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A Spatial Analysis of Climate Change Effects on Maize Productivity in Kenya

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A Spatial Analysis of Climate Change Effects on Maize Productivity in Kenya

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by

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SUMMARY

Climate change has intensified the risk of catastrophic natural disasters all over the world. Though impacts of the change are global, developing countries are more at risk. Although agriculture remains the backbone of Kenya's economy, the sector's dependence on natural resources increases its vulnerability to the aggravating impacts of climate change and variability. Climate system variations that impact staple food crops like maize (*Zea mays*) ultimately threaten the food security of the nation. This study examined environmental factors affecting maize productivity through regression analysis. A GIS suitability model for maize was also developed to identify Kenya's different levels of suitability for the crop as a basis for facilitating informed decisions in planning and designing climate change mitigation and adaptation measures. To achieve this, GIS and Analytical Hierarchy Process were used and suitability model results were compared with results from field work conducted in four counties in Western Kenya.

This report is sectioned into six chapters. Chapter 1 gives the background of the study. The chapter discusses climate change and its impacts on the already vulnerable agricultural communities in developing countries. It also links climate change, agriculture and food security and the researcher highlights the study's objectives, questions and motivation.

Chapter 2 is the literature review section. In this chapter, the author talks in detail about some past and current works in climate change, agriculture and food security. He also discusses some quantitative analyses done in these areas, most of which correlate climate change and agricultural productivity. Multi-Criteria Decision Making and GIS are also discussed here. Throughout this section, the researcher tries to identify some improvements that the current study incorporates.

The third chapter gives a discussion of the methodology and data analysis while Chapter 4 outlines the results of the analysis. Chapter 5 follows with a discussion of the results as well as the implications of the study results to the government, farming and research communities. Research limitations and suggestions for future research are given in Chapter 5 and the report concludes with study conclusions in Chapter 6.

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LIST OF ACRONYMS AND ABBREVIATIONS

AHP	Analytical Hierarchy Process
CSOs	Civil Society Organizations
DEM	Digital Elevation Model
EDA	Exploratory Data Analysis
FAO	Food and Agriculture Organization of the United Nations
FEWS NET	Famine Early Warning Systems Network
GCOS	Global Climate Observing System
GDP	Gross Domestic Product
GIS	Geographic Information Systems
IFDC	International Fertilizer Development Center
IPCC	Intergovernmental Panel on Climate Change
KALRO	Kenya Agricultural and Livestock Research Organization
KAPs	Knowledge, Attitude and Practices
KMD	Kenya Meteorological Department
MCE	Multi-criteria Evaluation
MODIS	Moderate-resolution Imaging Spectroradiometer
NAP	National Adaptation Plan
NASA	National Aeronautics and Space Administration
NCCAP	National Climate Change Action Plan
NCCRS	National Climate Change Response Strategy
NDVI	Normalized Difference Vegetation Index
OLI	Operational Land Imager
OLS	Ordinary Least Squares
SRTM	Shuttle Radar Topographic Mapping
UN	United Nations
WMO	World Meteorological Organization

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND OF THE STUDY

Climate change has intensified the risk of catastrophic natural disasters all over the world (Kabubo-Mariara and Kabara 2015). Though impacts of the changes are global, developing countries are more at risk, primarily because of their high dependence on natural resources, poverty, low capacity to adapt(Bryan et al. 2013; Kabubo-Mariara and Kabara 2015), lack of technological capability (Mwendwa and Giliba 2012) and the existence of environmental stress (Norrington-Davies and Thornton 2011). Moreover, little or no information about the change and applicable mitigation and adaptation measures exacerbate the situation in developing countries. Although agriculture remains the backbone of Kenya's economy directly and indirectly supporting more than 75 percent of the Kenyan population (FEWS NET 2013), the sector's dependence on natural resources makes it very vulnerable to the impacts of climate change and variability.

A lot of research has been conducted in the fields of climate change, agriculture and food security. However, most have focused on informing relevant agencies and people about the strong links among the three (Kabubo-Mariara and Kabara 2015; Gregory, Ingram, and Brklacich 2005) while others forecasted the future impacts of climate change and variability on food security and agriculture, mostly through climate simulation modelling (Thornton et al. 2009). Some studies have applied Geographic Information System (GIS), but most are inclined towards characterization of farming systems (Diwani et al. 2013), crop mapping (Dong et al. 2014), land cover mapping (Kuria et al. 2011) and land cover and use analysis (Schaab, Lung, and Mitchell 2004).

The World Food Summit of 1996 defined food security as "a state when all people, at all times, have physical and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life" (FAO 2006). To achieve this state, agriculture plays two major roles: it produces the food people eat; and provides the primary source of livelihood for 36 percent of the world's total workforce. However, the sector is one of the most sensitive and fragile regarding climate change as even minor fluctuations can have potential or actual effects on agricultural production and related procedures (Qian, Wang, and Liu 2014).

This study integrates GIS, quantitative analysis and suitability modelling in analyzing the effect of climate change and variability on maize production in Kenya. It was warranted by the researcher's experiences of the struggles that Kenyan rural farming communities go through due to variations in the climate system. The research correlates climate change and maize yields through regression analysis and then develops and tests a model to locate Kenya's land suitability levels for the crop. Community knowledge was also incorporated to form a basis for designing mitigation and adaptation measures to sustain maize farming in the changing and varying climate conditions.

1.2 RESEARCH OBJECTIVES

The overall goal of the research is to establish a relationship between climate change and maize productivity and then identify and map out Kenya's levels of suitability for maize farming using Multi-Criteria Decision Making (MCDM) and GIS.

The specific objectives include;

1. To examine whether there is a statistically significant change in maize yields resulting from changes in the climate in Kenya
2. To develop a site suitability model for maize growing based on identified environmental factors in the country
3. To identify local people's rating of the suitability of their areas to maize farming as well as their perceptions about climate change and its impacts on the practice.

1.3 RESEARCH QUESTIONS

1. Is there any statistically significant change in maize productivity as it relates to changes in the climate in the country?
2. What are the levels of suitability for maize growing in Kenya based on identified environmental conditions?
3. What is the local people's knowledge about the suitability of their area to maize farming, climate change and its impacts on the practice and what are they doing to stay sustainable?

1.4 RESEARCH MOTIVATION

The fast-growing population, rural to urban migration and climate change and variability all continue to contribute to the mounting pressure produce more food without negatively affecting the planet. Despite a dramatic increase in food production and availability in the recent times, undernourishment and food insecurity remain at unacceptably high levels (Premanandh 2011) as more than one in seven people still do not have access to sufficient protein and energy from their diet and even more suffer from some form of malnutrition (Godfray et al. 2012). Many scholars and researchers have proposed several viable solutions to this life threatening problem – sustainable intensification (Godfray et al. 2012), increasing production and improving food distribution (Gregory, Ingram, and Brklacich 2005), agroforestry and hydroponics (Premanandh 2011) and investing in agricultural research (CGIAR 2014[1]) among others. However, most of the suggestions point towards one sector; agriculture. Agricultural production is regarded critical for achieving global food security as are factors such as economic development for everyone, fair international trade agreements, and sound global and national governance (Sundstrom et al. 2014). According to FAO (2008), the sector plays two major roles in attaining food security: it produces the food people eat; and (perhaps even more important) it provides the primary source of livelihood for 36 percent of the world's total workforce. In sub-Saharan Africa, two-thirds of the working population still make their living from agriculture. In most cases, the sector is the primary provider of livelihood for most of the rural poor who practice subsistence food production.

Kenya's over-reliance on natural environmental conditions has been a major concern for many government and community development agencies including the agricultural, energy and natural resource sectors. Agricultural practices in this country are dictated by natural occurrences (rainfall, temperature among others) and this signals unforeseen threats resulting from unprecedented changes and variations in the natural conditions of an area.

The next chapter reviews existing literature in climate change, agriculture and food security, quantitative analysis of climate change and maize productivity correlation and GIS and multi-criteria decision making (MCDM). The researcher will then explain the addition into the body of knowledge that this study sought to make.

1.5 GLOSSARY

Climate change	Long-term changes in average weather conditions or; all changes in the climate system, including the drivers of change, the changes themselves and their effects
Food security	A state when all people at all times have physical or economic access to sufficient safe and nutritious food to meet their

[1] http://www.cgiar.org/consortium-news/feeding-the-world-2014-sustainable-solutions-for-a-global-crisis/

	dietary needs and food preferences for an active and healthy life.
Climate variability	Yearly fluctuations of the climate above or below a long-term average value.
Geographic Information System	A computer system for capturing, storing, checking, and displaying data related to positions on Earth's surface.
Climate adaptation	Refers to dealing with the impacts of climate change. It involves taking practical actions to manage risks from climate impacts, protect communities and strengthen the resilience of the economy.
Climate mitigation	Actions dealing with causes of climate change by reducing emissions. Can mean using modern technologies and renewable energies, making older equipment more energy efficient, or changing management practices or consumer behavior

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

There is considerable literature relating to climate change and its real or potential impacts on crop productivity and global food security in general. It is widely agreed in these studies that climate change has differentiated impacts, with high chances of the worst of these being felt by the already struggling developing countries. It is also noted that most of the developing countries are in sub-Saharan Africa (Kabubo-Mariara and Kabara 2015; Thornton et al. 2009; Jones and Thornton 2003a; Bryan et al. 2013; Challinor, A.J., Wheeler, T.R., Garforth, C., Craufurd, P., Kassam 2007; Claessens et al. 2012; Fisher et al. 2015).

This research is centered on three major themes. The first section discusses the concept of climate change, agriculture and food security as they relate to developing countries with a special focus on Kenya. Secondly, literature about application of quantitative analysis will be explored, focusing on establishing a statistically significant correlation between climate change and maize productivity. Finally, geographic technologies and their applications in adapting to and mitigating the impacts of climate change will be explored. More specifically, literature related to crop suitability modelling will be presented. In this section, too, the researcher will identify gaps in literature that his study aims to fill.

2.2 CLIMATE CHANGE, AGRICULTURE AND FOOD SECURITY

Climate refers to the characteristic conditions of the earth's lower surface atmosphere at a specific location (FAO 2008b). The day-to-day fluctuations in these conditions at the same location is what is referred to as weather. Commonly used elements by meteorologists to measure daily weather phenomena are air temperature, precipitation, atmospheric pressure, humidity, wind, sunshine and cloud cover. On the other hand is climate change which has no internationally agreed definition. Here, it is used to refer to: long-term changes in average weather conditions (WMO usage) or; all changes in the climate system, including the drivers of change, the changes themselves and their effects (GCOS usage) (FAO 2008b). Much as climate change is a common term, there is need to understand that there are varying perceptions of the causes of this change. There are ongoing debates among the scientific community about whether climate change is naturally or anthropogenically caused. Regardless of who is right, this study focuses on the impacts of the change on agriculture in developing countries.

There exists a strong link among climate change, agriculture and food security. In the sub-Saharan Africa especially, agriculture is ranked highly and thought to play a crucial role through its direct and indirect impacts on poverty, as well as in providing an indispensable platform for wider economic growth that reduces poverty far beyond the rural and agricultural sectors (Thornton et al. 2009). However, researchers are also in consensus that this sector is more vulnerable to changes in the climate which have overarching effects on the overall state of food security in a nation. The relationship can clearly be illustrated in terms of systems:

> "Dynamic interactions between and within the biogeophysical and human environments lead to the production, processing, distribution, preparation and consumption of food, resulting in food systems that underpin food security. Food systems encompass food availability (production, distribution and exchange), food access (affordability, allocation and preference) and food utilization (nutritional and societal values and safety), so that food security is, therefore, diminished when food systems are stressed." (Gregory, Ingram, and Brklacich 2005, p2139).

The above definition by Gregory, Ingram, and Brklacich (2005) clearly explains the vulnerability of food security from all angles. The Intergovernmental Panel on Climate Change (IPCC) reported that increases in droughts, floods, and other extreme events would add to stress on water resources, food security, human health, and infrastructure, and would constrain development in Africa (Mirza 2003). In fact, agriculture in its many different forms and locations remains highly sensitive to climate variations, the dominant source of the overall interannual variability of production in many regions and a continuing source of disruption to ecosystem services (Howden et al. 2007). Owing to the systems approach, any instability caused by climate change to agriculture, infrastructure or other sectors that contribute towards achievement of food security ultimately threatens the food security of a nation.

Though many scholars and researchers have proposed several viable solutions to this life threatening problem: sustainable intensification (Godfray et al. 2012), increasing production and improving food distribution (Gregory, Ingram, and Brklacich 2005), agroforestry and hydroponics (Premanandh 2011) and investing in agricultural research (CGIAR 2014[2]) among others, all point towards one sector; agriculture. Agricultural production is regarded critical for achieving global food

[2] http://www.cgiar.org/consortium-news/feeding-the-world-2014-sustainable-solutions-for-a-global-crisis/

security as are factors such as economic development for everyone, fair international trade agreements, and sound global and national governance (Sundstrom et al. 2014).

2.2.1 Climate Change, Agriculture and Food Security in Developing Countries

Climate change impacts would be worst felt in developing countries. Mirza (2003) explains that the change is likely to increase the frequency and magnitude of some extreme weather events and disasters. Africa is a big landmass extending from 35^0 N to 35^0 S and has differentiated impacts from climate change. Some areas of Africa would become drier, others wetter, and some regions may derive economic benefit, while most are adversely affected (Collier, Conway, and Venables 2008).

More specifically in Kenya, a developing country, climate change impacts have been felt over the past years. Mwendwa and Giliba (2012 p23) summarize these impacts as follows:

> The La-Nina related drought of 1999/2001 was thought to be the "worst in the living memory". It was preceded by El-Nino related floods of 1997/98 which were some of the worst in recent times. As a result, floods sparked major emergency relief as hundreds of people lost their lives and thousands were displaced from their homes. Another drought occurred in 2004/05 and led to famine in the marginal rainfall areas in Kenya. The following year 2006, nearly 3.5 million Kenyans required food aid and other humanitarian assistance following poor rains. Livestock losses of up to 70% were reported in the arid and semiarid lands. The ice cap on Mount Kenya has shrunk by 40% since 1963 and a number of seasonal rivers that used to flow from atop the mountain to the surrounding areas have since dried up. Kenya is estimated to have lost 10 percent of its plant species in the past century.

These authors reported that the climate was likely to become more variable and Kenya can expect more droughts and more floods than it has seen in the past, and planning for this situation would be wise. True to this, Kenya has experienced a number of life threatening weather events which are believed to be associated with climate change and variability. The 2011 drought that occurred the East Africa region affected approximately 10 million people and has been regarded as the worst in 60 years. Besides, the 2015 El Nino occurrence and 2013 floods and landslides have all occurred on a large scale and negatively affected agricultural communities.

With all these changes, Kenya, with only 20 per cent of its land classified as arable (Mwendwa and Giliba 2012), is still dependent on agriculture as its economic backbone and central to its current development strategy – Kenya Vision 2030. Of the 70 percent of the population living in rural areas, 80 percent are dependent on agriculture as a source of livelihood (FEWS NET 2013). Besides, the sector directly contributes about 25.4 percent of the country's Gross Domestic Product and another 27 percent indirectly via linkages to agro-based industries and the service sector (Osumba and Rioux 2015). In addition, this sector accounts for 65 percent of total export earnings (Government of Kenya 2008). In fact, the Kenyan economy is so dependent on agriculture that people's livelihood is threatened if the sector fails.

Over-reliance on natural environmental conditions has been a major concern for many government and community development agencies in the country. Given the inherent link to natural resources, agricultural production is subject to uncertainties driven by climate variation (Rosenthal and Kurukulasuriya 2003).

Much work has been done regarding adaptive strategies especially in agriculture. However, Claessens et al. (2012) report that most of the existing research has focused on impacts of climate change and adaptation to climate change in the agricultures of industrialized countries. In relatively few studies conducted in sub-Saharan Africa, agricultural research has either focused on individual crops, has used aggregated data and models or used statistical analysis that does not allow for site-specific adaptation strategies. Others have been found to have very low spatial resolutions, often conducted at the global, continental, regional level, thus allowing no contextualization of adaptation strategies.

2.3 QUANTITATIVE ANALYSIS OF CLIMATE CHANGE AND MAIZE PRODUCTIVITY CORRELATION

2.3.1 Ordinary Least Squares and Geographically Weighted Regression

Ordinary Least Squares (OLS) is a traditional regression technique that provides a global model of a variable or process under investigation. The model creates a single regression equation to represent the process. It fits a line to data such that the squared vertical distance from each data point to the line is minimized across all data points (Kilmer and Rodriguez 2016; Abdi 2010). It is the proper starting point for all spatial regression analyses[3]. An OLS model equation is expressed as (1) below:

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \varepsilon \qquad (1)$$

[3] http://pro.arcgis.com/en/pro-app/tool-reference/spatial-statistics/how-ols-regression-works.htm

where; x_i is the independent variable, y is the dependent variable, k is the number of independent variables, β_0 is the intercept, β_i is the coefficient and ε is the error (Su, Xiao, and Zhang 2012 p363).

Su, Xiao, and Zhang (2012) note that OLS relies on the assumptions that model residuals are uncorrelated and error varies inconstantly. Violation of these assumptions when performing OLS on spatial data may result in spatial autocorrelation and non-stationarity issues. Besides, OLS may fail to reveal important local variations in model variables. These may lead to misleading results. To minimize these issues, GWR was developed.

