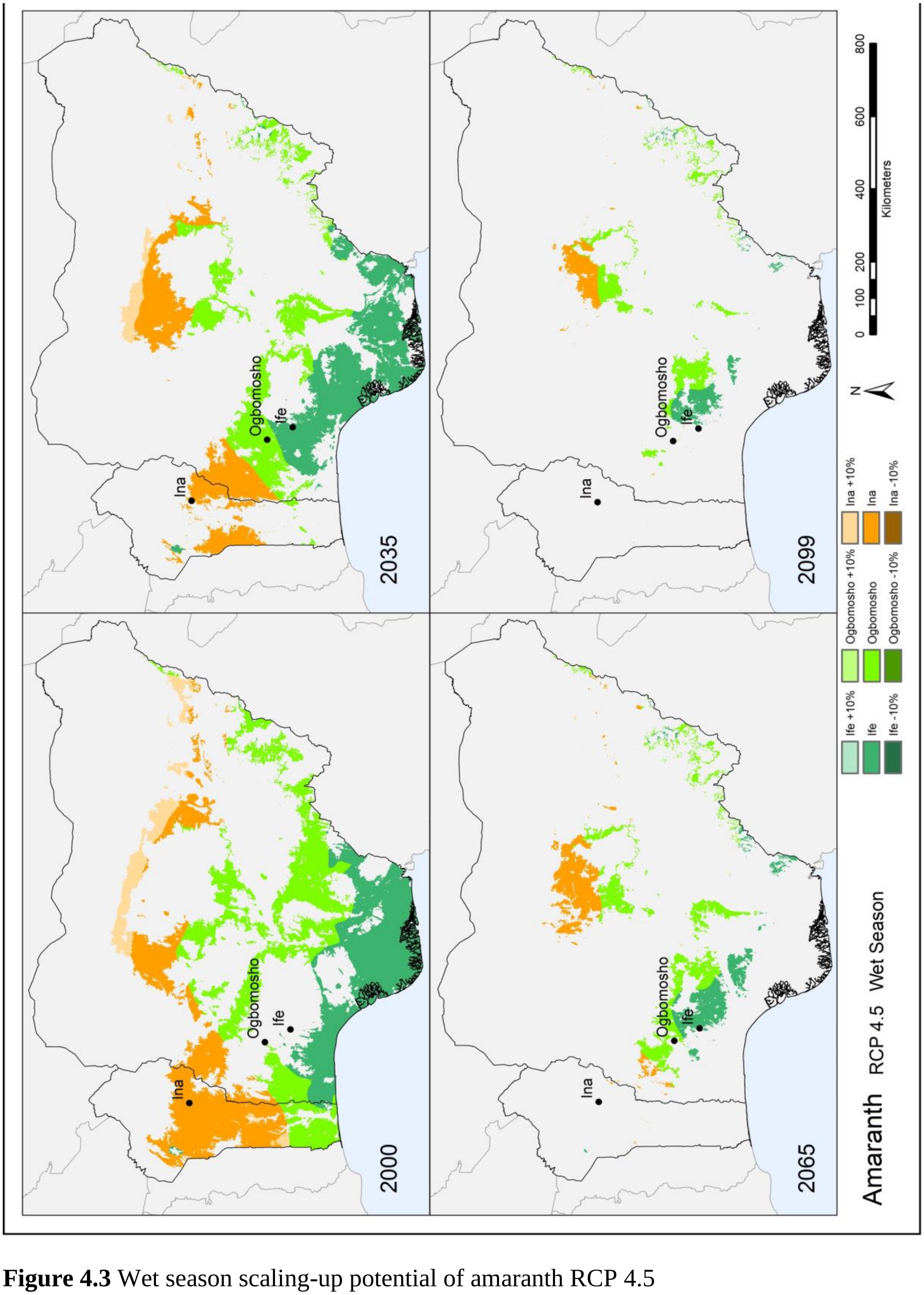

Figure 4.3 Wet season scaling-up potential of amaranth RCP 4.5

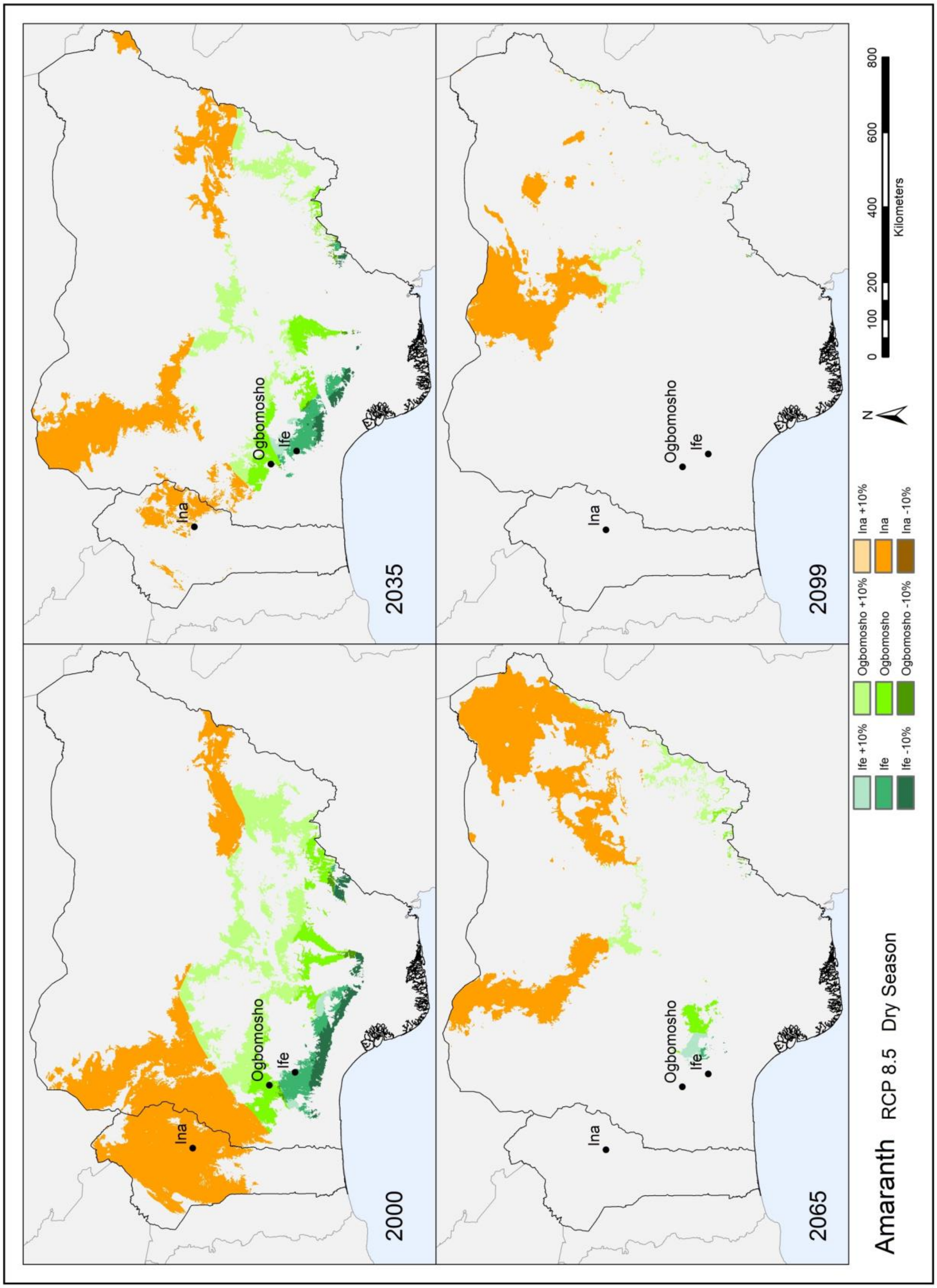

Figure 4.4 Dry season scaling-up potential of amaranth RCP 8.5

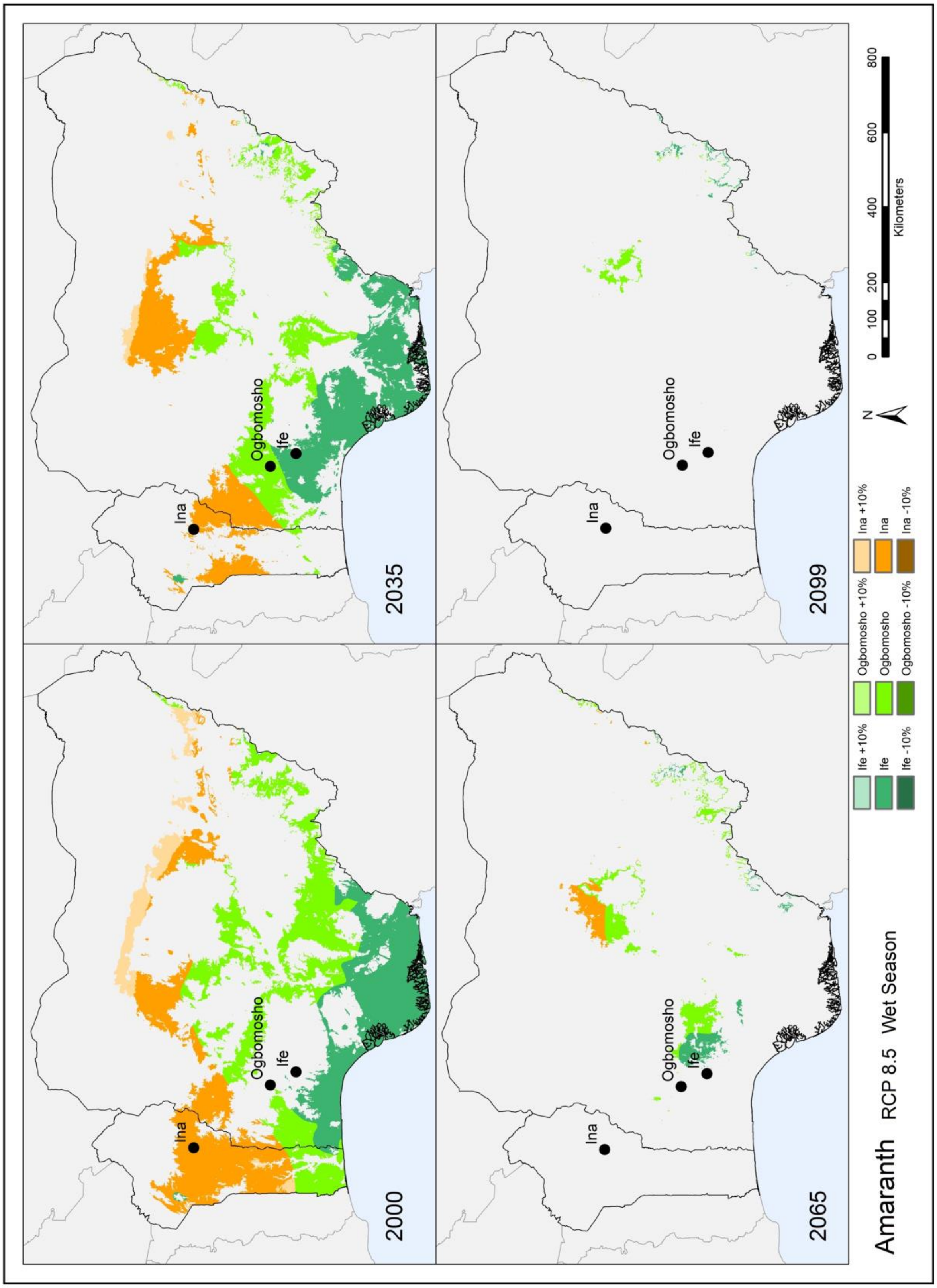

Figure 4.5 Wet Season Scaling-Up Potential of Amaranth RCP 8.5

All four figures in this series show a spatial shift in the location for ideal growing conditions for amaranth. Prominently, especially for the dry season, of both RCP 4.5 and 8.5 is a northeastern shift of the scaling-up potential. Current scaling-up potential of amaranth in the dry season is 325,506 cells. By 2099, dry seasons have been modelled to decrease to 166,775 (-49%) and 76,531 (-76%) cells, for RCP 4.5 and 8.5 respectively. Additionally, the dry season scaling-up potential for RCP 4.5 is modelled to have a noticeable shift by 2099. The modelled potential is along the shores of Lake Chad. This shift is present in RCP 8.5, but with drastically reduced potential.

SAVINGS has modelled the decrease to be more drastic in the wet season compared to the dry season for amaranth. The current modelled Scaling-up the potential for amaranth in the wet season is 355,756 cells. This is modelled to decrease by up to 50,050 (-86%) and 7,018 (-98%) cells, for RCP 4.5 and 8.5 respectively. SAVINGS is modelling the scaling-up potential shift for the wet season, similar to the dry season. Spatially, this shift is modelled to extend northeastward until 2065, where it will recede to the north-central part of Nigeria. This shift is apparent in both RCP 4.5 and 8.5.

Solanum has a similar scaling-up potential, with many of the cells overlapping with amaranth. Under both RCPs the dry seasons scaling-up potential is slightly lower than compared to amaranth, but the scaling-up potential is the same for the wet season.

The UIV that sees the most substantial decrease is parsley, with zero cells being modelled any time after 2035 for the dry season, for both RCPs. By 2099, wet season potential for parsley is reduced from 139,992 to 11,770, and 34 cells, for RCP 4.5 and 8.5 respectively.

Fluted pumpkin has been modelled to have a significant decrease by 2099. Under RCP 4.5 the modelled area will decrease by 77 and 83%, of its current scaling-up potential, for dry and wet seasons, respectively. Under RCP 8.5 this decrease is modelled to be 95 and 97%, for dry and wet seasons, respectively.

4.6 Discussion

Climate change will introduce new complexities within the agricultural sector, especially for farmers of West Africa. Combatting food insecurity requires research to occur and for the research to be scaled quickly and efficiently. The use of GIS allows for a scaling-up perspective not available by conventional measures. The GIS approach has incorporated climate models, which shows an estimate where research resources may be better spent and allow for an understanding of the possible duration by which land may remain viable for a particular UIV. This information can be related back to food security by reviewing the agronomy data. As the modeled areas diminish, communication on land tenure and crop management will become increasingly important. Vegetable crops, such as the UIVs, can be harvested multiple times within a season, strategies may need to be developed to enhance the amount harvested (in total or per harvest) or different varieties if other limitations are unfeasible.

The objective of this research was to develop a new tool for combatting food insecurity through knowledge dissemination, SAVINGS. Operating as a package of python scripts SAVINGS is a versatile tool that can consecutively run multiple iterations, with minimal expertise in GIS software being required. By modifying key elements within the script different scenarios, countries, and crops can be inputted. The model is now able to serve as a communication and dissemination platform for agricultural development in the Benin Republic and Nigeria.

The absolute values of each UIVs scaling-up potential are less important than the visualization from the SAVINGS model that illustrate where scaling-up should occur. SAVINGS illustrates data constraints and physiological limitations expected from each UIV and ecoregion. Data from Minielly et al. (2018) and Adebooye et al. (2017), suggest that water is the most limiting variable within the system. By using the same parameters as Minielly et al. (2018), SAVINGS suggests where and approximately the scale at which scaling-up can occur for each UIV. By restricting precipitation and temperature parameters used, SAVINGS matched the outputs of the three research sites, which were used as case studies in Minielly et al. (2018). SAVINGS was able to show where water resources may become scarcer. The projected precipitation patterns were determined by Adeniyi (2016), and contradict the moisture regimes of the region reported by Adebooye et al. (2017). The year 2099 is modeled to have vast expanses of land which may receive too much precipitation. Temperature changes are being modelled to be less drastic compared to precipitation. However, a rise in forecasted temperature may play a more significant role for the UIVs, which is contrary to the scaling-up model (chapter 3).

Areas not highlighted by the SAVINGS model (grey backgrounds) can still grow UIVs. However, these areas did not meet the criteria determined by Adebooye et al. (2017) and are not expected to produce similar yields compared to the case study research sites. Economically these sites are not expected to perform well; farmers at these sites may even lose money if they use the MiroVeg tools.

The SAVINGS model is designed to be actively updated. However,there exists a need for the model to be validated and calibrated. Currently, data limitations are restricting the model from under going any validation methods.

When new climate and agronomic data is available, the model can be easily updated to reflect the new data. Also, IPCC data or estimates for future climate can be updated directly in the model's code. The design of the model allows for the addition of new parameters, new crops (indigenous or western varieties), and additional countries. Moreover, the SAVINGS model can serve as a multi-discipline, multi-national communication tool to develop a plan for climate change mitigation and to improve food security.

4.7 Conclusion

The SAVINGS model is a crucial tool for understanding expected yields and the success of microdosing and the MicroVeg project, in its entirety. The objective of this study was to create a model about food security, under the pretense that the climate will experience some degree of change. The focus of this model was to be on the West African countries of the Benin Republic and Nigeria. The SAVINGS model produced data in tables and maps and used the best available data for the region, including climate data and agronomic data. By using two RCPs, from the IPCC, the SAVINGS model forecasted the scaling-up potential of each of the UIVs within the study. From the outputted data two trends emerged. First, it is expected that all four UIVs will decrease in land area by 2099. Secondly, geographically the land that is suitable for growing the UIVs shifts in a northeasterly pattern from the current research sites. This shift may become problematic, as the areas which are modelled to grow the UIVs by 2099 are not currently being used for agriculture, and to convert the land and cultural practices may take longer than the model can predict. Thus, the SAVINGS model can serve as a communication tool and advocate for better land management strategies or stewardship, which may contradict local cultural practices. However, if intervention starts early enough, these options may be viable

After 2035 the model predictions become poor. The inputted data suggests that temperature will play a more important role than precipitation. Future research needs to focus on the roles that temperature and precipitation, and other variables.

The SAVINGS model is versatile, in its early stages of development, for use by different groups, and in a multi-disciplinary team to view the scaling-up potential of the UIVs, or other crops outside the scope of the project. The SAVINGS model can be easily modified and updated. Additionally, the SAVINGS model can run multiple iterations consistently, thus reducing the amount of expertise required to run a complex model.

5 DISCUSSION

Although GIS is a powerful tool for scaling-up agricultural research, it had some limitations that became apparent when writing this thesis. First of all, crop type was kept independent in the model, and specific water requirement for UIVs was converted into an irrigation percentage value. This conversion creates an apparent overlap in data, especially when reviewing the outputs from SAVINGS model. The most apparent overlap comes from amaranth and fluted pumpkin. As an example, amaranth and fluted pumpkin may occupy a similar region near Ogbomosho. Overlapping cells may be beneficial, depending on the management strategies. However, if the plant needs are different, according to Adebooye et al. (2018), cultural experience or supplier, this complicates recommendations for farmers. Therefore, treating UIVs independently allows for stronger management strategies to be conceptualized separating the crops into different administrative boundaries.