GWR was introduced by Brunsdon, Fotheringham, and Charlton (1996) to perform a local form of linear regression for spatially heterogenous variables. The underlying idea of GWR is that parameters may be estimated anywhere in the study area given a dependent variable and a set of one or more independent variables which have been measured at places whose locations are known (Charlton and Fotheringham 1998). GWR is a the traditional relatively simple technique that extends regression framework of equation (1) above. It allows local variations in rates of change so that the coefficients in the model rather than being global estimates are specific to a location *j* (Naibbi and Healey 2014). The GWR equation can be expressed as (2) below:

$$y_j = \beta_0(u_j, v_j) + \sum_{i=1}^{k} \beta_i(u_j, v_j)x_{ij} + \varepsilon_j \qquad (2)$$

where u_j and v_j are the spatial position of location j, y_j is the value of the dependent variable at location j, x_{ij} is the value of the independent variable at location j, $\beta_0(u_j, v_j)$ is the intercept, $\beta_i(u_j, v_j)$ is the local estimated coefficient for independent variable and k is the number of independent variables (Su, Xiao, and Zhang 2012 p363).

2.3.2 Climate Change and Maize Productivity Correlation

Many climate change and agricultural productivity studies have been conducted. Most of them have used simulation and statistical models. Notable ones include: Thornton et al. (2009) whose aim was to investigate the different types of crop response to climate change as represented by a combination of two climate models and two contrasting greenhouse-gas emission scenarios. For the East Africa region, they analyzed the spatial differences in simulated main-season maize and secondary – season Phaseolus bean yields to 2050, and attempted a basic characterization of crop response. The object of doing this was to assess the possibility of using such information for preliminary targeting of adaptation options at relatively high resolution. It can already be noted that this research utilized crop simulations. Thornton et al. (2010) also indicate use of simulation modelling of crop yield response to different climate scenarios. In this study, the researchers aimed to investigate the differences in productivity and production of maize and beans in different production systems, and then to assess different options of adapting to these changes in the future, based on differing locations and situations. In another instance, a basic model of yield was used by Torriani et al. (2007) along with climate scenarios to assess the impact of climate change on grain maize productivity and associated economic risk in Switzerland. The research would study the sensitivity of rainfed maize production and associated production risk to changes in the precipitation regime; study the response of maize yield to climate change given a climate scenario; and finally provide a qualitative measure of how uncertainties in climate projections may affect yield scenarios. Results show that changes in the precipitation regime alone were shown to affect the distribution of yield considerably, with shifts not only in the mean but also in the standard deviation and the skewness. Results showed that production risk responded more markedly to changes in the long-term mean than in the inter-annual variability of seasonal precipitation amounts. In most cases, studies using simulation modelling usually deal with anticipated impacts of climate change on agricultural productivity.

Poudel and Shaw (2016) conducted a statistical analysis of climate change effects on crop productivity. This research aimed to explore the impact of climate change on major crop yields in the mountainous parts of Nepal and to determine their relationships based on a regression model between historical climatic data and yield data for food crops. The study analyzed 30 years of climatic data from Lamjung district and Mann-Kendall and Sen's Slope methods used for the trend analysis and quantification. Aside from the statistical analysis, this research utilized key informant interviews, a methodology that enabled the authors to gather qualitative information on the community's perception of climate change and experience of extreme weather events, such as erratic rainfall, floods, droughts, landslides among others. The results showed an increase in temperature of approximately 0.02^0C to 0.07^0C per year in different seasons and a mixed trend in precipitation. Although there was no significant impact of the climate variables on the yields of all crops, the regression analysis revealed negative relationships between maize yield and summer precipitation and between wheat yield and winter minimum temperature, and a positive relationship between millet yield and summer maximum temperature.

2.4 GIS AND MULTI-CRITERIA DECISION MAKING IN CROP SUITABILITY ANALYSIS

MCDM is a well-known branch of decision making. It is a branch of a general class of operations research models which deal with decision problems under the presence of a number of decision criteria (Pohekar and Ramachandran 2004). It can be thought of as a process that combines spatial and aspatial data (input) into a resultant decision (output) (Malczewski 2004). MCDM procedures (or decision rules) do define the relationship between the input maps and the output map. The procedures involve the utilization of geographical data, the decision maker's preferences and the manipulation of the data and preferences per specified decision rules (*ibid.*).

Zanakis et al. (1998) report that MCDM problems are commonly categorized as continuous or discrete, depending on the domain of alternatives. They note that these methods have previously been classified as either Multi-Objective Decision Making (MODM) or Multi-Attribute Decision Making (MADM). These methodologies share common characteristics of conflict among criteria, incomparable units and difficulties in selection of alternatives (Pohekar and Ramachandran 2004). In MODM, decision variable values are determined in a continuous or integer domain, of infinite or large number of choices to best fit the decision maker's constraints, preferences or priorities. MADM methods, on the other hand, have discrete, usually limited number of prespecified alternatives, requiring inter and intra-attribute comparisons, involving implicit or explicit trade-offs (Zanakis et al. 1998). Analytical Hierarchy Process (AHP) is an MADM method of MCDM developed by Thomas L. Saaty in 1971-75 (R. W. Saaty 1987). AHP is a general theory of measurement through pairwise comparisons and relies on the judgements of experts to derive priority scales (T. L. Saaty 2008).

According to T. L. Saaty (2008), human actions are the result of some decision. The author notes that to decide, people need to know the problem, the need and purpose of the decision, the criteria of the decision, their sub-criteria, stakeholders and groups affected and the alternative actions to take. With these, they would then try to determine the best alternative or priorities.

AHP has been used in several climate and crop yield studies. A study conducted in Oyo State in Nigeria by Linda, Oluwatola, and Opeyemi (2015) examines land suitability for maize production through the analysis of the physical and chemical variations in soil properties and other land attributes over space using GIS. In another research, Kihoro, Bosco, and Murage (2013) developed a suitability map for rice growing in three counties in central and eastern Kenya based on physical and climatic factors of production using a Multi-Criteria Evaluation (MCE) and GIS. Pairwise comparisons were done and the suitable areas for the crops were generated and graduated. The two studies note that MCE using AHP could provide a superior database and guide map for decision makers considering crop substitution to achieve better agricultural production. The studies did not report inclusion of field work of any kind, a component that will be incorporated in the current research.

Mighty (2015) modelled suitable areas for growing coffee in the island of Jamaica. The research explored how crop suitability knowledge could be used to guide future development of the industry to regain the presence it once had in the ever-competitive specialty coffee market. Based on a multi-criteria decision making (MCDM) approach, this work used AHP to create a suitability model considering several biophysical factors (elevation, temperature, geology, soil type, slope, precipitation) and transport infrastructure. The model highlighted that the most suitable areas for growing coffee were found in the mountainous core of central and eastern Jamaica. This conformed to the pattern of the suitability of several of the input criteria. The model was validated using field collected data from farmers.

In summary, research conducted on climate change and agricultural productivity correlation and crop suitability analyses have adopted different methodologies to achieve their objectives. Some have used simulation modelling (Jones and Thornton 2003b; Claessens et al. 2012; Thornton et al. 2010; Gizachew and Shimelis 2014). Analytical hierarchical process is also common (Linda, Oluwatola, and Opeyemi 2015; Kihoro, Bosco, and Murage 2013; Mighty 2015) while regression and trend analysis has been used by Poudel and Shaw (2016).

CHAPTER 3

METHODOLOGY AND DATA ANALYSIS

3.1 STUDY AREA

The country of Kenya is referenced by 0.0236° S and 37.9062° E coordinates. Its capital and largest city is Nairobi. It lies across the equator in east-central Africa, on the coast of the Indian Ocean. Kenya borders Somalia to the east, Ethiopia to the north, Tanzania to the south, Uganda to the west, and Sudan to the northwest. In the north, the land is arid; the southwest corner is in the fertile Lake Victoria Basin; and a length of the eastern depression of the Great Rift Valley separates western highlands from those that rise from the lowland coastal strip[4]. Figure 1 here shows the map of Kenya and four counties in which field work was conducted.

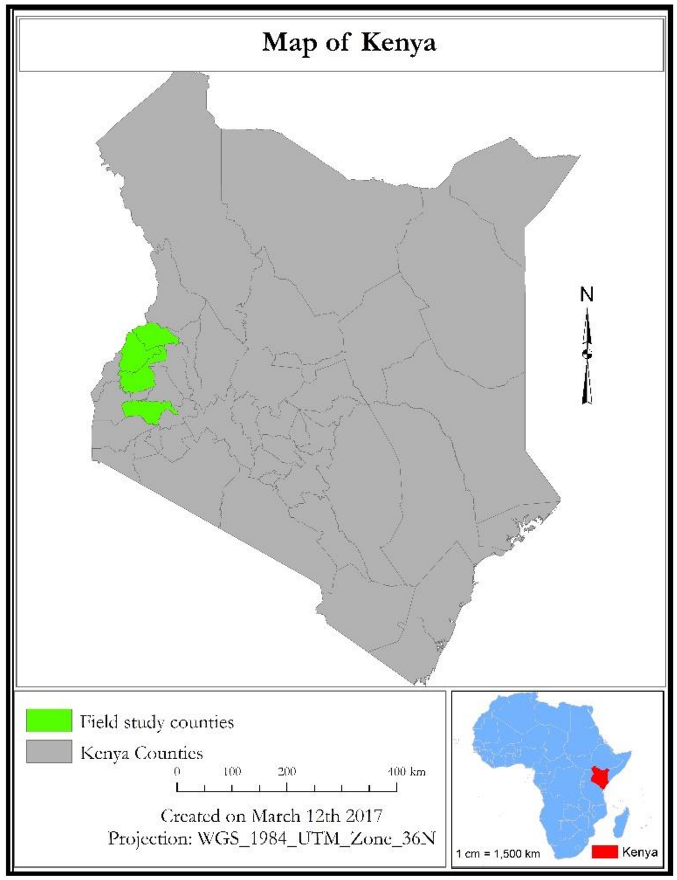

Figure 1: Study area map. Counties where field work was conducted are highlighted in green.

Seven datasets: climate (30-year average rainfall and temperature), soil characteristics (soil type and PH), topographic data (slope and elevation) and maize yields are used to examine the correlation between climate change/variability and maize productivity, and finally develop an area suitability model for the crop. The intended model is based on an integration of FAO land suitability classification (http://www.fao.org/docrep/x5310e/x5310e04.htm.) and Sys's 1991 land grading guidelines adopted from Wang (2015). The choice of the maize crop is based on its important dietary contribution among Kenyan population as well as its widespread cultivation across the nation.

[4] http://www.infoplease.com/country/kenya.html.

3.2 DATA SOURCES

Data for this project was obtained from various sources. Maize yields, weather data (30-year averages of maximum and minimum temperature and precipitation over growing season) and soil properties (drainage, PH and depth) were downloaded from the CIMMYT (International Maize and Wheat Improvement Center) website. The data was developed and made available through the Africa Maize Research Atlas (Version 3.0) project. Kenya boundaries, hydrology and protected areas were obtained from International Livestock Research Institute (ILRI) GIS Services (http://192.156.137.110/gis/) and World Resources Institute (http://www.wri.org/resources/data-sets/kenya-gis-data). Soil data was obtained from the Global Environmental Facility Project - Soil Organic Carbon Stocks (GEFSOC) Project (http://www.reading.ac.uk/GEFSOC). Elevation was obtained from the Shuttle Radar Topography Mission (SRTM) DEM. Qualitative data was also used. This data was collected from communities in Kakamega, Kisumu, Bungoma and Trans Nzoia counties through semi-structured interviews.

3.3 DATA PREPROCESSING

Initial preprocessing performed included:

- Defining projection and projecting datasets to the WGS_1984_UTM_Zone_36N.
- Necessary clipping of datasets to Kenya boundary.
- Elevation, soil properties (drainage, PH and depth), growing season characteristics (average maximum and minimum temperatures, total precipitation and season's starting months) and maize yields statistics were converted to raster for use. Zonal statistics for these datasets were calculated to the county level. Multi values were then extracted to points as the researcher built an attribute table with variables to be used in the regression analysis.
- Percentage slope was derived from DEM data.
- Datasets for the suitability analysis were converted to raster. These included temperature means over growing season, precipitation totals over growing season, elevation, soil types, soil PH and slope. These datasets were acquired with 3-arcMinute spatial resolution.

3.4 CONCEPTUAL FRAMEWORK

Figure 2 below is a flow-chart of the methods used in this analysis.

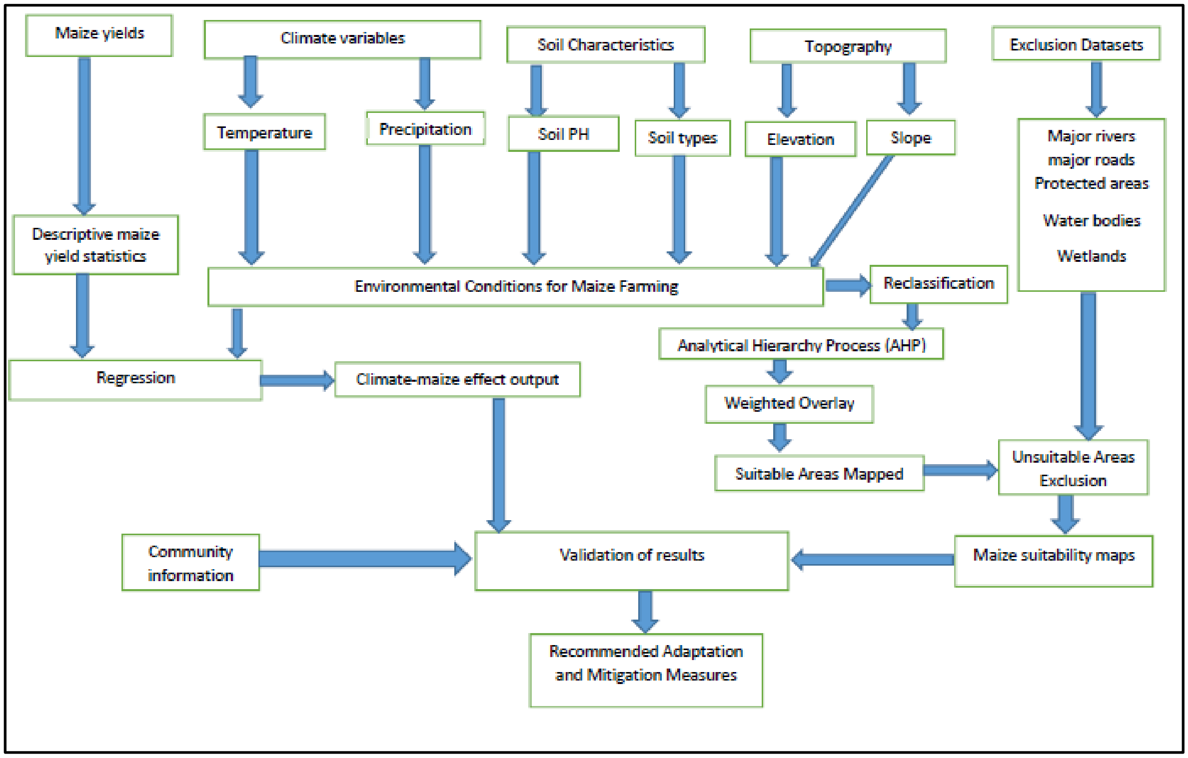

Figure 2: Conceptual Framework

3.5 REGRESSION MODELS

For this research question, maize yield was used as the dependent variable while total precipitation and mean temperature (both over growing season), soil types, soil PH, elevation and slope were used as independent variables. First, exploratory data analysis (EDA) was performed on the datasets. EDA is defined as "an approach to learning from data, aimed at understanding the world and aiding scientific research" (Behrens and Yu, n.d.). By using EDA, one makes attempts to identify the major features of a dataset of interest and to generate ideas for further investigation (Cox and Jones 2006). Four themes are apparent in exploratory data analysis: displays, residuals, transformations and resistance (*ibid*). This analysis employs displays to reveal the major features of data (visually identifying relationships between maize yields and each of the independent variables) and help in the production of ideas for further investigation. The analysis was done in R and ArcGIS software packages and information gathered from this analysis was used to inform the development of the regression models.

The next step was to run OLS regression using maize yields against the total precipitation, mean temperature (both over growing season), soil types, soil PH, slope and elevation. The Ordinary Squares Regression (OLS) tool in ArcGIS was used to perform global linear regression to model maize yields in terms of its relationships with the rest of the six variables. Several OLS models were created and run. Various model diagnostic statistics were examined and adjustments made to the independent variables (mostly involved removing some independent variables, one at a time, from the model) and modified models run. Diagnostic statistics reviewed include:

- Multiple and Adjusted R^2 – to test model performance.
- Variance Inflation Factor (VIF) – measures redundancy among explanatory variables. Explanatory variables with VIF values larger than 7.5 should be removed, one at a time, from the model.
- Joint F-Statistic and Joint Wald Statistic – measure overall model statistical significance
- Koenker (BP) Statistic - measures non-stationarity
- Jarque-Bera Statistic – measures distribution of model residuals. If model residuals are not normally distributed, the model may be biased in its prediction.
- Residual spatial autocorrelation – I ran the Spatial Autocorrelation (Moran's I) on model residuals to make sure they are randomly distributed. A random distribution of residuals is a sign of a well-specified model[5].

This was done until a well-specified OLS model was obtained. Variables in the final model were used in the next step of the regression analysis. These were; total precipitation and mean temperature.