Combining the data into fewer maps, showing and allowing for overlap, will visually simplify the maps. One way this can be achieved is to rerun the data (using the same model, or an additional sub-model) only to include sites which are 100% similar to the research sites, and then combine all four UIVs into one map. This was out of scope for this research. Furthermore, this would visually simplify the climate change maps and modelling. This simplified approach would be useful if the absolute count of cells for any UIV is important. However, the model needs to be calibrated and validated in order to know if the modeled areas are sustainable. As the resulting data stands, this simplified approach would not be beneficial, as this model is being used to understand how each UIV may be independently scaled-up within the region. By using the inference area created by the buffers, different adoption strategies may be developed over larger areas for each UIV or a particular administrations.

Resolution of precipitation and temperature in available datasets is an additional limitation. Without finer resolutions, homogeneity is assumed within each value. Adeniyi (2016) subdivided West Africa into smaller regions, thereby increasing the data resolution. Temperature data from IPCC (2014) was not available at a regional or continental level; thus, the resulting data may be an overestimation or underestimation for the region. The accuracy of the model can be refined, if temperature estimates became more region specific.

The two manuscripts illustrate the versatility and practicality of using a GIS approach for scaling-up development research. Models have been used within climate change and food security projects, but a comprehensive database illustrating the nexus between food security and climate change does not exist. SAVINGS was designed to bridge the gap in literature, by using research data and public datasets. By reviewing related literature, we can start to understand the complexities of these models and the associated elements.

Fick and Hijmans (2017) is the most comprehensive model of climate change and biodiversity. Available, and pertinent, data includes annual temperature, and precipitation data at a resolution of 1 km^2, data represents the 1970-2000 climate normal. Many other databases and resources exist with similar, but varying in the publication year, source and data resolution. By combining multiple resources, including (Fick and Hijmans 2017), FAO and other, we were able to create the most comprehensive food security database available.

Climate change models differ from food security models in many ways. A climate change model requires sea level rise, ice coverage, and other elements. The duration of data is usually more extended, and it can establish a different trend. The IPCC is a leading resource on climate modelling and predictions on future climate. With the most recent report released, the AR5 illustrated four likely outcomes. These likely outcomes, or RCPs, are designed with a global perspective. This global perspective makes the data coarse, but with each successive report release, the IPCC makes great strides in improving resolution. Data collected and presented by the IPCC comes from a vast collection of global research groups, who operate with GCMs and design the future estimates from those specialize models.

Higher resolution climate data exist in some areas of the world. An average resolution of data used by RCMs is 50 km^2, which is twenty-five times finer than AR5. Municipal governments use this sharper resolution data for planning and disaster prevention strategies. Data for RCMs can be either obtained by statistically downscaling coarser GCMs, or via other data collection methods.

An essential element, often overlooked, in many predictive models is scaling-up or an indication of how a model may respond if a factor such as time were modified. This idea of scaling-up allows for inference spaces to be compared. Various methods and techniques exist to create these inference spaces and to scale-up, but data type, sample population and sample resolution force these methods to be data and time intensive.

The inherent nature of the IPCC models makes it challenging to disseminate data for food security. Moreover, the multitude of sources, time series, and the complexity of climate and food security models have added to the challenge of hybridizing a comprehensive database. Factoring in the scaling-up element, no combination of methods and methodologies publicly exist to create a food security model, geared toward poor farmers in the developing nations of West Africa.

The first step to creating this model was to understand all possible elements that could be used in the creation of the database, as well as where the sources of data originate. Upon completion of this step synthesis of our model commenced. Designed with a farmer's perspective, we used climate data at a resolution of $1km^2$. At this resolution, our outputs can be used by local farmers, not directly, but via knowledge dissemination. Added into this model was research data from three research trials. At these research sites, Akponikpe et al. (2016) and Adebooye et al. (2018) collected yield and water data on the projects four UIVs, during the dry season. Additional data was collected from the research sites, using the sites geographic location.

The model then combined the climate data and the research trials, using GIS to create a visual perspective of the possible spatial capacity of the research data. This model has the versatility to add and modify variables. This knowledge and model were used to illustrate gaps in the research and to understand better how each UIV can be scaled. To better understand both the impacts of climate change and the scalability of each crop into the near future, the model was refined and converted into a python script whereby multiple iterations were run simultaneously. SAVINGS then became an innovation. The SAVINGS model simplifies the technical experience required of the users. With a few modifications the model can be used with any GIS software. This fluidity of the model is a significant advantage, as the model has been designed to support researchers and NGOs who work closely with the smallholder farmers in West Africa.

Reviewing the inputted agronomy data, provided by Akponikpe et al. (2016) and Adebooye et al. (2018), modeled food security outputs by 2100 do not look promising. There is only confidence in the model to recommend adoption of the MicroVeg tools until 2035. After 2035, temperature and precipitation change in importance. The climate is being modelled as warmer and wetter than current conditions, and the model is not responsive enough to capture this change. Under all climate change scenarios ran by the model, land management and cultural issues will need to be addressed for the region to become food secure. Both the scaling-up and SAVINGS models can be executed for neighbouring countries. With collaborations from additional countries, and shifting crop production between countries, the region may be able to become food secure. Moreover, the outputs of the models can show regions that may benefit from being converted from agriculture to other land management practices, such as agroforestry.

A vital component of the model's success will be measured by the ability of farmers NGOs, and researchers in West Africa to use and improve the model. For many groups in Africa, access to resources such as climate and yield data is limited. To overcome this obstacle, the SAVINGS model was placed in part on an interactive online database. This webGIS platform allows for the further and more detailed dissemination of the data, further aiding to the alleviation of food insecurity.

The SAVINGS model and the accompanying webGIS are not designed to be stagnant entities. As new climate data, and finer resolution data, becomes available it should be reflected in the model to give users the best-modelled outcome available. Future research needs to include calibration and validation of the model. This validation should first reflect the webGIS interface, then the updated in the SAVINGS code. Calibration of the model needs to include refining the yield and water estimates and the consideration of additional crops and countries. Refining of yield and water data could be as simple as new estimates or as complicated as subdividing the ecoregions if other variables are driving the water usage. Future research should include soil and elevation, which are important variables but because of poor data resolution were omitted. Soil and elevation both will influence food security and crop production in various ways. Having additional data, regarding resolution and tabular descriptions, would allow these variables to be used in the model. Other variables should be considered. If any variable has high quality and reliable data, it should be introduced into the SAVINGS model.

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APPENDIX A: LIST OF UIVS NAME WITHIN THE BENIN REPUBLIC AND NIGERIA

Linnaean Name	Name Used	Benin Republic Common Name	Nigeria Common Name
Amaranthus cruentus L.	Amaranth	Fotete	Tete
Solanum macrocarpon L.	Solanum	Gboma	Igbagba
Telfairia occidentalis f. Hooke	Fluted Pumpkin	N/A	Ugu
Ocimum gratissimum L.	Parsley	Tchayo or Tchiayo	N/A

APPENDIX B: “SAVINGS” MODEL SCRIPT

```
print "Welcome to SAVINGS. created by the University of Saskatchewan."
print "Loading Libraries"
#import time extensions
import os, datetime, time
start_delta = datetime.datetime.now()
pause = 0
from time import sleep
sleep = time.sleep(pause)

import arcpy
from arcpy import env
from shutil import copyfile
from arcpy.sa import *
arcpy.CheckOutExtension("Spatial")

# THIS Is the only file to edit ##
#try:
   #os.stat(Save_folder_name)
#except:
	#os.makedirs(Save_folder_name)
#out_folder_path = "C:\Users\Soilchem\Desktop\SAVINGS_model\\" + Save_folder_name

# output log file
log_existing_i = 1
```

```
log_new = "C:\Users\Soilchem\Desktop\SAVINGS_model\Log\SAVINGS_run_" + str(log_existing_i) + ".log"
while True:
	if not (os.path.isfile(log_new)):
		break
	else:
		log_existing_i = log_existing_i + 1
		log_new =  "C:\Users\Soilchem\Desktop\SAVINGS_model\Log\SAVINGS_run_" + str(log_existing_i) + ".log"

log_file = open(log_new, "w")
log_file.write(str(start_delta) + "\n")

def calcDelta(msg):
	secs = datetime.datetime.now() - start_delta - datetime.timedelta(seconds=pause)
	log_file.write(msg + str(secs)[:-3] + "\n")
	print msg + str(secs)[:-3]

calcDelta("library loaded time: ")


#Constants
crops = ['Amaranth', 'Solanum', 'Telfairia', 'Ocimum']
param_rcp = ["R4", "R8"]
param_year = ["Y3", "Y6", "Y9"]
param_stat = ["Min", "Mean", "Max"]
```

```
#MicroVeg seaons
param_season = ["wet", "dry"]
wet_months = range(3,10+1)
dry_months = [1,2,11,12]
#Temperature projections
proj_temp = {
        "Y3" : {"R4": 0.7, "R8": 0.7},
        "Y6" : {"R4": 1.4, "R8": 2.0},
        "Y9" : {"R4": 1.8, "R8": 3.7}
}
#precipitaion projections
season_CC = {"S1": [4,5,6,7,8,9], "S2": [1, 2, 3], "S3": [10, 11, 12], "S4": range(1,12+1)}
#defined by Adeniyi (2016)
#remap values
lut_prcp = {
        #New value: Original From, To
        0: [-2500,0],
        10: [0,10],
        20: [10,20],
        30: [20,29],
        40: [29,40],
        50: [40,50],
        60: [50,60],
        70: [60,70],
        80: [70,80],
```

```
        90: [80,90],
        100: [90,4000]
}

lut_temp = {
        #New value: Original From, To
        1: [0,20],
        2: [20,22],
        3: [22,24],
        4: [24,26],
        5: [26,27],
        6: [27,30],
        7: [30, 50]
}

lut_water_needed = {
        #New value: Original From, To
        0: [-2500, 0],
        10: [0,10],
        20: [10,20],
        30: [20,30],
        40: [30,40],
        50: [40,50],
        60: [50,60],
        70: [60,70],
```

```
        80: [70,80],
        90: [80,90],
        100: [90,200]
}
# Define ALL workspaces
#original datasources
inputs_workspace = "C:\Users\Soilchem\Desktop\SAVINGS_model\Inputs.gdb"
prcp_workspace = "C:\Users\Soilchem\Desktop\Africa_FoodSecurity\Precip_2000.gdb"
temp_workspace = "C:\Users\Soilchem\Desktop\Africa_FoodSecurity\Temp_2000.gdb"
ecoregion_workspace = "C:\Users\Soilchem\Desktop\Africa_FoodSecurity\Ecoregions.gdb"
crop_workspace = "C:\Users\Soilchem\Desktop\Africa_FoodSecurity\Crop.gdb"
#cliamte change datasources
workspace_precipCC = "C:\Users\Soilchem\Desktop\SAVINGS_model\Run_10_01_04\Precip.gdb"
# Execute CreateFileGDB
##arcpy.CreateFileGDB_management(out_folder_path, "Precip.gdb")
##workspace_precipCC = out_folder_path + "\Precip.gdb"
workspace_tempCC = "C:\Users\Soilchem\Desktop\SAVINGS_model\Run_10_01_04\Temp.gdb"
##arcpy.CreateFileGDB_management(out_folder_path, "Temp.gdb")
##workspace_tempCC = out_folder_path + "\Temp.gdb"
workspace_outputCC = "C:\Users\Soilchem\Desktop\SAVINGS_model\Run_10_01_04\ScalingUp.gdb"
##arcpy.CreateFileGDB_management(out_folder_path, "ScalingUp.gdb")
```

```
##workspace_outputCC = out_folder_path + "\ScalingUp.gdb"
#used with scaling up and join flag
workspace_excel_CSV= "C:\Users\Soilchem\Desktop\Africa_FoodSecurity\Excel_DBF"
csv_crop = 'remap_scalingUp'
# path_scalingup =
"C:\Users\Soilchem\Desktop\Africa_FoodSecurity\Climate_Change\CC_ScalingUp1.gdb"
path_scalingup = workspace_outputCC
#workspaces for join and save flags
path_adm2= "C:\Users\Soilchem\Desktop\Africa_FoodSecurity\CountryBoundaries.gdb"
#Output Location
workspace_zonal = "C:\Users\Soilchem\Desktop\SAVINGS_model\Run_10_01_04\zonal.gdb"
##arcpy.CreateFileGDB_management(out_folder_path, "zonal.gdb")
##workspace_zonal = out_folder_path + "\zonal.gdb"
#workspace_save = out_folder_path + "\Zonal"
calcDelta("environments loaded time: ")
# Zonal Stats Constants
## the clean_template.dbf and some attributes we need
clean_dbf = "clean_template"
clean_dbf_path = workspace_excel_CSV + "\\" + clean_dbf + ".dbf"
# count of fields for the clean_template.dbf, should be 9
```

```
count_field_clean_dbf = len(arcpy.ListFields(clean_dbf_path))
#settings for zonal stats
zones_table = path_adm2 + "\\" + "Microveg_ADM2_cc"
file_pattern = 'Scaling_up_CC_*'
stat_type = "ALL"
count_stats_field = 13
#List of options: http://desktop.arcgis.com/en/arcmap/10.3/tools/spatial-analyst-toolbox/zonal-statistics-as-table.htm
index_count_field = 2 # 2nd, with index starts from 1

#Determine Flags