A GWR model was run to explore more regional variations in the relationships between maize yields and total precipitation and mean temperature. The Geographically Weighted Regression (GWR) tool of ArcGIS was used in this part of the analysis. Tool parameters set included maize yields as the dependent variable and total precipitation and mean temperature both as independent variables while default values for the rest of the parameters (Kernel type, Bandwidth method, Distance, Number of neighbors and Weights) were used. After executing the tool, model diagnostic statistics were reviewed. These included the Adjusted R^2 (measure of model performance) and t-tests (measure of the

[5] More information about OLS model interpretation can be sought at http://desktop.arcgis.com/en/arcmap/10.3/tools/spatial-statistics-toolbox/interpreting-ols-results.htm

significance of the model coefficients). The GWR AICc (the small-sample-size corrected version of Akaike Information Criterion (AIC)) which measures model performance was compared against the OLS AICc to identify a better-fitting model for the maize yields, total precipitation and mean temperature. The model with a smaller AICc value is a better fit[6].

3.6 MAIZE SUITABILITY CRITERIA AND DATA RECLASSIFICATION

Tropic environments for plant growth are mostly determined by the amount and distribution of annual rainfall, and of solar radiation which in turn determines temperatures (International Institute of Tropical Agriculture 1982). Information gathered from literature and talks with employees at the Kenya Agriculture and Livestock Organization identified temperature, precipitation, soil types, soil PH, elevation and slope as the major factors determining maize yields in the study area. In this analysis, these conditions were reclassified into 5 classes. These classes represented different grades for each specific weather or environmental factor as pertains to maize productivity. Except for precipitation and elevation, the grades were adopted from Wang (2015). Each grade has a specific measure of attainable maize yields expressed as a percentage. These are shown in Figure 3 below:

Grade	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5
% Attainable Yield	95-100	85-95	60-85	40-60	0-40

Figure 3: Extracted from *(Wang 2015)* The author extracted this table from Sys et al (1991)

The classes were defined as: Grade 1 is highly suitable, Grade 2 is moderately suitable, Grade 3 is marginally suitable, Grade 4 is unsuitable and Grade 5 is most unsuitable.

An area's suitability for maize growing depends on the following factors:

3.6.1 Temperature

Temperature affects the growth and development rate of crops, as low temperature may result in poor seed set and delay the flowering and maturation stages, while high temperature could shorten the crop growth duration and reduce the productivity of the crops (Wang 2015). Besides, optimal photosynthesis rate of the crop can be achieved at certain temperature ranges. There are different

[6] Find more information about interpreting GWR model results here: http://desktop.arcgis.com/en/arcmap/10.3/tools/spatial-statistics-toolbox/interpreting-gwr-results.htm

specifications for optimal conditions from different researches. The International Institute of Tropical Agriculture (1982) quotes that the greatest yield is possible where temperatures range between 21^0C and 27^0C during the growing season with a freeze-free season lasting between 120 and 180 days while Xydi (2015) quotes that best yield (about 95%) is attained with a temperature range of 22^0C and 26^0C. Figure 4 below shows temperature class ranges from Wang (2015) that were used to define the various temperature grades in this study.

Grade	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5
Temperature (^{0}C)	22-26	18-22 26-32	16-18 32-35	14-16 35-40	<14 >40

Figure 4*:* Extracted from *(Wang 2015)* The author extracted this table from Sys et al (1991)

Figure 5 below shows two temperature maps: one representing the original dataset while the other showing the five classes.

Mean Temperature over Growing Season

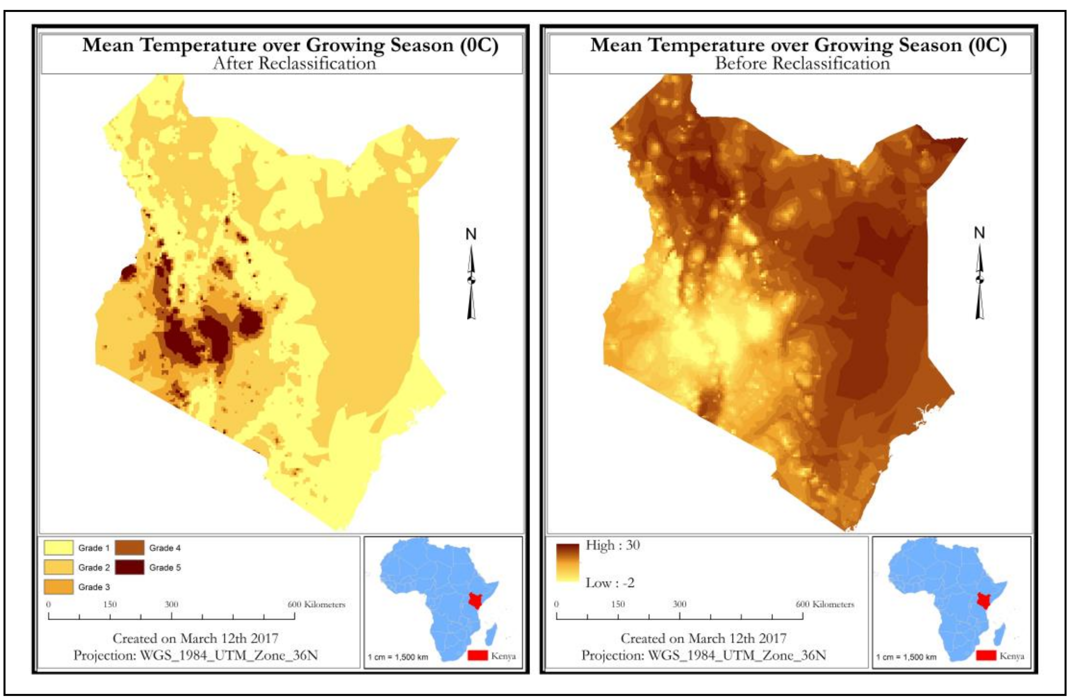

Figure 5: Mean temperature over growing season

3.6.2 Water Requirement

Maize is grown in areas where annual precipitation ranges from 2500 to 5000 millimeters. In most cases, 150 millimeters of rain per month is the lowest limit for maize production without irrigation (International Institute of Tropical Agriculture 1982). According to Brouwer and Heibloem (1986) maize requires 500-800 millimeters of water per total growing period with a medium to high sensitivity to drought. In Kenya, it is very common for maize yields to fluctuate widely with extreme variations in rainfall. Figure 6 below shows the different class ranges for precipitation while Figure 7 shows the unclassified and the reclassified precipitation maps.

Grade	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5
Rainfall (mm/growing season)	>1000	800-1000	500-800	300-500	=<300

Figure 6: Precipitation Grades

Total Precipitation over Growing Season

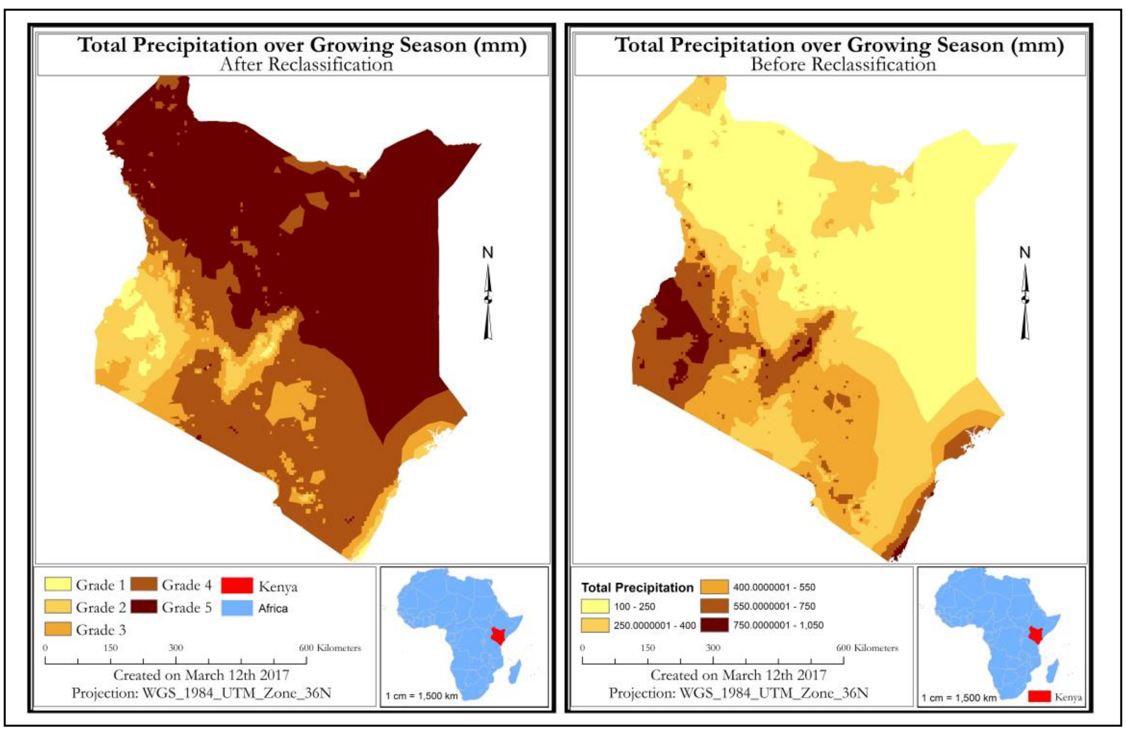

Figure 7: Average Total precipitation amounts and grades over growing season

3.6.3 Soil Type

Maize is a very demanding crop, giving higher yields compared to other cereals where climate and soils are favorable but suffering severe depression of yields in poor soils. For a good crop, normal conditions for high fertility should exist. Maize can adapt to a variety of soil textures that are well drained and well aerated such as deep loam and silt loam soils (Wang 2015).

Figure 8 below lists soil textures in every grade as pertains to suitability to maize growing.

Grade	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5
Soil texture	Silty loam	Sandy clay	Sandy loam	Fine sand	Coarse sand
	Silty clay	Loam	Loamy fine sand	Sand	
	Silty clay loam	Sandy clay loam	Loamy sand	Loam coarse sand	
	Clay loam				
	Silt				

Figure 8: Soil class characteristics

Constituent characteristics of each of these soils have been derived from the (United States Department of Agriculture (1987). These are as follows:

Grade 1

1. Silty loam – has 50% or more silt and 12-27% clay OR contains 50-80% silt and less that 12% clay
2. Silty clay – 40% or more clay and 40% or more silt
3. Silty clay loam – 27 – 40% or more clay and less than 20% or more sand
4. Clay loam – 27-40% clay and 20-45% sand
5. Silt – 80% or more silt and less than 12% clay

Grade 2

1. Sandy clay – 35% or more clay and 45% or more sand

2. Loam – 7-27% clay, 28-50% silt and less than 52% sand
3. Sandy clay loam – 20-35% percent clay, less than 28% silt and 45% or more sand

Grade 3

1. Sandy loam – less than 7% clay, less than 50% silt and between 43 and 52% sand OR 20% or less clay and the percentage of silt plus twice the percentage of clay exceeds 30 and has 52% or more sand.
2. Loamy fine sand – 50% or more fine sand
3. Loamy sand – 70-90% sand and the percentage of silt plus twice the percentage of clay should range from 20 to 30.

Grade 4

1. Fine sand – 50% or more of fine sand
2. Sand – 25% or more of very coarse, coarse, and medium sand and less than 50% fine or very fine sand
3. Loam coarse sand – 25% or more of very coarse and coarse sand and less than 50% of any other subdivision of sand

Grade 5

1. Coarse sand – 25% or more of very coarse and coarse sand and less than 50% of any other subdivision of sand

For lack of soil particle size data in the soils dataset, grades 4 and 5 was mapped based more on the percentage content of sand other than the sand particle sizes.

The soil types were grouped using the Select by Attributes tool in ArcGIS. Figure 9 represents the initial and the reclassified soil datasets.

Kenya's Soil Types

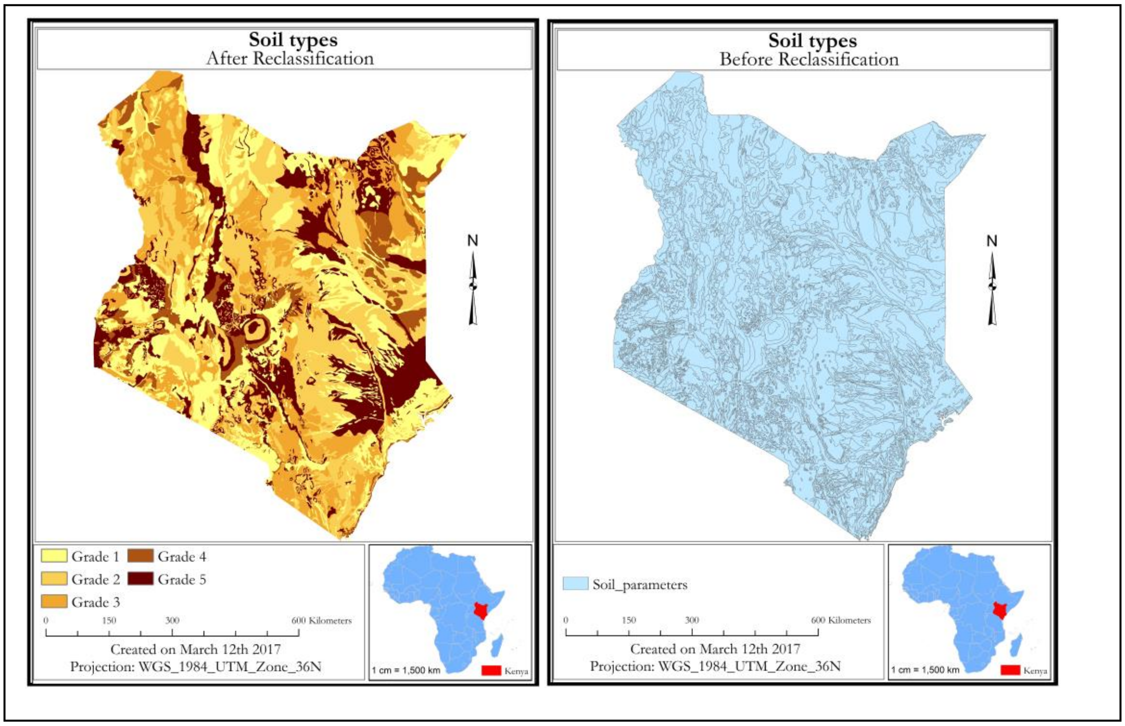

Figure 9:Kenya's soil grades

3.6.4 Soil PH

Maize can be grown in soils with PH in water (PH-H_2O) ranging from 5.2 to 8.5 (Wang 2015) on the alkalinity and acidity scale of 0 to 14. The Ministry of Agriculture (2014) reported that the target (critical) PH level should be greater or equal to 5.5. However, the analysis found that percentage of areas have their soil PH lower than this which is unsuitable for maize farming. Figures 10 and 11 represent soil PH ranges and distribution for each grade as it relates to suitability for maize farming, adopted from Wang (2015).

Grade	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5
Soil PH	6.2-7.0	5.8-6.2	5.5-5.8	5.2-5.5	<5.2
		7.0-7.8	7.8-8.2	8.2-8.5	>8.5

Figure 10: Extracted from (Wang 2015) The author extracted this table from Sys et al (1991)

Soil PH Categories

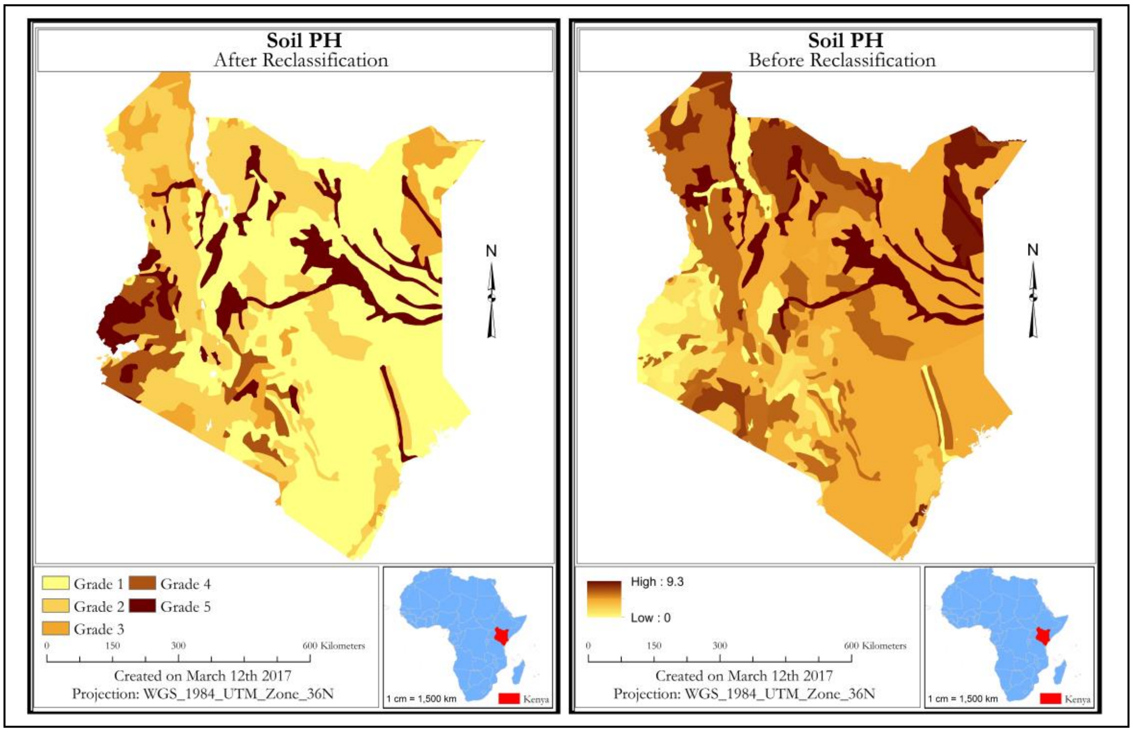

Figure 11: Soil PH

3.6.5 Slope

Land slope can affect the amount of run-off which in turn affects water availability. In low-lying areas, small precipitation can accumulate and cause waterlogging for crops while areas with steep slopes are prone to severe water run-off which limits amount of water available for crops as well as decreased soil fertility (Wang 2015). The factor values were reclassified based on the ranges in Figure 12 below.