#several layers can be run in order or individually. Trunig a flag on will run the associated script
overwrite                  = True
# True means new file to be made
# False requires new output locations or names ##
#preapare prcp
prcp_rasterize_flag = False
prcp_flag                  = False
#prepare temperature
tmp_flag                   = False
#run SAVINGS model
SAVINGS_flag               = False
#Run Stats and Scaling up
scalingUp_flag     = False
zonal_flag                 = True
join_flag                  = True
```

```
exporting_flag     = True

#automatically overwrite output, use with caution!!!
arcpy.env.overwriteOutput = overwrite

print "Model has been modified to run under climate change"
print "\n Model Variables"
print "True values will be executed in the next iteration"
print start_delta
print "The time stamps will be saved in: SAVINGS_run_" + log_new

print "Automatically overwrite files: " + str(overwrite)

print "\nPreperation of precipitaion raster"
print "    Convert csv to feature class: Must be done in ArcGIS"
print "    Convert to Raster: \t" + str(prcp_rasterize_flag)
print "    Run precipitaion calculations: " + str(prcp_flag)

print "\nPreparation of temperature raster"
print "    temperature: " + str(tmp_flag)

print "\nSAVINGS model: \t\t" + str(SAVINGS_flag)

print "\nZonal Statistics will be run next"
print "Scaling up Value selection: \t" + str(scalingUp_flag)
```

```
print "zonal: \t\t" + str(zonal_flag)
print "join: \t\t" + str(join_flag)
print "exporting: \t" + str(exporting_flag)
#pause the process
print "\nSAVINGS is paused for " + str(pause) + " seconds to allow you to check variables"
print "SAVINGS processing is commencing!!!"
#projected Precipitation
if prcp_rasterize_flag:
    ###################### produce 72 rasters from the joined table
    env.workspace = inputs_workspace
    joined_fc = 'MicroVeg_Precip_Regions_RCP'
    arcpy.CopyFeatures_management(joined_fc, workspace_precipCC +
"\\MicroVeg_Precip_Regions_RCP")
    env.workspace = workspace_precipCC
    bound_fields = arcpy.ListFields(joined_fc)
    # First cells are default values, and there are 7 fields.
    # Therefore, the offset needs to start after that point.
    # Since 72 fields are needed, ofset will be 7 to 72+7-1
    offset = 7
    for i in range(offset, 72+ offset):
        arcpy.FeatureToRaster_conversion(joined_fc, bound_fields[i].name, "r_" +
bound_fields[i].name, 0.0083333333)
```

```
else:
	print "Precipitaion Raster prep is....... SKIPPED"

calcDelta("Precip rasterized time: ")

if prcp_flag:

	# define output workspace
	workspace_output = workspace_precipCC
	# "C:\Users\Soilchem\Desktop\Africa_FoodSecurity\Precip_CimateChange.gdb"

	# _rcp: climate model
	# _year: projected year in future (2035, 2065, 2099)
	# _stat: stat terms of projected model
	def calc_projected_single_model(_rcp, _year, _stat):
		# find the season for a month
		def find_season(_month):
			for i in range(0, len(season_CC)):
				key = season_CC.keys()[i]
				val = season_CC.values()[i]
				if(_month in val):
					return key
			return None

		## calc prcp raster for wet season
```

```
    wet_prcp = 0
    for m in wet_months:
        # grab original prcp as `prcp1`
        # grab projected prcp as `projected1` from 72 projected rasters
        prcp1 = arcpy.Raster(prcp_workspace + "\\Precip_MicroVeg_" + str(m).zfill(2))
        projected1 = arcpy.Raster("r_" + _rcp + "_" + _year + "_" + _stat + "_" +
find_season(m))
        wet_prcp = wet_prcp + prcp1 * (1 + projected1 * 1.0 / 100)

    # export wet raster
    wet_prcp.save(workspace_output + "/r_" + _rcp + "_" + _year + "_" + _stat +"_wet")
    print "\t [OK] wet raster generated"

    ## calc prcp raster for wet season
    dry_prcp = 0
    for m in dry_months:
        # grab original prcp as `prcp1`
        # grab projected prcp as `projected1` from 72 projected rasters
        prcp1 = arcpy.Raster(prcp_workspace + "\\Precip_MicroVeg_" + str(m).zfill(2))
        projected1 = arcpy.Raster("r_" + _rcp + "_" + _year + "_" + _stat + "_" +
find_season(m))
        dry_prcp = dry_prcp + prcp1 * (1 + projected1 * 1.0 / 100)

    # export dry raster
    dry_prcp.save(workspace_output + "/r_" + _rcp + "_" + _year + "_" + _stat +"_dry")
    print "\t [OK] dry raster generated"
```

```

        ## calc prcp raster for wet season
        annual_prcp = 0
        for m in wet_months:
            # grab original prcp as `prcp1`
            # grab projected prcp as `projected1` from 72 projected rasters
            prcp1 = arcpy.Raster(prcp_workspace + "\\Precip_MicroVeg_" + str(m).zfill(2))
            projected1 = arcpy.Raster("r_" + _rcp + "_" + _year + "_" + _stat + "_" + find_season(m))
            annual_prcp = annual_prcp + prcp1 * (1 + projected1 * 1.0 / 100)
        for m in dry_months:
            # grab original prcp as `prcp1`
            # grab projected prcp as `projected1` from 72 projected rasters
            prcp1 = arcpy.Raster(prcp_workspace + "\\Precip_MicroVeg_" + str(m).zfill(2))
            projected1 = arcpy.Raster("r_" + _rcp + "_" + _year + "_" + _stat + "_" + find_season(m))
            annual_prcp = annual_prcp + prcp1 * (1 + projected1 * 1.0 / 100)

        # export annual raster
        annual_prcp.save(workspace_output + "/r_" + _rcp + "_" + _year + "_" + _stat +"_annual")
        print "\t [OK] annual raster generated"

    i_n = len(param_rcp)
    j_n = len(param_year)
    k_n = len(param_stat)

```

```
	i = 0
	for p_rcp in param_rcp:
		i = i + 1
		j = 0
		for p_year in param_year:
			j = j + 1
			k = 0
			for p_stat in param_stat:
				k = k + 1
				prog = ((i-1)*j_n*k_n + (j-1)*k_n + k) * 100.0 / (i_n * j_n * k_n)
				print "Progress:%.1f%%"% prog
				calc_projected_single_model(p_rcp, p_year, p_stat)
	print "Precipitation data is prepared"
else:
	print "Precipitaion calculations are ....... SKIPPED"

calcDelta("Precip calculations time: ")

#projected temperature
# Value used from IPCC AR5 Report (https://www.ipcc.ch/pdf/assessment-
report/ar5/syr/SYR_AR5_FINAL_full.pdf, page 10)
# RCP models used RCP 4.5 (R4) and RCP 8.5(R8)
if tmp_flag:

	param_season_length = {"Wet": 8, "Dry": 4} # in months
	parm_time = 10.0/100 # years in a decade
```

```
    env.workspace = workspace_tempCC

    def calc_projected_single_model(_rcp, _year):
        delta = proj_temp[_year][_rcp]

        # grab original temp as `temp2000`
        wet2000 = arcpy.Raster(temp_workspace + "\\Temp_MicroVeg_Wet")
        dry2000 = arcpy.Raster(temp_workspace + "\\Temp_MicroVeg_Dry")
        def annual2000():
            r_sum = 0
            for m in range(1,13):
                r_sum = r_sum + arcpy.Raster(temp_workspace + "\\Temp_MicroVeg_" + str(m).zfill(2))
            return r_sum
        #Tmean wet season
        wet_temp_mean = wet2000 + delta
        wet_temp_mean.save(env.workspace + "\\" + "r_" + _rcp + "_" + _year  + "_wet")
        print "\t [OK] wet Tmean generated"

        #Tmean dry season
        dry_temp_mean = dry2000 + delta
        dry_temp_mean.save(env.workspace + "\\" + "r_" + _rcp + "_" + _year  + "_dry")
        print "\t [OK] dry Tmean generated"

        ## Tmean annual
        annual_temp_mean = annual2000()/ 12 + delta
```

```
        annual_temp_mean.save(env.workspace + "\\" + "r_" + _rcp + "_" + _year  + "_annual")
        print "\t [OK] annual Tmean generated"

    n_rcp = 2
    n_year = len(proj_temp)
    i_year = 0
    for p_year in proj_temp:
        i_year = i_year + 1
        i_rcp = 0
        for p_rcp in proj_temp[p_year]:
            i_rcp = i_rcp + 1
            prog = ((i_year-1)*n_rcp + i_rcp) * 100.0 / (n_year * n_rcp)
            print "Progress:%.1f%% (%s%s)"% (prog, p_rcp, p_year)
            calc_projected_single_model(p_rcp, p_year)
    print "Temperature data is prepared"
else:
    print "Temperature Raster prep is....... SKIPPED"

calcDelta("Temperature Raster time: ")

##SAVINGS
if SAVINGS_flag:
    env.workspace = workspace_outputCC

    def SAVINGS_func(_prcp, _temp, _ecoregion, _output_name):
```

```
		# define water usage lookup table
		def dict2array(dict):
			lut_tmp = []
			for k in sorted(dict.keys()):
				lut_tmp.append([dict[k][0],dict[k][1],k])
			return RemapValue(lut_tmp)

		lut_prcp_array = dict2array(lut_prcp)
		lut_temp_array = dict2array(lut_temp)
		lut_water_needed_array = dict2array(lut_water_needed)

		# grab crop's water_needed layers
		rast_crops = {}
		for crop_id in range(0, len(crops)):
			rast_crops[crops[crop_id]] = arcpy.Raster(crop_workspace + "\\" + crops[crop_id])

		remap_temp = Reclassify(_temp,"Value", lut_temp_array, "NODATA")
		remap_prcp = Reclassify(_prcp, "Value", lut_prcp_array, "NODATA")

		# 9 rows, each is a tuple in the format of (season, crop, water_needed)
		#index=0 is for ecoregion type, index=1 is crop type, index=2 is water_needed
		for plant_id in range(0, len(crops)):
			print "\tcrop:" + crops[plant_id]
			water_needed = rast_crops[crops[plant_id]]
			# wet season
```

```
            # calc %age for dry season and reclassify it
            outRaster = (water_needed - _prcp) / water_needed * 100
            remap_water_needed = Reclassify(outRaster, "Value", lut_water_needed_array, "NODATA")
            rast_out = _ecoregion * 1000 + remap_temp + remap_water_needed
            arcpy.BuildRasterAttributeTable_management(rast_out, "NONE")

            # save the output
            rast_out.save(workspace_outputCC + "/" + _output_name + "_" + crops[plant_id])
            #ensure tables exist

    ### load all layers ###
    # grab 2 temp rasters
    ecoregion = arcpy.Raster(ecoregion_workspace + "\\" + "Microveg_raster")

    #####Run SAVINGS###
    env.workspace = workspace_outputCC

    i_n = len(param_rcp)
    j_n = len(param_year)
    i = 0
    for p_rcp in param_rcp:
        i = i + 1
        j = 0
        for p_year in param_year:
```

```
            j = j + 1
            prog = ((i-1)*j_n + j) * 100.0 / (i_n * j_n)
            print "Progress:%.1f%%"% prog
            print "-------- wet season ------"
            temp = arcpy.Raster(workspace_tempCC + "\\" + "r_" + p_rcp + "_" + p_year + "_wet")
            for p_stat in param_stat:
                prcp = arcpy.Raster(workspace_precipCC + "\\" + "r_" + p_rcp + "_" + p_year + "_" + p_stat + "_wet")
                print "\t --%s,%s,%s --"% (p_rcp, p_year, p_stat)
                SAVINGS_func(prcp, temp, ecoregion, "CC_" + p_rcp + "_" + p_year + "_" + p_stat + "_wet")

            print "-------- dry season ------"
            temp = arcpy.Raster(workspace_tempCC + "\\" + "r_" + p_rcp + "_" + p_year + "_dry")
            for p_stat in param_stat:
                print "\t --%s,%s,%s --"% (p_rcp, p_year, p_stat)
                prcp = arcpy.Raster(workspace_precipCC + "\\" + "r_" + p_rcp + "_" + p_year + "_" + p_stat + "_dry")
                SAVINGS_func(prcp, temp, ecoregion, "CC_" + p_rcp + "_" + p_year + "_" + p_stat + "_dry")
    print "SAVINGS has finished"

else:
    print "SAVINGS has been..... SKIPPED"

calcDelta("SAVINGS completion time: ")
```

```
### Run Stats

#run scaling up value selection
# this will only select the values which match the critera. This is to represent the research sites while being expanded to +/- 10% of the sites value. This can be changed by modifying the input CSV

if scalingUp_flag:
    #target CSV
    import glob
    import csv
    import ntpath

    env.workspace = workspace_outputCC

    lut_csv = {}

    # remap
    csvs = glob.glob(workspace_excel_CSV + "\\remap_scalingUp*")
    for remap_csv in glob.glob(workspace_excel_CSV + "\\remap_scalingUp*"):
        values = []
        with open(remap_csv, 'rb') as csvfile:
            read = csv.reader(csvfile)
            h = 0
            for row in read:
                if h == 0:
```

```
                    h = 1
                else:
                    values.append(row[2])
        lut_csv[ntpath.basename(remap_csv).lower()] = list(set(values))

    # set null
    cc_rasters = arcpy.ListRasters('CC*')
    i_n = len(cc_rasters)
    i = 0
    for cc_r in cc_rasters:
        i = i + 1
        print "progress:%.1f%%"% (i * 100.0 / i_n)
        lut_name = csv_crop + cc_r.split('_')[5] + '_' + cc_r.split('_')[4] + '.csv'
        lut = lut_csv[lut_name.lower()]
        outRaster = SetNull(cc_r,  cc_r, "Value NOT IN(" + ",".join(lut)  + ")")
        outRaster.save(path_scalingup + "\\Scaling_up_" + cc_r)
    print "Scaling up Value selection is Done!"
else:
    print "Scaling up Value selection was SKIPPED!"

calcDelta("Scaling up Value selection time: ")

if zonal_flag:
    env.workspace = path_scalingup
    # zonal stats Loop (don't edit)
```

```
    cc_s = arcpy.ListRasters(file_pattern)
    i_n = len(cc_s)
    i = 0
    #Scaling_up_CC_R4_Y3_Max_dry_Amaranth
    print "processing Zonal"
    for cc_i in cc_s:
        i = i + 1
        print "progress:%.1f%%"% (i * 100.0 / i_n)
        ZonalStatisticsAsTable(zones_table,'ID_2', cc_i, workspace_zonal + "\\" + "zonal_" + cc_i, "DATA", stat_type)
    print 'Zonal Stats are..........DONE!'
else:
    print 'Zonal Stats are..........SKIPPED!'

calcDelta("Zonal Stats time: ")

if join_flag:
    env.workspace = workspace_zonal
    # clean_dbf = workspace_excel_CSV + "\join11_zonal.dbf.bak"
    for each_rcp in param_rcp:
        for each_season in param_season:
            output_dbf = "Join_" + each_rcp + "_" + each_season
            arcpy.Delete_management(output_dbf)
            arcpy.TableToGeodatabase_conversion(clean_dbf_path, env.workspace)
            arcpy.Rename_management(clean_dbf, output_dbf)