Grade	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5
Slope (%)	0-4	4-8	8-16	16-30	>30

Figure 12: Extracted from (Wang 2015). The author extracted this article from Sys et al (1991)

Kenya's Percentage Slope

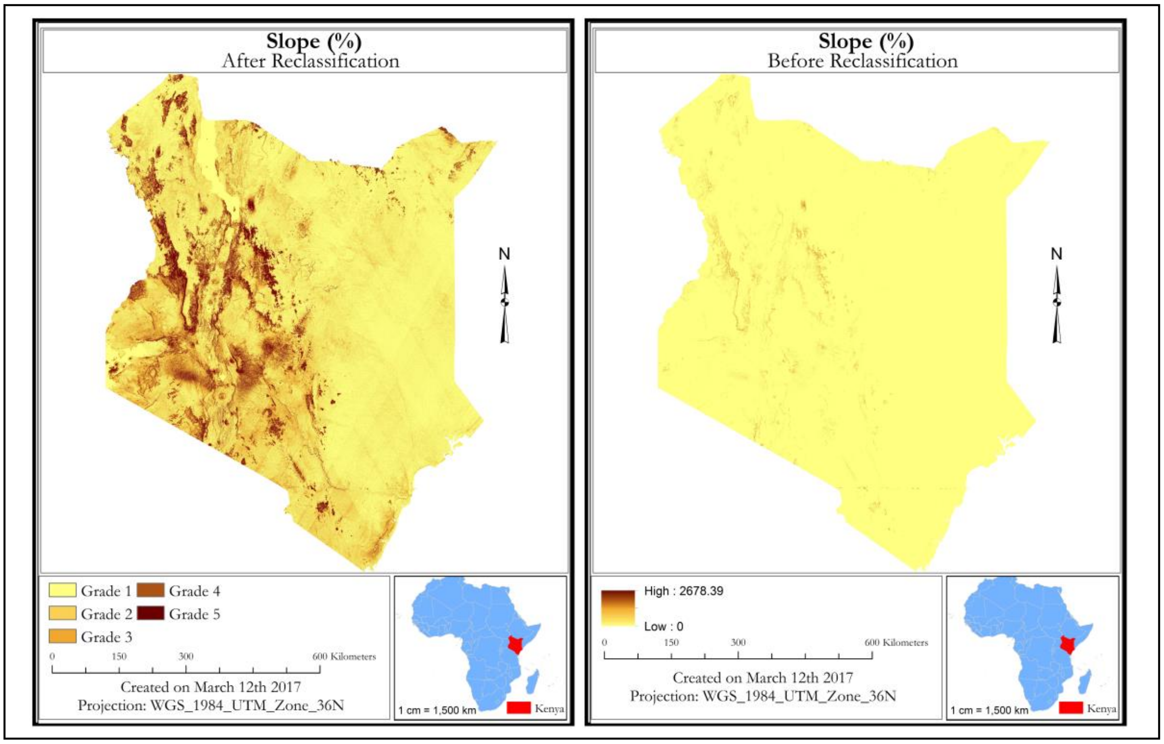

Figure 13: Kenya's Percentage Slope

Figure 13 above shows Kenya's slope, its classes and their distribution.

3.6.6 Elevation

There is limited literature on the effect of elevation on maize productivity. The researcher applied the idea that temperature varies with altitude. To get the classes, he sampled temperature class values and cross-checked with elevation values at those points. Using the minimum and maximum possible elevation values for each of those values, the researcher delineated the factor values into five grades. Figure 14 below denotes how the dataset was reclassified.

Grade	**Grade 1**	**Grade 2**	**Grade 3**	**Grade 4**	**Grade 5**
Elevation (m)	>1500	1200-1500	750-1200	250-750	<250

Figure 14: Elevation Grade

The spatial distribution of elevation and its classes is shown in Figure 15 below.

Kenya's Elevation

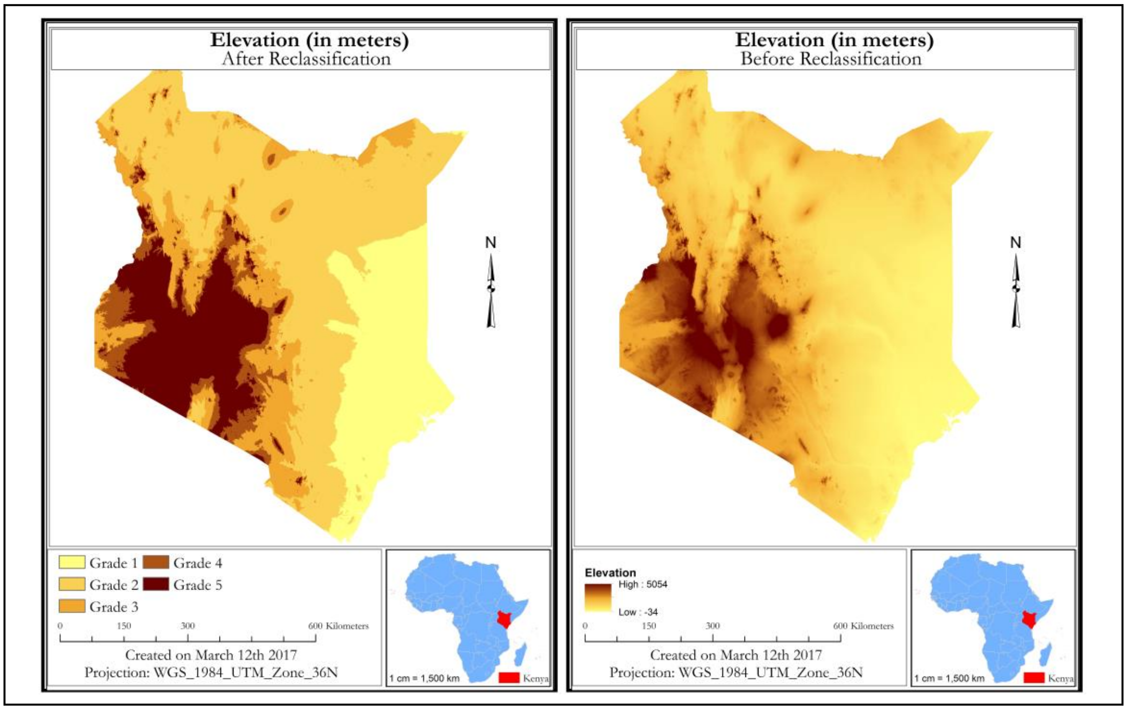

Figure 15: Kenya's elevation

3.6.7 Excluded Areas

The National Environmental Management Authority (2011) guidelines were used to identify all unsuitable areas in the study area. These were:

1. Provide buffer zones of between 2m-30m measured from the highest water mark for rivers/streams.
2. Provide buffer zones of 30m from lakes for purposes of minimizing soil erosion, run-off of pesticides, fertilizers and other non-point contaminants into streams, rivers, lakes, wetlands and marine habitats.

The areas were all combined in one layer called the Exclusion Layer. This layer constitutes water bodies (lakes and rivers), wetlands, roads and protected areas. These datasets were obtained from the World Resources Institute[7]. The National Environmental Management Authority guidelines listed

[7] http://www.wri.org/resources/data-sets/kenya-gis-data

above were used to define buffer distances from these features and the zones were mapped out using the Buffer tool in ArcMap. The exclusion layer was then rasterized using the Polygon to Raster tool. The areas are shown in Figure 16.

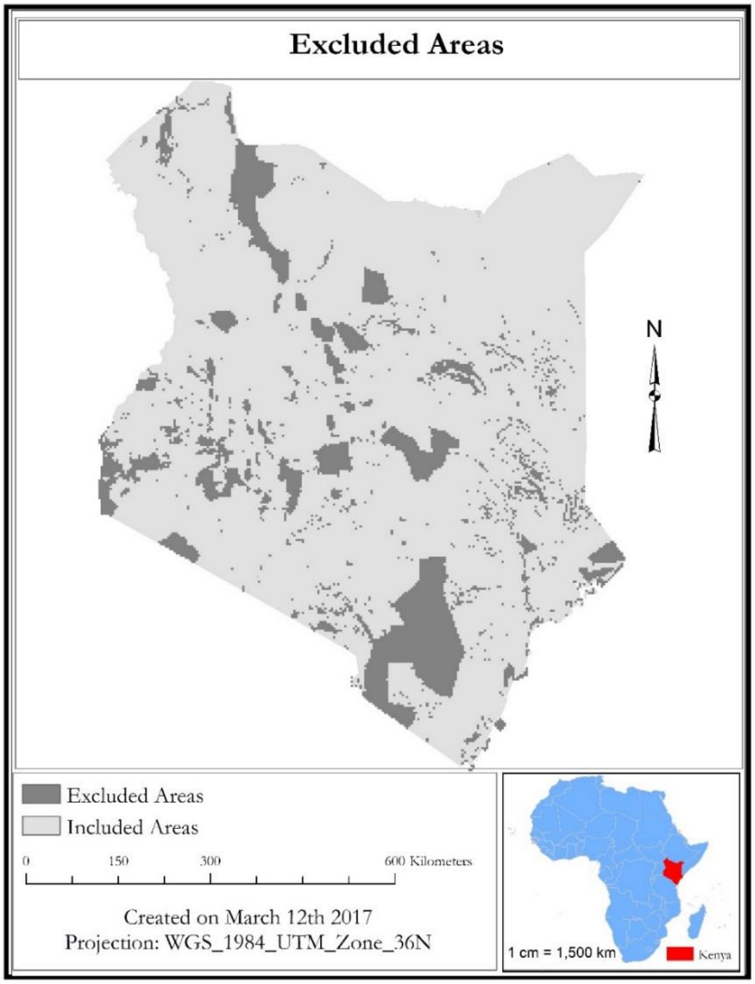

Figure 16: Excluded areas

3.7 FACTOR WEIGHTING: ANALYTICAL HIERARCHY PROCESS (AHP)

T. L. Saaty (2008) outlines the following steps as a breakdown of the AHP decision-making process:

1. Defining the problem and determining the kind of knowledge sought
2. Structuring the decision hierarchy from the top with the goal of the decision, then the objectives from a broad perspective, through the intermediate levels to the lowest level.
3. Constructing a set of pairwise comparison matrices. In this step, each element in an upper level is used to compare the elements immediately below with respect to it.

4. Using the priorities obtained from the comparisons to weigh the priorities in the level immediately below. This is done for each element. Then for each element in the level below, add its weighed values to obtain its overall global priority. This process is repeated until the final priorities of the alternatives in the bottom most level are obtained.

To make comparisons in the analysis, a scale of 1 to 9 was used to indicate how many times a factor is dominant or important over the other with respect to maize productivity in Kenya. The scale of numbers is explained in Figure 17 below.

Intensity of Importance	Definition	Explanation
1	Equal importance	Two factors contribute equally to the objective
2	Weak or slight	
3	Moderate importance	Experiences and judgement slightly favor one activity over the other
4	Moderate plus	
5	Strong importance	Experience and judgement strongly favor one activity over the other
6	Strong plus	
7	Very strong or demonstrated importance	An activity is favored very strongly over another, its dominance demonstrated in practice
8	Very, very strong	
9	Extreme importance	The evidence favoring one activity over another is of the highest possible order of affirmation
Reciprocals of the above	If activity a has one of the above non-zero numbers assigned to it when compared to activity b, then b has the reciprocal value when compared with a.	A reasonable assumption

Figure 17 Extracted from Saaty (2008)

Information from agricultural experts was used in developing weights for suitability model criteria. A pairwise comparison matrix was developed to compare and weigh each environmental factor's influence on maize productivity. In this activity, factors were compared in pairs and relative weights assigned to each. As such, factors were arranged in a table and then each of them on the left was compared against the other on the right. Experts then indicated how strong the former factor is compared to the latter. Reciprocals were automatically assigned in each pairwise comparison (Al-Subhi Al-Harbi 2001). The pairwise comparison matrix is provided in Appendix 1.

The priority vector or eigenvector was calculated by first multiplying the values in every row together and calculating the sixth root of the product. This is so because the researcher was working with a six by six pairwise matrix – comparing precipitation, temperature, elevation, soil type, soil PH and slope against each other. The resultant values were then added together and then normalized to attain the priority vector.

The next step was to calculate the Consistency Index. To get this statistic, the researcher first added the pairwise values in each column and each sum was multiplied by the corresponding priority vector. The resultant values are then summed up to get Lambda max (l-max). Lambda-max refers to the largest principal eigenvalue of a positive reciprocal pairwise comparison matrix of size *n* (Wedley 1993).

The Consistency Index (CI) was then calculated by the following formula

$$CI = \frac{\lambda max - n}{n-1} \tag{3}$$

Where n is the size of the comparison matrix.

Having found the CI, the researcher located the standard random consistency ratio (RI) provided in Wedley (1993). This is a statistic obtained from a large number of simulation runs and varies depending upon the order of the matrix (Kousalya, P., Reddy, G., Supraja, S. and Prasad 2012). In this analysis, this would be 1.24 since the size of my matrix is 6. Finally, the Consistency Ratio for the pairwise comparisons was calculated. This measure checks whether the decision-maker was consistent in his pairwise comparisons or not. Wedley (1993) explains that this statistic measures the degree of departure from pure inconsistency. The CR was calculated using the following formula.

$$CR = \frac{CI}{RI} \tag{4}$$

Where; CI is the Consistency Index

RI is the Random Consistency Index

According to Wedley (1993), Saaty recommended an acceptable CR of 0.124 and a tolerable one of 0.248 for a size six pairwise matrix. The researcher obtained a CI of 0.1664 and a CR of 0.13. Since the CR value is lower than the tolerable index, he would use weights from this pairwise comparison in the suitability analysis.

To get the average weights for each factor, the researcher normalized the column values and then averaged out the row values. These values were then converted to percentages and rounded off to the nearest whole percent. The weights would then be used in the Weighted Overlay tool in ArcMap.

3.8 SUITABILITY ANALYSIS: WEIGHTED OVERLAY

ESRI's Weighted Overlay tool was used to bring together the six factors to get the weighted scores for Kenya's suitability for maize farming. Weighted Overlay is a technique for applying a common measurement scale of values to diverse and dissimilar inputs to create an integrated analysis (Esri Developer Network, Accessed on February 19th 2017). This method is used when one has criteria defined by distinct categories and class ranges (Mitchell 2012).

As explained in Mitchell (2012), one implements this method into the GIS by mathematically overlaying the source layers corresponding to the criteria. One first assigns each category or class in each layer a numeric value corresponding to how suitable it is for the proposed purpose. An advantage to using this method is the possibility of assigning different importance to the criteria by specifying a weight for each source layer. It is also possible to assign equal importance to the suitability factors.

Raster overlay is more commonly used. Raster data is more suited to mathematical overlay since the format uses coincident cells between layers, so the cell values can simply be summed to create the overall suitability layer (*ibid.).*

The tool combines the following steps:

- Reclassifies values in the input rasters into a common evaluation scale of suitability or preference, risk, or some similarly unifying scale
- Multiplies the cell values of each input raster by the raster weight of importance
- Adds the resulting cell values together to produce the output raster ((Esri, n.d.)

For this analysis, weights from the AHP were input into the Weighted Overlay tool to bring all factors together in finding suitability levels for maize farming. Final weights used in the analysis are tabulated in Figure 18 below.

Factor	Weight (%)	Rank
Precipitation	47	1
Temperature	13	3
Elevation	8	5
Soil type	16	2
Slope	3	6
Soil PH	13	3
Sum	100	

Figure 18: Factor weights from AHP

The final suitability model is shown in Figure 19 below.

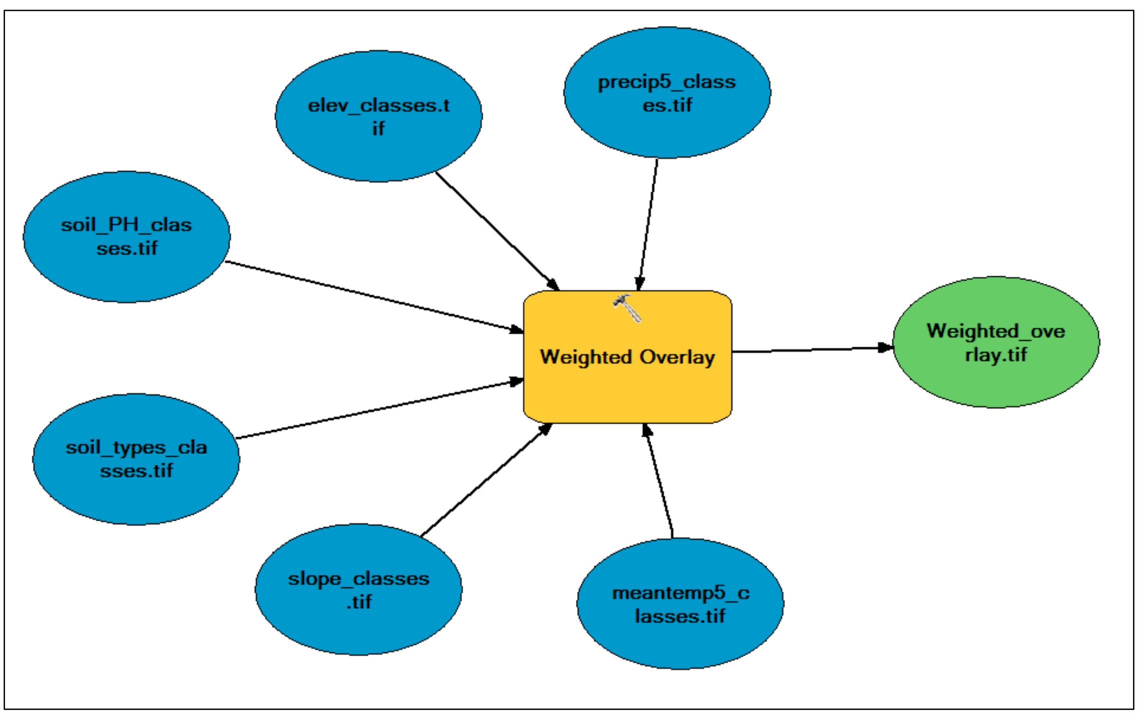

Figure 19: Suitability model developed in ESRI's ArcGIS ModelBuilder

3.9 QUALITATIVE DATA ANALYSIS

A total of 47 semi-structured interviews were held in Bungoma, Kakamega, Trans Nzoia and Kisumu counties. The counties were chosen due to their assumed suitability for maize farming coupled with the local people's maize growing and consumption cultures. The researcher first typed out all the responses in a standard systematic format to ease retrieval and ensuring safe custody for future uses.

The researcher then used guidelines from Tobacco Control Evaluation Center (2007), to code the collected data. Coding is the process of organizing and sorting data. Codes serve to label, compile and organize data and allow the researcher to summarize and synthesize what is happening in their data. In linking data collection and interpreting the data, coding becomes the basis for developing the analysis. In this part of data analysis, the researcher read through all the responses to each question in a systematic way while identifying ideas, concepts and themes that would be assigned distinct categories. Some descriptive statistics (mean, median and standard deviation) of the coded data were then calculated in SPSS software.

3.10 SUITABILITY RESULTS COMPARISON

One of the outputs from qualitative data analysis exercise was the local people's average rating of their area's suitability for maize farming. Since GPS points of interview locations were collected, the researcher used the Mean Center tool in ArcGIS to calculate the mean location of interviewees and then the feature was populated with the average suitability ratings calculated in SPSS. This output was displayed over the suitability map from the Weighted Overlay tool. The researcher then visually compared these outputs to identify any similarities.

CHAPTER 4

RESEARCH RESULTS

4.1 REGRESSION ANALYSIS RESULTS

An exploratory data analysis revealed that elevation and precipitation have the greatest influence on maize yields at 22.4% and 55.1% respectively. This is shown in the graphs in Figure 20 below.

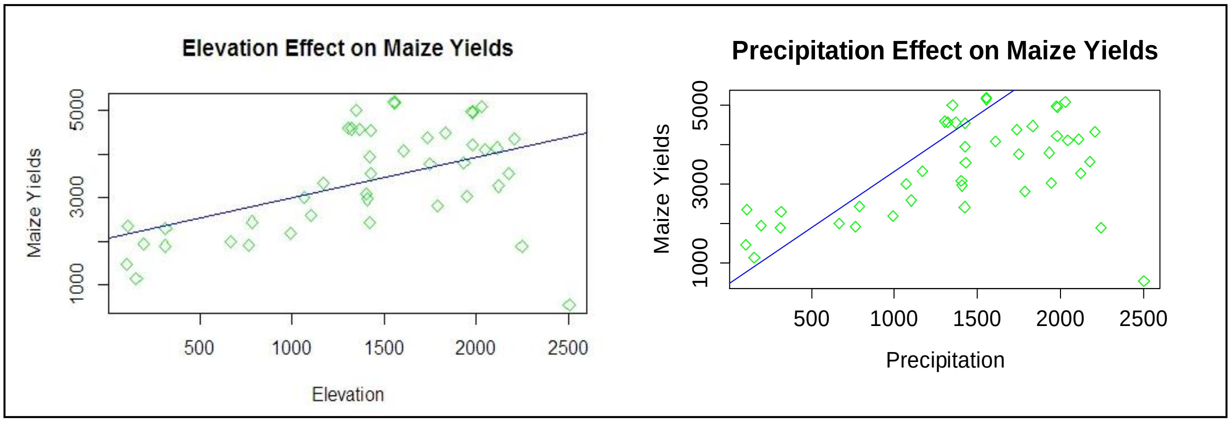

Figure 20: Linear model results for maize yields against (1) elevation and: (2) precipitation.

An OLS regression with all variables indicated redundancy between temperature range and elevation showing VIF higher than 7.5 and therefore, it can be inferred that the two variables have a similar impact on maize yields. This is true because elevation affects temperature since the higher one goes, the cooler it becomes. Owing to this, subsequent analyses would use temperature in the place of elevation. The OLS yielded statistically significant R squared of 73.6% with a residual standard error of 628.3 on 34 degrees of freedom and a p-value of 2.379e-09. Another statistic from this regression is that elevation

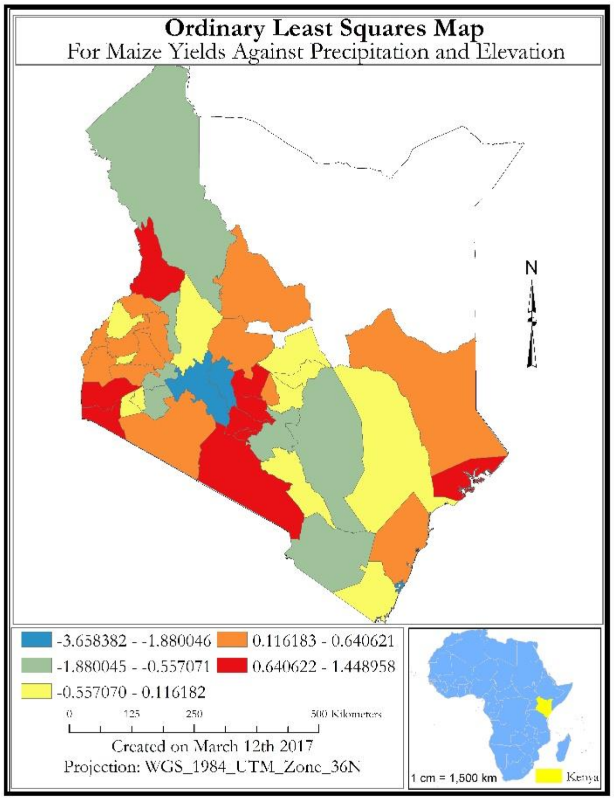

Figure 21: OLS map

and precipitation were found to have statistically significant coefficients.

An OLS with these two variables yielded an Adjusted R squared of 56.7% and an AICc of 703. This shows a strong relationship with the dependent variable. However, this model turned out with a statistically significant Jarque-Bera statistic meaning that it had biased predictions. It is worth noting that every OLS model was followed with an analysis of the spatial autocorrelation of its resultant residuals and all were random.

A GWR with all the independent variables brought back an error and therefore yields were modelled against elevation and annual precipitation. This resulted in an impressive statistic: an Adjusted R2 of 74.9% with a relatively lower AICc of 684.1. This shows a very strong and solid spatial relationship between the two independent variables and maize yields. As shown in Figure 22, this model also had random residuals.

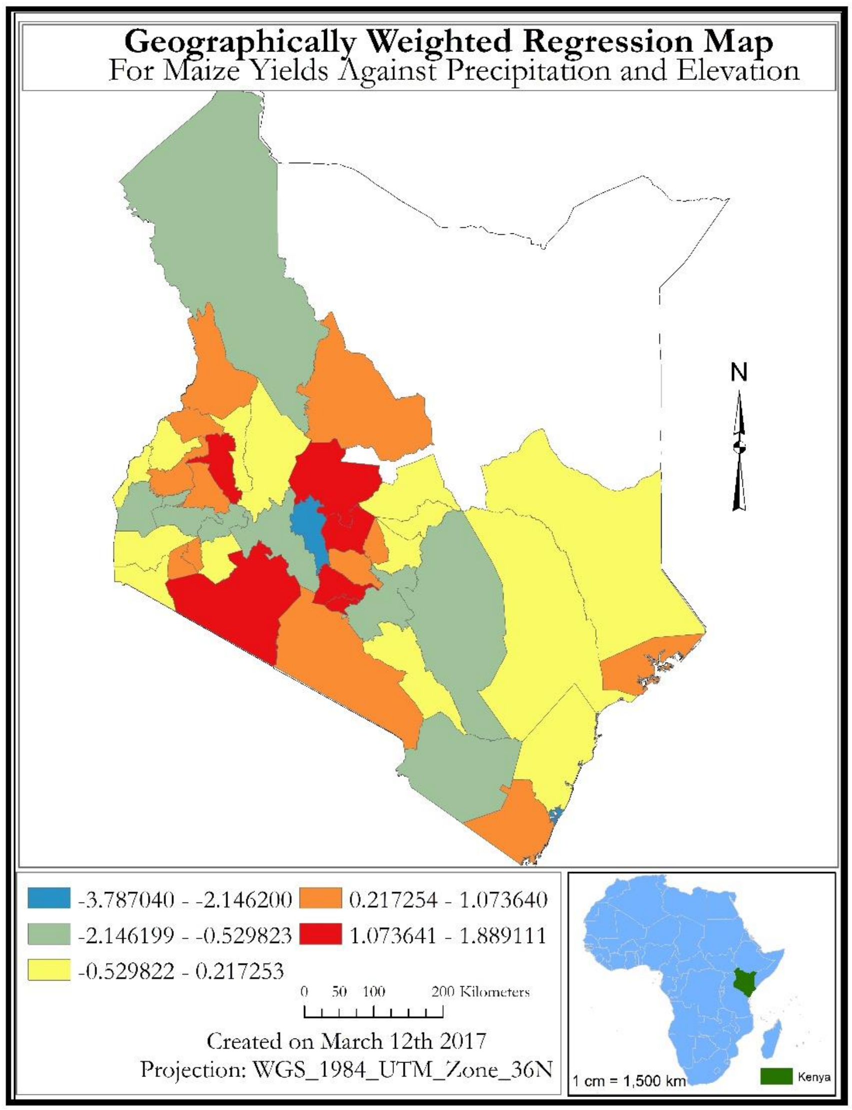

Figure 22: GWR map of maize yields against precipitation and elevation in Kenya

T-statistic was also explored. The t-statistic is obtained by dividing variable coefficient by the standard error[8] and is used to assess whether an explanatory variable is statistically significant[9].

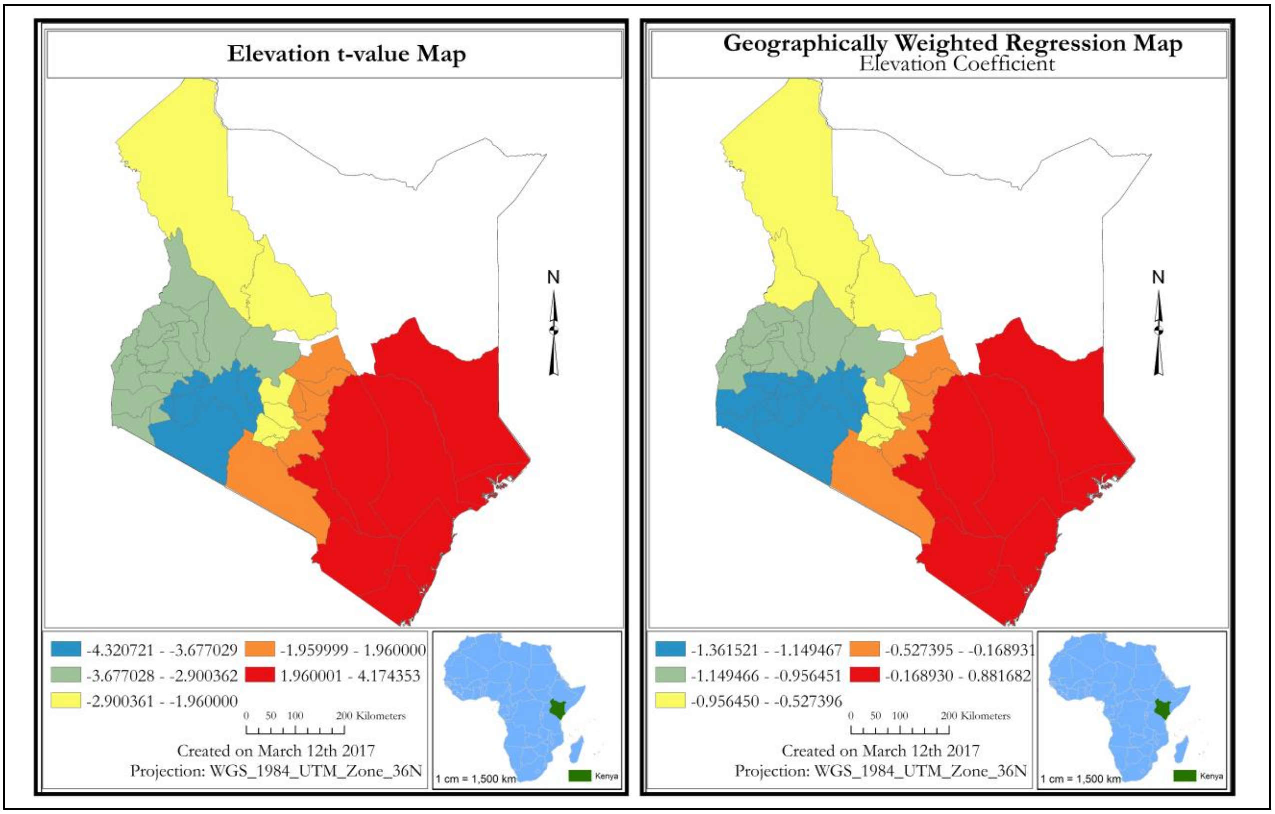

Figure 23: Elevation t-value and coefficient maps

The maps in Figure 23 above show the significance of elevation in different areas. T-values and model coefficients show a similar spatial variation in Kenya.

Elevation coefficients from the GWR model range from -1.36 to 0.88 while t-values vary from -4.32 to 4.17. Since t-values greater than 1.96 show statistical significance[10], this model yielded very significant t-values. This shows a very strong evidence to trust the elevation (and temperature by extension) coefficients except for a small region (symbolized in orange).

8 Read more about t-statistic here: http://dss.princeton.edu/online_help/analysis/interpreting_regression.htm
9 http://desktop.arcgis.com/en/arcmap/10.3/tools/spatial-statistics-toolbox/interpreting-ols-results.htm
10 https://web.csulb.edu/~msaintg/ppa696/696stsig.htm

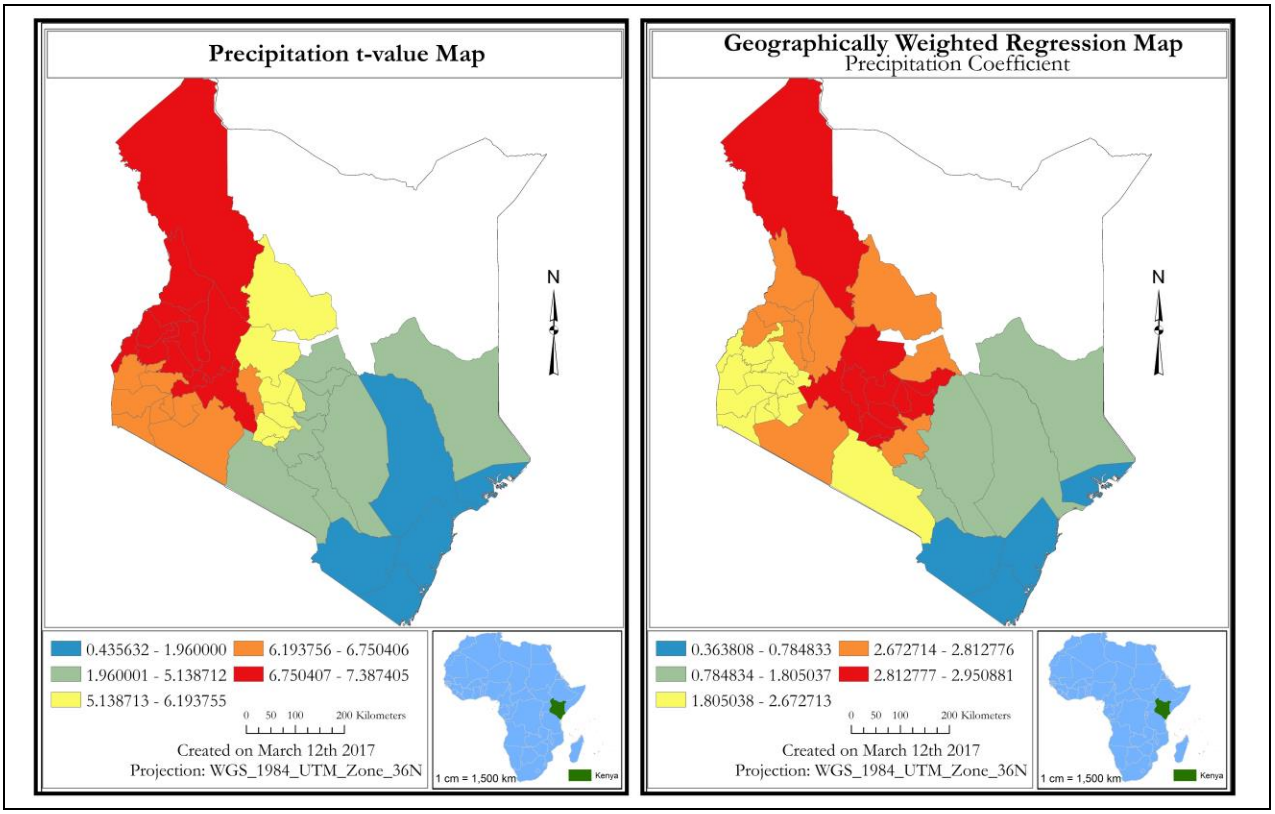

Figure 24: Precipitation t-values and coefficient maps

The maps in Figure 24 show precipitation t-values and coefficients from the GWR model. The coefficients range from 0.36 to 2.95 while t-values vary from 0.4 to 7.38. Based on these results, one can trust the precipitation coefficients except for the area shown in blue, whose t-value falls below 1.96.