```

```
            # grab external dbf files and do join
            zoneTables = arcpy.ListTables("zonal_Scaling_up_CC_" + each_rcp + "_*_*_" + each_season + "_*")
            for zone_join in zoneTables:
                strFields = zone_join.split('_')
                print "Progress:%s%s%s%s%s"% (each_rcp, each_season, strFields[5], strFields[6], strFields[8])
                arcpy.JoinField_management(output_dbf, 'ID_2', zone_join, 'ID_2')
    print "Joins are .........Done"
else:
    print "Joins are .........SKIPPED"

calcDelta("Joins time: ")

# clean the huge join table output and export as external csv
if exporting_flag:
    env.workspace = workspace_zonal

    for each_rcp in param_rcp:
        for each_season in param_season:
            join_tab_name = "Join_" + each_rcp + "_" + each_season

            print "-- working on " + join_tab_name
            zoneTables = arcpy.ListTables("zonal_Scaling_up_CC_" + each_rcp + "_*_*_" + each_season + "_*")

            # delete garbage fields
```

```
		old_fields = arcpy.ListFields(join_tab_name)
		if len(old_fields) == count_field_clean_dbf + count_stats_field * len(zoneTables):
			print "-- we have correct number of fields"
		else:
			raise Exception("field deletion failed!!!!!!")

		offset_skip = count_field_clean_dbf
		fields_to_be_deleted = []
		for table_i in range(0, len(zoneTables)):
			# index of ID_2* field for this table
			inx_id = offset_skip + table_i*count_stats_field + 0
			# push its name to the list
			fields_to_be_deleted.append(old_fields[inx_id].name)
			# index of useless stats fields for this table
			for j in range(2, 13): # useless fields range from 2 to 11
				index_useless =  offset_skip + table_i*count_stats_field + j
				fields_to_be_deleted.append(old_fields[index_useless].name)

		print "-- deleting fields..." + str(join_tab_name)
		arcpy.DeleteField_management(join_tab_name, fields_to_be_deleted)

		# rename all count fields properly
		print "-- renaming fields..."
		old_fields = arcpy.ListFields(join_tab_name) # get fields

```

```
            for i in range(0, len(zoneTables)):
                strFields = zoneTables[i].split('_')
                strYear = strFields[5]
                strStat = strFields[6]
                strCrop = strFields[8]
                # print "-- rename, new name:%s%s%s"% (strYear, strStat, strCrop)
                old_field_index = count_field_clean_dbf + i
                new_field_name = strYear + "_" + strStat + "_" + strCrop # + "_count"
                # print "----join_table_name: " + join_tab_name
                # print "----old_field_index: " + str(old_field_index)
                # print "----new_field_name: " + new_field_name
                arcpy.AlterField_management(join_tab_name,
                    old_fields[old_field_index].name, new_field_name)
else:
    print "Exporting has been.... SKIPPED"

calcDelta("Exporting time: ")

print "SAVINGS has finished running !!!!!!!!!!!!"
print "All file saved in gdb: " + workspace_zonal
print "################"

calcDelta("End time: ")
end_time = datetime.datetime.now()
log_file.write (str(end_time) + "\n")
log_file.close()
```