4.2 ANALYTICAL HIERARCHY PROCESS RESULTS

An analysis of the average pairwise comparisons from the two experts returned a Consistency Ratio of 0.13 which is deemed to be within the tolerable range as noted by Wedley (1993). This was therefore used to calculate weights for precipitation, temperature, elevation, soil PH, soil types and slope in relation to how these factors affect maize productivity. Results show that total precipitation over the growing season hold the most significance (at 47%) followed by soil types (at 16%). Temperature and soil PH were found to be equally important both at 13% while elevation and slope stood out as the two least key factors in maize farming (at 8% and 3% respectively). Based on the AHP and regression analyses, it is correct to say that precipitation is very important in maize farming.

4.3 SUITABILITY ANALYSIS RESULTS

4.3.1 Data Reclassification Results

Results from the reclassification of temperature, precipitation, soil PH, soil types, elevation and slope datasets show the spatial distribution of the different suitability levels for maize farming. Figure 25 below summarizes results from this exercise.

Factor	% in Grade 1	% in Grade 2	% in Grade 3	% Grade 4	% in Grade 5
Total Precipitation	1.5	7.2	9.1	29.6	52.6*
Mean temperature	37.0	51.2	5.2	3.7	2.9
Soil type	24.1	29.4	20.3	6.8	19.4
Soil PH	10.9	5.5	8.4	26.5	48.7
Slope	51.7	28.0	11.1	5.3	3.9
Elevation	15.4	6.9	15.1	43	19.6

Figure 25: Summary of results from data reclassification

*Areas in this grade are mostly arid and semi-arid. They are mostly found in the northeastern parts of Kenya. Very minimal maize farming is practiced in this region.

4.3.2 Suitability Model Results

The map provided in Figure 26 shows maize suitability areas on a Grade 1 (most suitable) to Grade 5 (least suitable) scale. The results show that Kenya has limited land under "maximum suitability" category. There is approximately 0.2% of land under this class, most of which is located at the Kenyan coast (symbolized by blue on map). In these areas, one can get maximum attainable yields (95-100%) due to the area's very optimal environmental and edaphic conditions. There is 5.8% of land in the second grade. These areas (shown in green on map) are the second most suitable for maize growing considering the six factors under investigation. In these areas, a farmer can get between 85-95% of attainable yields if they follow most or all recommended practices in maize farming.

Results indicate that most of Kenya's land is in the third grade (symbolized by yellow in the map). These areas constitute 55.6% of the total. With this statistic, we can note that most of the Kenyan land is marginally suitable for maize production. Areas in this grade will yield about 60-85% of attainable yields based on the topographic, environmental and soil factors under discussion. This conflicts with reports that only 20% or less of Kenyan land is arable – capable of producing crops; suitable for farming; suited to the plow and for tillage.

There is 23.5% of land classified as grade 4 (symbolized in brown color on map). This land is generally concentrated in the north which have most times been classified as arid regions of the country. A farmer growing maize in this area will likely yield about 40-60% of the attainable yields.

Finally, there is only 0.1% of land classified as the least suitable (grade 5). These areas (shown in red on map) are concentrated around Laikipia County. A farmer would get 0-40% of attainable yields if they practiced maize farming in these areas.

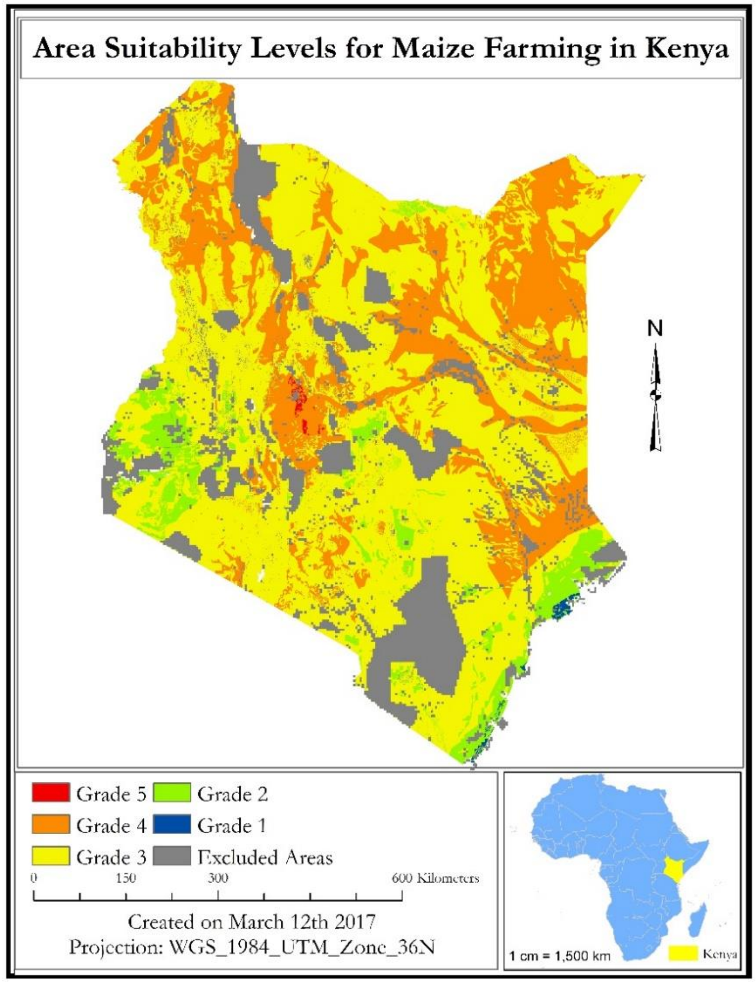

Figure 26: Maize Suitability Map of Kenya. Areas are symbolized such that: Blue, Green, Yellow, Brown and Red represent Grade 1 (most suitable), Grade 2, Grade 3, Grade 4 and Grade 5 (most unsuitable).

4.3.3 Excluded Areas

Study results show that 14.8% of total land area in Kenya is unsuitable for maize farming. These areas include water bodies (lakes and rivers), wetlands, major roads and protected areas (forest reserves, national parks and reserves and conservation areas).

4.4 FIELD STUDY RESULTS

This section of the study majorly focused on people's perceptions about their areas' suitability for maize farming, their knowledge about climate change and its impacts on maize productivity as well as their adaptation to and mitigation of the change. The following results were obtained. Worth noting is that the descriptive statistics were presented per county to detect any variations over space. Figure 27 is provided to show the mean location and total number of interviews per county.

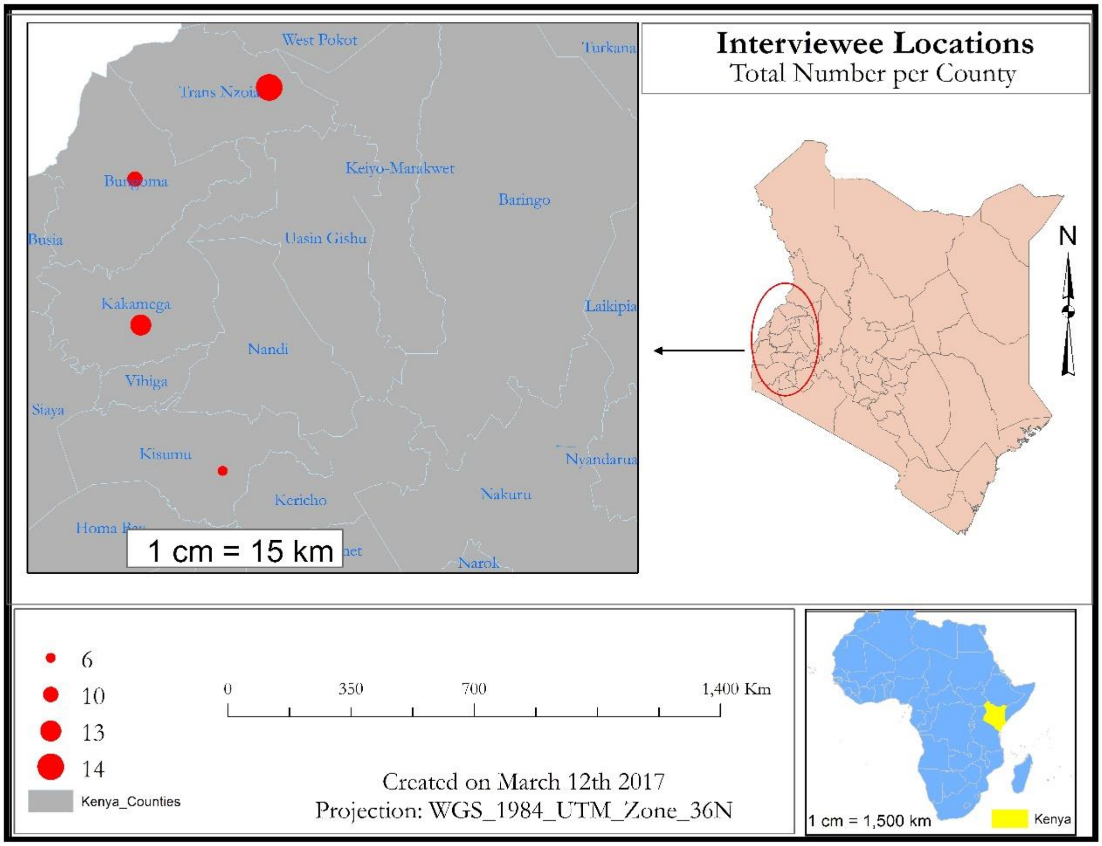

Figure 27: Field study locations

4.4.1 Bungoma County

Because maze farming is a very important economic activity in the county, finding the various effects, mitigation measures and efforts to find lasting solutions to the problems would be a very welcome idea to the locals in the county.

The researcher expected to find people getting ready to have their second season harvests, which wasn't the case for most of them. The area was dry with no sign of rainfall in the recent weeks. A notable change in the environment was the shrunk areas under trees resulting from uncontrolled deforestation by the people to meet their energy needs. This may be one reason why there are noticeable changes in the rainfall patterns as well as fast increase in temperatures in the area over the recent times.

The study involved 10 interviewees. Of these, 3 had been involved in maize farming for less than 5 years, 2 had been farmers for more than 5 but less than 10 years while 3 of them have been in this practice for more than 10 but less than 20 years. The remaining interviewees have been maize farmers for over 30 years.

Weather and climate stood out as a major factor affecting the productivity of the crop (at 50%) followed by availability of farm inputs (at 20%) with the rest reporting more than one factor. This is shown in Figure 28 below.

Factors Affecting Maize Productivity in Bungoma County			
Factor	Frequency	Percent	Cumulative Percent
Farm inputs	2	20.0	20.0
Soil fertility	1	10.0	30.0
Weather and climate factors	5	50.0	80.0
More than 1	2	20.0	100.0
Total	10	100.0	

Figure 28: Factors affecting maize farming in Bungoma

The respondents also scored the area as moderately suitable for maize farming. They also reported that they have detected changes in the climate and weather systems. Most of the changes were observed in rainfall amounts and pattern of occurrence (at 60%). 40% of the people said that more than one weather elements (predominantly rainfall and temperature) have changed over their farming period. They all agreed that the observed changes have shrunk maize yields over time.

To adapt to the changes, a few measures were reported. These included:

1. Proper timing of the rains including dry planting – reported by 5 respondents
2. Crop diversification – reported by 4 respondents
3. Small-scale irrigation – reported once
4. Soil fertility retention and restoration including use of farmyard manure – reported once
5. Greenhouse farming – reported once
6. Capacity building including joining grass-root farming support organizations – reported once

The graph in Figure 29 below depicts frequencies of the adaptation measures.

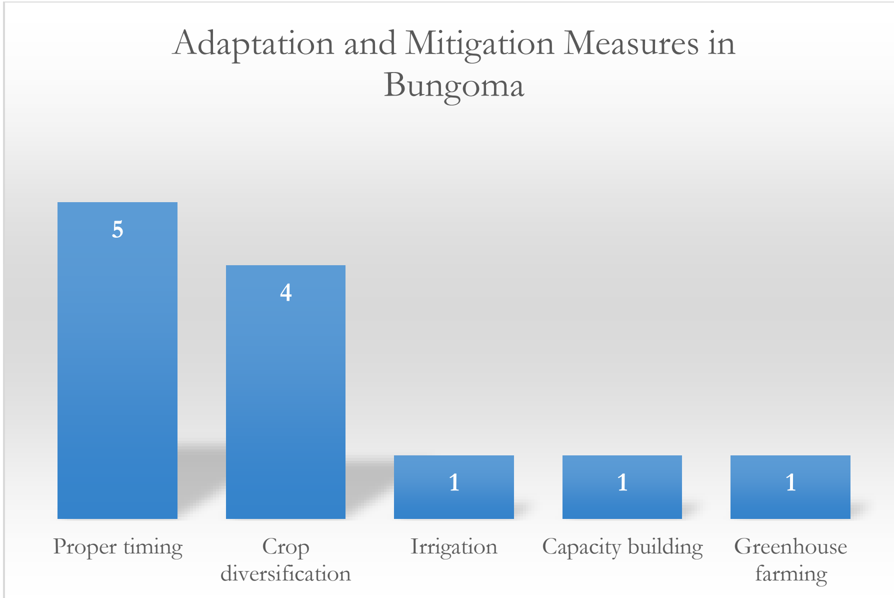

Figure 29: Adaptation measures in Bungoma

4.4.2 Trans Nzoia County

Generally, this area was more forested and greener than Bungoma. The research was done in an area called Sinyereri. The study area is populated with both small and large scale farms. The latter are usually called 'schemes' where most of the maize is produced on a large scale.

Information was collected from 14 farmers, 7 of which had farmed for over 30 years. 3 of the total were young farmers (0-5 years in practice) while the rest had been in the practice either for 6 to 10 years (2 of total) or 21 to 30 years. In this area, farm inputs were scored as the greatest determiner of maize yields at 57%. Soil fertility and weather and climate factors were equally rated at 14% each while the rest reported more than one factor, most of which was a combination of these. Despite this, the area was rated as marginally suitable (average) in terms of maize farming. The pie chart in Figure 30 represents the relative percentages of the factors affecting maize productivity in the county as reported by the respondents.

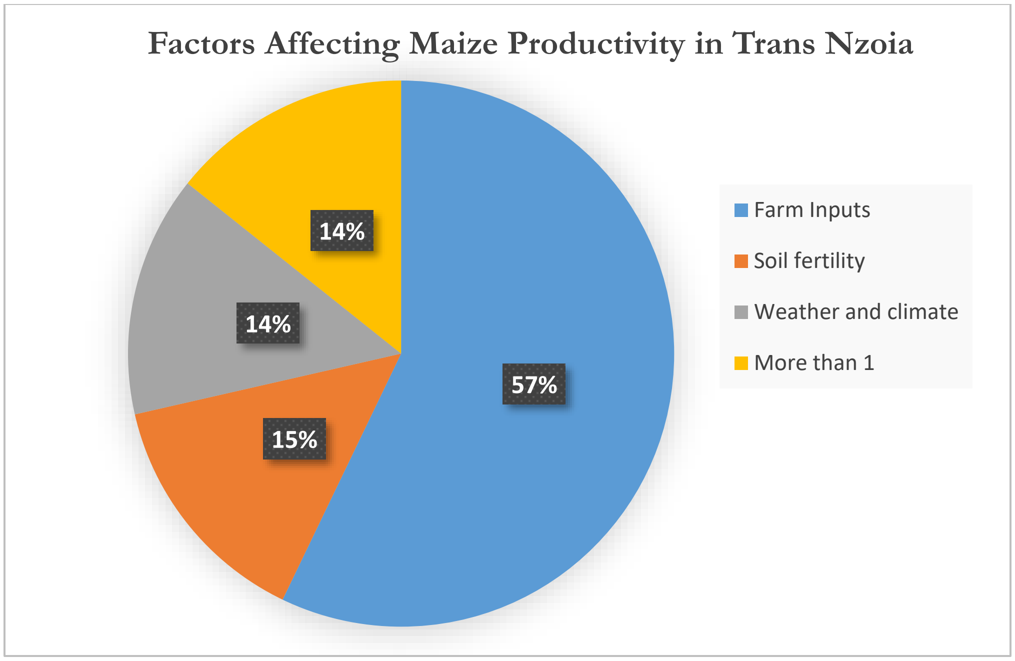

Figure 30: Factors affecting maize farming in Trans Nzoia County

Majority of the respondents (85%) reported to have noticed change in the climate and weather system. One respondent said that there hasn't been any change while the other had not stayed in the area long enough to notice any change. It was also reported that there has been lots of fluctuations in rainfall amounts and patterns (reported by 4 respondents), increased temperatures and an occurrence of frost and hailstorms (each reported once) with most farmers (43%) reporting changes in more than one weather element. The research also shows that climate change is associated with fluctuations in maize yields. This was reported by 64% of the respondents. 29% of the total reported no change to their yields while the remaining 7% did not live in the area long enough to comment on this.

To adapt to the changes in the climate and weather systems, the people reported a wide variety of activities. These are listed below:

1. Crop diversification – reported by 4 respondents
2. Growing improved seed varieties including faster maturing varieties and drought-resistant varieties – reported by 4 respondents
3. Proper timing of the rainfall including early harvesting, early planting and dry planting – reported by 4 respondents
4. Soil fertility retention and restoration including use of farmyard manure, manual weeding of the farms, digging of furrows and use of adequate commercial fertilizers – reported by 4 respondents

5. Spraying of crops to protect them from frost damage – reported by 4 respondents
6. Supporting maize stems to withstand strong winds – reported by 1 respondent

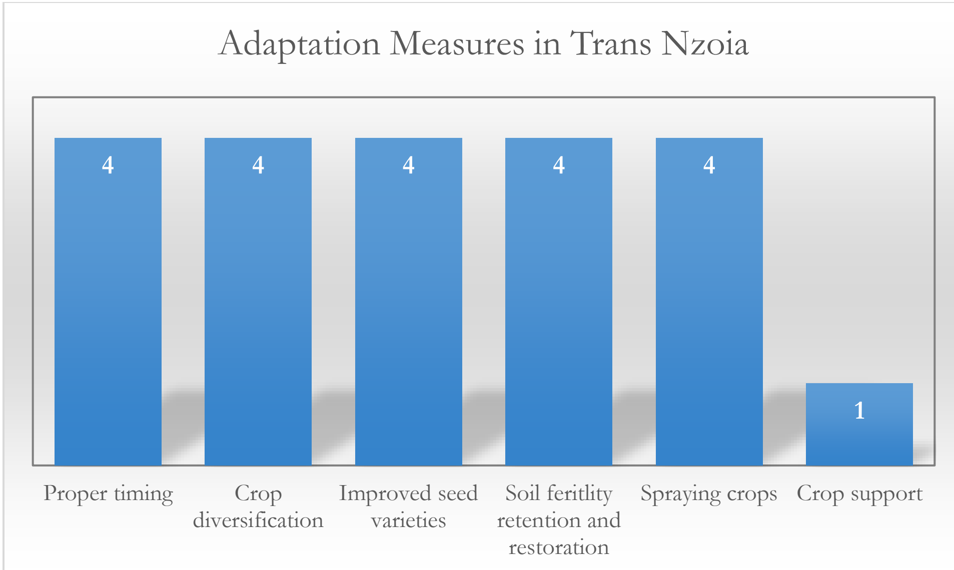

Figure 31: Adaptation measures in Trans Nzoia

Figure 31 shows a graphical representation of the reported adaptation measures in Trans Nzoia County.

4.4.3 Kakamega County

In this county, the researcher gathered data about farmers' perceptions about climate change and the consequences that the change has had on maize farming in the area. He also collected information about their adaptation and mitigation measures. This area was none like Bungoma or Trans Nzoia. There seemed to be different challenges affecting farmers. The area was generally dry although there were some farms with maize crops on them. Apart from farmers, the researcher talked to researchers at the Kenya Agricultural and Livestock Research Organization (KALRO) as well as the meteorological department.

The researcher talked to a total of 13 respondents, 10 of which were maize farmers, 2 researchers from KALRO and an employee of the Kenya Meteorological Department (KMD) in Kakamega County. In summary, 5 of these had been in the maize farming field for 6 to 10 years, 6 had over 20 years while 1 had less than 5 years. The remaining 1 had been in the field for a period of 11 and 20 years.

Farm inputs and soil fertility were equally ranked (each at 31%) as the major factors affecting maize productivity in the area. Weather and climatic factors followed in at 23% with the rest reporting more than one factor usually a combination of these three. These statistics are tabulated in Figure 32 below.

Factors Affecting Maize Productivity			
	Frequency	Percent	Cumulative Percent
Farm inputs	4	30.8	30.8
Soil fertility	4	30.8	61.5
Weather and climate factors	3	23.1	84.6
More than 1	2	15.4	100.0
Total	13	100.0	

Figure 32: Factors affecting maize farming in Kakamega

The respondents also scored the area as being moderately suitable for maize farming. All interviewees were in consensus that the weather and climate system had changed over their farming period. Majority of these (54%) said rainfall amounts and patterns had changed. The remaining noted changes in more than two elements which were mostly rainfall and temperature. All of them were also in agreement that the reported changes had reduced maize yields over time.

Among the reported adaptation and mitigation measures were:

1. Crop diversification – reported by 6 respondents
2. Capacity building including demonstrations on farms and joining grass-root farming support organizations – reported by 2 respondents
3. Crop rotation – reported by 2 respondents
4. Integrated mitigation measures - reported by 2 respondents
5. Proper timing of the rain – reported by 3 respondents
6. Soil fertility retention and restoration including use of farmyard manure, planting of Napier grass and terracing – reported by 3 respondents
7. Using improved quality seeds including research for such seed varieties – reported by 2 respondents

These are shown in the pie chart in Figure 33 below.

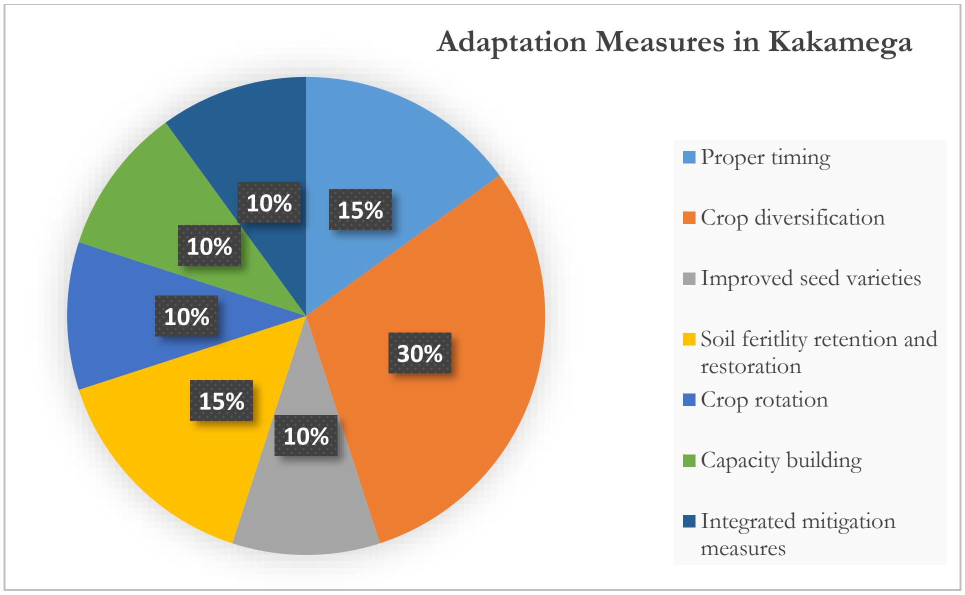

Figure 33: Adaptation measures in Kakamega

4.4.4 Kisumu County

This county was chosen because of local people's maize consuming culture as well as its apparent suitability for maize production. Looking around, the county was possibly the driest with little or no maize farming going on. It was very hot as well and people didn't seem to be benefiting from maize farming.

The researcher interviewed a total of 6 farmers. 3 of these had been farming for a duration between 6 and 10 years. 2 of them had been in the field for over 30 years. One last respondent had been planting maize for a period between 11 and 20 years. They rated the area as being marginally suitable for growing the crop. Ranking of factors affecting maize productivity was as follows: 67% of the respondents reported that weather and climate, 17% reported soil fertility while the remaining reported a combination of these two factors. 100% of the respondents reported that the weather had changed, a change that was mainly noted in temperatures, rainfall and the increased occurrence of extended droughts and more severe floods.

To adapt to the changes, the respondents reported:

1. Building dykes to contain floods – reported by 2 respondents
2. Crop diversification – reported by 4 people
3. Proper timing of the rains – reported by 1 respondent
4. Intercropping – reported by 1 respondent
5. Irrigation of the farms near water sources – reported once

6. Spraying of the crops – reported once

The above information is graphed in Figure 34 below.

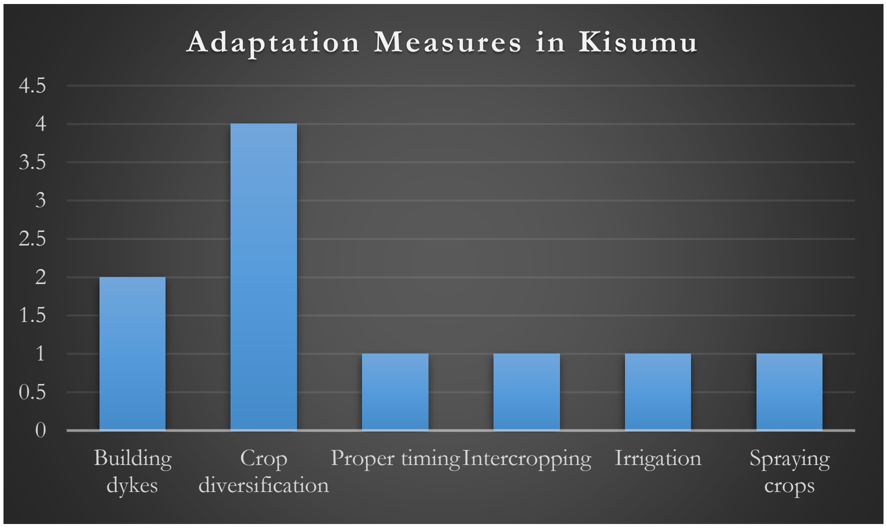

Figure 34: Adaptation Measures in Kisumu

4.4.5 SUITABILITY RESULTS COMPARISON

In the field work, farmers and people working in the agricultural sector were asked to rate the suitability of their area for maize farming. Three of four average suitability ratings from the people coincide with suitability scores from the model. The remaining rates the area as a Grade 3 while it is in an area rated as Grade 2 by the model. The comparison map is shown in Figure 35.

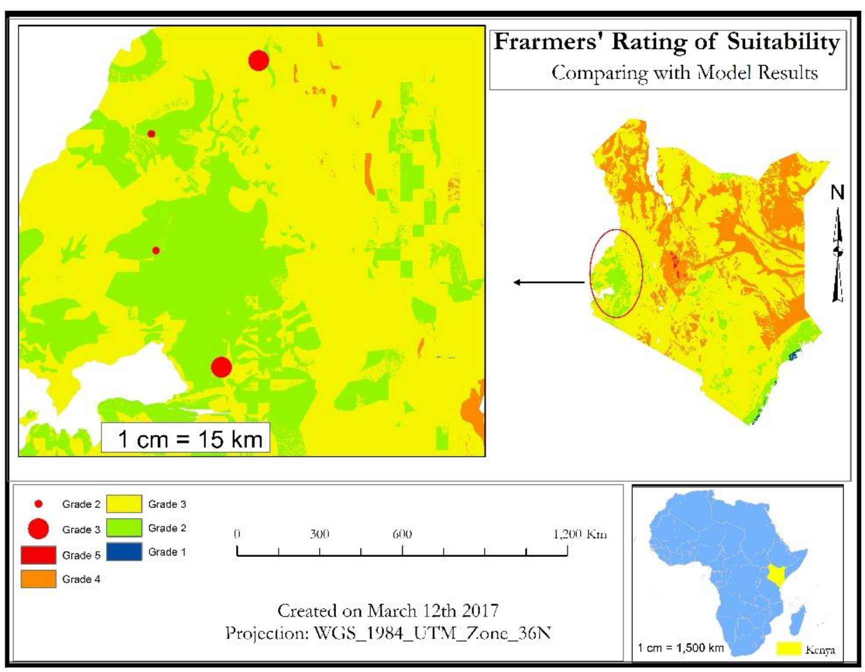

Figure 35: Comparison map of model and local people's rating of suitability scores

CHAPTER 5

DISCUSSION OF RESULTS

5.1 INTRODUCTION

This section of the study discusses major findings from the study. The researcher discusses major implications of the GWR results, findings about climate change and the effect of the change on agriculture and maize farming and finally Kenya's levels of suitability for maize farming. The researcher will also compare these results to findings from similar studies. At that point, various implications of these results (to the government, farming community and the research community) will be discussed. The implications will mostly be practices aimed at adapting to and mitigating climate change.

5.2 GEOGRAPHICALLY WEIGHTED REGRESSION

The overall goal of the research was to establish a correlation between climate change and maize productivity and then identify and map Kenya's levels of suitability for maize farming using Multi-Criteria Evaluation and GIS. To correlate climate change and maize productivity, the researcher ultimately used GWR due to its known reputation to perform a local form of linear regression for spatially heterogenous variables. This is because GWR can model spatial non-stationarity: a condition in which a simple 'global" model cannot explain the relationships between some sets of variables (Brunsdon, Fotheringham, and Charlton 1996).

Results from the regression analysis reveals that precipitation and temperature are the two major variables influencing maize productivity in Kenya. The exploratory data analysis revealed that precipitation is almost twice as important than temperature in maize farming. The GWR model revealed that the variables together influence close to 75% of maize yields in Kenya.

From the regression analysis, a VIF of 7.5 in models with temperature and elevation indicated redundancy. This means that the two variables have a similar influence on maize productivity. Temperature has been revealed to vary closely with altitude in Kenya. In fact, the higher one goes, the cooler it becomes. This has been confirmed in a report by FEWS NET (2013) which explains that mean temperatures in the country are consistent over the year, but considerable seasonal spatial variations exist, mostly related to altitude. To illustrate this, the report notes that highlands tend to have the lowest temperatures, while the low-lying northern, northeastern and eastern regions are the hottest. For this reason, elevation was used as a proxy for explaining temperature effects on maize productivity.

Results from the GWR model also shows that precipitation has the greatest influence on maize productivity. It controls most of the maize farming activities, which perfectly fits into reports that Kenya's agriculture is mostly rain-fed and therefore dependent on bimodal rainfall (Claessens et al. 2012; Government of Kenya 2009; Bryan et al. 2013; Thornton et al. 2009). Implications of these include;

- One can grow more than one crop over the year (Thornton et al. 2010).
- Since the rainy season is followed by a very dry spell, rainfall distribution and amounts are two very important factors. As such, there is a high risk of crop failure due to increased frequency of dry spells and an uneven rainfall distribution (Government of Kenya 2009)

Per the analysis, variables other than precipitation and temperature cause only 25.1% of the variation in maize yields in Kenya. This indicates that for maize farming to stay sustainable, governments, local agencies and people should focus their efforts on optimization of the country's precipitation and temperature conditions.

5.3 CLIMATE CHANGE AND MAIZE PRODUCTIVITY IN KENYA

As much as rainfall and temperature have been reported being very important in maize farming, reports indicate that these weather elements have been changing over time. In the field research, farmers talked about their struggles to survive because of the changing environmental conditions.

5.3.1 Accounts of changes in Rainfall

Based on information from the field, rainfall has changed a lot, a change that has several implications on the farming communities in Kenya. The amount and patterns of rainfall have reduced over time and left people struggling in environments they thought they were well adapted to. Having two rainy seasons (long rains in March to June and short rains in September to November) (Bryan et al. 2013), this has had different consequences on communities that heavily depend on rain-fed agriculture for survival.

Major anomalies in rainfall have been reported. Rainfall amounts seems to reduce during the seasons over time. In other times, too much rainfall within a brief period leads to floods which washes away peoples' crops and property. Besides, there are many cases of irregularities in the patterns as it either delays or disappears sometimes in the middle of the season. As respondents reported, rainfall has become very unpredictable and thus trapping people in an endless struggle to survive. This finding is in line with a FAO (2008) projection that countries, particularly those in developing countries, would face changes in rainfall patterns that would contribute to severe water shortages or flooding. These usually affect crop growth and ultimately the yields. On the same account, worst yields coincide with years that experience sudden rainfall amount and pattern changes.

Maize does very well when there is sufficient rainfall during the growing season. However, an important aspect here is the amount of spread of rainy days over the growing season. Maize is a very sensitive crop and there is a high chance of failure if rainfall fails for over a week especially in an area with very high temperatures. A paper by Bryan et al. (2013) also reports that increases in rainfall are unlikely to increase agricultural productivity as a result of unfavorable spacing and timing of precipitation.

5.3.2 Changes in Temperature

Results from the field work indicate that it has become overly cold or hot in many parts of the country. There have been fluctuations in the air temperature over the years. Increased evaporation rates are reducing water volumes in rivers and some have since dried up. There are more frequent occurrences of heat waves in the country with the most recent one reported in March 2016. Increasing temperatures have also been reported by Norrington-Davies and Thornton (2011) noting that average annual temperatures in Kenya increased by 1.0°C between 1960 and 2003. Consequently, glaciers on Mount Kenya are melting (Kanyiri 2014) and the ice cap on the mountain has shrunk by 40% since 1963. It has also been reported that a number of seasonal rivers that used to flow from atop the mountain to the surrounding areas have since dried up (Mwendwa and Giliba 2012).

Very high temperatures increase evapotranspiration rates and therefore reduces amount of water available for the maize crop. Faster growth rates in the crop are also inevitable in these conditions leading to a reduction in yields due to a reduced duration of the grain-filling period (Hartfield and Prueger 2015). Very low temperatures on the other hand slows down maize growth. Persistence of these low temperature conditions affects the crop as it runs the risk of growing into the dry months.

5.3.3 Other Changes

From the field work results, frost has been reported from the in some agricultural areas of Trans Nzoia and Kakamega. Climate variability has been common and farmers have not been able to predict occurrence of suitable rainfall and temperature for them to plant their crop. As their growing times shift with changes in rainfall especially, there have been times when rainfall disappeared at times when it was very cold and therefore very suitable for frost occurrence. This heightens farmers' risk to climate change as a result of crop failure.

In summary, climate variability has led to changes in rainfall patterns and amounts and altered heat intensity levels and consequently, maize yields have reduced with time. Most of the yield reduction has been coincident with greatest variations in rainfall spacing and timing. Because agricultural production remains the main source of income for most rural communities in Kenya, Bryan et al. (2013) note that adaptation is imperative to enhance the resilience of the agriculture sector, protect the livelihoods of the poor, and ensure food security.

5.4 SUITABILITY ANALYSIS RESULTS

Results from the suitability modelling indicate the various levels of suitability for Kenya in terms of the land's suitability form maize farming. It was expected that western areas around Lake Victoria would be the most suitable with near-maximum attainable yield potential. This assumption is based on reports that these areas are the prime maize growing areas owing to their proximity to the large fresh water body, major mountain and hills. However, most of these areas' suitability was rated either a level or two lower (with an attainable yield potential of 85-95% and 60-85% respectively).

Very small proportions of Kenya's land are classified as either optimal or totally unsuitable for maize production. Optimal areas represent only 0.2% of Kenya, all of which are located at the Kenya coast. Much as these areas have been found with maximum suitability, growing maize there is a near impossibility owing to their locations – located at the coast where most of the land is used for tourism. Most unsuitable ones constitute only 0.1% of the land and are all found in Laikipia County.

Areas with the second-best yield potential sum up to only 5.8%. These areas have a yield potential of 85-95% and are spread over the entire country with a concentration noted at the Lake Victoria and coastal regions. Most of Kenya's land (55.6% of the total) is at least marginally suitable. This means that, based on total precipitation and mean temperature over growing season, elevation, soil types, soil PH and slope, farmers can get about 60-85% of attainable yields in most parts of the country. 23.5% of the remaining land is classified as unsuitable. These areas are generally concentrated in the northern regions which have mostly been classified as the Arid and Semi-Arid Lands (ASALs).

Based on rainfall alone, most of the north-eastern parts of Kenya are most unsuitable for maize farming with an attainable yield potential of 0-40%. However, the region has better temperature, elevation, slope and soil suitability scores which is why most of the areas here end up with a higher suitability score for maize farming.

Similar AHP results have been found in a study by Linda, Oluwatola, and Opeyemi (2015). The study used this methodology to rank various land characteristics for maize production in Nigeria. Land characteristics studied here included rainfall, temperature, soil characteristics and slope. Rainfall was ranked first in this analysis with 47.9% followed by temperature at 30.8%. The methodology has also been used by Kihoro, Bosco, and Murage (2013) and Ayehu and Besufekad (2015). In both analyses, temperature was ranked as most important. The three studies conclude that AHP could provide a superior database and guide map for decision makers to achieve better agricultural production.

Maize (*Zea mays*) is the primary staple food crop in the Kenyan diet with an annual per capita consumption rate of 98 kilograms contributing about 35 per cent of the daily dietary energy consumption. Additionally, it contributes about 15 per cent of the total GDP earned from food crops. 90 per cent of the rural households in Kenya grow maize and production is dominated by small scale farmers who produce 75 per cent of the overall production. These farmers cultivate less than 1 hectare of land to produce food mainly for home consumption with their surplus sold for badly needed cash. Since maize production is entirely dependent on bimodal rainfall in the nation, Kenyan communities are greatly at risk. Occurrence of destructive floods, droughts, reduction in river volumes as well as spatial and temporal irregularities in rainfall occurrence together with inadequacies in farm inputs, technologies and lack of relevant information have reduced maize yields over the years. The Kenyan government has acknowledged these changes, identifying, for example, in its National Climate Change Action Plan 2013-2017, "prolonged droughts; frost in some of the productive agricultural areas; hailstorms; extreme flooding; receding lake levels; drying of rivers and other wetlands" and associating these changes to "large economic losses and adverse impacts on food security." (Human Rights Watch 2015). With the above state of affairs, I will now explain what the study results imply to the welfare of the people and the sustainability of the nation of Kenya.

5.5 IMPLICATIONS OF THE STUDY RESULTS

5.5.1 The Government

The Kenyan government has put forth efforts aiming to confront the impacts of climate change on national food security. For instance, it is operationalizing various policies and plans through the implementation of climate change actions in various areas (Ministry of Environment and Natural

Resources 2015). Founded on what the government aims to achieve, this study serves to inform the government on the general suitability of the land for growing maize. Because the government doesn't have any known reference about the spatial variation of the land and their suitability to maize farming, their decisions may not be well informed. This study fills this void. The suitability map can be used to inform government officials of how a specific area ranks in terms of its optimality for maize farming based on the precipitation, temperature, soil types, soil PH, slope and elevation. This way, they may know which areas they can invest in to expand area under maize farming. This will surely help curb the maize demand and supply imbalances that the country has been struggling with for a while now. Moreover, the GIS model developed here can be edited and used to analyze suitability using newer datasets so we can keep up with any changes in the land suitability for maize production. It can also be used for another crop but care should be taken as this will require adjusting the suitability criteria and yield potentials.

From these results, policymakers will understand the major factors affecting maize production and therefore can prioritize efforts to stay sustainable in the changing climate conditions. As the government struggles with unlimited funds against a myriad of needs, it makes sense to provide a platform where they can rank various activities based on need and contribution to the solution to the problem at hand. In this case, government officials can invest time and money more into projects that will reduce water deficits (including irrigation projects), fund research into more drought resistant maize varieties, and build the capacity of farmers on best farming practices that would help reduce climate change impacts.

Agricultural research and government agencies should incorporate a more participatory approach in their decision making and dealings with farmers especially to climate variability. To help ease the struggle on farmers, these agencies should perform such practices as soil testing, demonstration of best practices on farms and at every stage, farmers should be informed of any important feedback. Besides, agencies should realize how far local peoples' indigenous knowledge can go in solving current climate change problems. These people own very invaluable information that, together with improved technical knowhow, is very crucial in adapting to climate change and ensuring sustainability. People's involvement in the decision-making process also improves the authenticity and therefore eases the adoption and implementation of the resolutions.

Capacity building is key to surviving climate change. The government should initiate information exchange fora where farmers and other agricultural personnel are informed of important and/or emerging issues. This will provide an opportunity where information is shared and acquired for people to adapt to climate change and ensure their livelihood is sustained.

5.5.2 Farmers

Farmers can use this information as a decision-making tool. This study offers farmers with information about the level of suitability of their area to maize production. They can zoom into their specific locations and check the strengths and weaknesses of their areas' weather, topographical and soil conditions. Based on what they find, they can then make relevant decisions. For instance, farmers in the north-eastern part of Kenya can initiate projects to provide water into the region either through initiating irrigation projects or installing water harvesting and storage facilities whenever it rains. They should also incorporate such efforts with planting fast maturing maize varieties.

There is need for a lifestyle change among farmers. As the climate varies/changes, people should look to incorporate practices that will ensure their survival on less resources. With reduced yields in most of the crops serving their livelihoods, people need to consider adopting smaller family sizes through practicing family planning. This will cut down on the pressure on the limited resources, most of which are derived from the strained maize farming practice.

Crop diversification is key in surviving climate change. People should not trust growing only one crop (maize farming in this case). With the changing and unpredictable rainfall patterns and amounts, it is very difficult to know if maize will do well in a specific season. People are encouraged to consider planting other crops to bridge the supply gap left due to the reduced maize yields. These include; ground nuts, soy beans, cassava and sweet potatoes (in and around Bungoma, Trans Nzoia, Kakamega and Kisumu counties). Apart from meeting the food needs of the people, most of these crops improve the fertility of the soil as well.

Proper timing is key. Farmers are encouraged to ensure early preparation of their farms and be ready with farm inputs as they await the rains. In some instances, they are encouraged to practice dry planting – a practice in which farmers plant their seeds up to two weeks earlier before the rains fall. This is meant to ensure the crops mature within the shrinking rainy seasons. However, caution should be taken as dry planting may be affected by soil characteristics. For instance, presence of some organisms in the soil may cause rotting of the seeds before they germinate and therefore having seeds in such soils for a long time poses the risk of failure to germinate.

People are also encouraged to practice crop rotation. This is the system in which a farmer varies the kind of crop they grow on their soil to preserve soil fertility, improve yields and control weeds and diseases in the soil. This will go a long way to promote people's survival and may also be a way to identify crops that do best in the environmental conditions of a place.

There is a need to join or work closely with agricultural Civil Society Organizations (CSOs). People in such organizations as One Acre Fund in most of western Kenya have shown more preparedness to face climate change. The organizations are known to not only provide financial assistance in providing farm inputs but also train and guide farmers on the best practices that would ensure good yields in changing environmental conditions. Members of the organizations have benefited from the use of better quality maize seeds as well very informative demonstrations on select farms in the localities where the agricultural CSOs operate. They have also received more information and resources to enable them to adopt smart energies like solar lighting systems.

5.5.3 The Research Community

This research works as a current update that the Kenya climate has experienced various changes and variabilities in the recent times. It also works to inform the research community about what aspects of the climate has changed and the implications of this change to farming communities and the government of Kenya. An understanding that rainfall variations are becoming unbearably extreme is clear and research efforts to save the struggling maize farmer in Kenya should be put forward. These efforts may include research into fast maturing and more drought resistant maize seeds which will boost people's chances of getting good yields despite the unfavorable spacing and timing of rainfall.

This work is also a successful integration of Geographically Weighted Regression, Analytical Hierarchy Process and semi-structured interviews in the analysis of area suitability and climate change impacts on crop productivity. Results from one method can be used to validate results from another and this can be used as a platform for creating new knowledge. Models created in this study can be modified to investigate area suitability for other crops.

In a nutshell, climate change affects a wide variety of sectors in Kenya. To adapt to this change, there is need for an integrated adaptation approach. Borrowing from the idea of Systemic Integrated

Adaptation (SIA) Research Program from the Consultative Group for International Agricultural Research (CGIAR) (http://www.cgiar.org/), decision makers should draw together diverse forms of knowledge generation and sense-making from across disciplines, sectors and social worlds towards the interrelated goals of climate adaptation, sustainable development and food security. Farmers should not be left behind in this endeavor as they own very invaluable knowledge that can help shape the efforts towards community and national resilience to climate change.

CHAPTER 5

RESEARCH LIMITATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

This research aimed to find any significant statistical relationship between climate change and variability and maize productivity. Observation data for this analysis was difficult to find and the researcher ended up using simulated datasets. Creation of the data may have propagated unknown errors which may reduce the accuracy of the study results.

Unavailability of current or more recent weather data meant that the researcher would utilize the next best available data. These were 30-year monthly averages created in 1997 using the Spatial Characterization tool and availed by CIMMYT. Again, this brings about another possible source of error. However, this study is treated as a first of a two-time project. Once more current data is available, the researcher hopes to run a similar analysis and compare the results with the current results. This will provide a platform to understanding the spatial and temporal variations in Kenya's land suitability for maize farming over time.

Again, data availability comes into play here. The researcher could not find good land use land cover data for the study area. Although features like protected areas, water bodies, roads and forests have been excluded in the suitability map, future research should consider an overlay with land use land cover map to help narrow down the suitability areas.

Sampling was used to recruit people for the semi-structured interviews. As such, this exercise may have been exposed to various sampling errors. These include population misspecification, sampling frame errors and selection errors. However, the researcher believes that this didn't impact the research as he spread the research over four presumably arable counties to get more varied responses.

Closely tied to the above limitation, the researcher did not get enough time to conduct field visits in many areas in the country. As such, this may limit the information about area-specific climate change adaptation and mitigation measures. To propose more conclusive measures, future research should consider spreading the field study sites to more areas in the country.

CHAPTER 6

CONCLUSION

Precipitation and temperature are the two major factors influencing maize productivity in Kenya. Much as this is the case, variations have been noted in patterns of occurrence of these weather elements. Frost and increased soil PH have also been reported. As a result, maize yields have reduced with time. Most of the yield reduction has been coincident with greatest variations in rainfall spacing and timing. Consequently, farmers have been affected due to their overdependence on the crop and rain-fed agriculture. Because agricultural production remains the main source of income for most rural communities in Kenya, it is very important that farmers adapt to climate change to enhance the resilience of the agriculture sector, protect the livelihoods of the poor, and ensure food security.

To adapt to climate change, farmers in western Kenya are utilizing a number of strategies. These include crop diversification, crop rotation, proper timing in farming, soil fertility retention and restoration, use of improved seed varieties, strengthening crop stems during weeding (to reduce chances of being affected by strong winds), greenhouse farming, capacity building, irrigation, intercropping, building dykes and spraying crops. Among these, crop diversification is common although it suffers resistance from people's cultural practices. As such, it is very difficult for people to grow other crops when they have lived entirely on maize foods. A promising one is capacity building though gaining membership into local Civil Society Organizations (CSOs). CSOs are very helpful in providing financial support, trainings and demonstrations to farmers.

There is need for an integrated adaptation approach. Borrowing from the idea of Systemic Integrated Adaptation (SIA) Research Program from CGIAR (http://www.cgiar.org/), decision makers should draw together diverse forms of knowledge generation and sense-making from across disciplines, sectors and social worlds towards the interrelated goals of climate adaptation, sustainable development and food security. Farmers should not be left behind in this endeavor as they own invaluable knowledge that can help shape the efforts towards community and national resilience to climate change.

This study demonstrates a successful integration of Geographically Weighted Regression, Analytical Hierarchy Process and semi-structured interviews in the analysis of area suitability and climate change impacts on crop productivity. With such valuable information as an area's suitability levels for a specific purpose, this methodology can be used as a decision-making tool to inform governments, farmers and planning agencies. The methodology can be used not only for maize farming but any other land use where spatial location is key.

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APPENDICES

APPENDIX 1: AHP PAIRWISE COMPARISON QUESTIONNAIRE

A Spatial Analysis of Climate Change Effects on Maize Productivity in Kenya

In this analysis, my aim is to use GIS in developing a suitability model that will identify most suitable areas for maize growing based on identified criteria. To do this, I would like your expert opinion about how different variables rank against each other, in terms of how much influence they have on maize productivity.

For this weighing, a scale of 1 to 9 is used. Please use the explanation in the table below to assign a weight in each pair comparison. Please note that circling a number in RED means Criteria A is more important than Criteria B. Circling a number in BLUE means Criteria B is more important than Criteria A.

Intensity of Importance	Definition	Explanation
1	Equal importance	Two factors contribute equally to the objective
2	Weak or slight	
3	Moderate importance	Experiences and judgement slightly favor one activity over the other
4	Moderate plus	
5	Strong importance	Experience and judgement strongly favor one activity over the other
6	Strong plus	
7	Very strong or demonstrated importance	An activity is favored very strongly over another, its dominance demonstrated in practice
8	Very, very strong	
9	Extreme importance	The evidence favoring one activity over another is of the highest possible order of affirmation

FACTORS BEING COMPARED: precipitation, temperature, elevation, soil type, slope, soil PH

Criteria A	**Relative Importance**																	**Criteria B**
Precipitation	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Temperature
Precipitation	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Elevation
Precipitation	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Soil type
Precipitation	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Slope
Precipitation	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Soil PH
Temperature	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Elevation
Temperature	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Soil type
Temperature	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Slope
Temperature	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Soil PH
Elevation	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Soil type
Elevation	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Slope
Elevation	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Soil PH
Soil type	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Slope
Soil type	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Soil PH
Slope	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Soil PH

Comments:

APPENDIX 2: AHP WEIGHTING WORKSHEET

Factor	Precipitation	Temperature	Elevation	Soil type	Slope	Soil PH	6th root number	Priority Vector	Lambda max
Precipitation	1.000	5.000	7.000	5.000	8.000	5.000	4.374	0.505	
Temperature	0.200	1.000	3.000	2.000	3.000	1.000	1.239	0.143	
Elevation	0.143	0.333	1.000	1.000	4.000	0.200	0.580	0.067	
Soil type	0.200	0.500	1.000	1.000	6.000	5.000	1.201	0.139	
Slope	0.125	0.333	0.250	0.167	1.000	0.200	0.265	0.031	
Soil PH	0.200	1.000	5.000	0.200	5.000	1.000	1.000	0.115	
Sum	1.868	8.167	17.250	9.367	27.000	12.400	8.659	1.000	
Sum*PV	0.943	1.168	1.156	1.302	0.837	1.426			6.832
Normalized values							Total	Average weights	Weights in whole %
Precipitation	0.56	0.61	0.41	0.53	0.3	0.4	2.81	0.46833	47
Temperature	0.1	0.12	0.17	0.21	0.1	0.08	0.78	0.13	13
Elevation	0.08	0.04	0.06	0.11	0.15	0.02	0.46	0.07667	8
Soil type	0.1	0.06	0.06	0.11	0.22	0.4	0.95	0.15833	16
Slope	0.06	0.05	0.01	0.02	0.04	0.02	0.2	0.03333	3
Soil PH	0.1	0.12	0.29	0.02	0.19	0.08	0.8	0.13333	13
Sum	1	1	1	1	1	1			100

Steps used to calculate variable weights are:

1. Calculate the priority vector
2. Calculate Lamd max (l-max)
3. Calculate the Consistency Interval
4. Calculate the Consistency Ratio
5. Normalize column values to obtain weights for each variable. The values were converted to percentage by multiplying them by 100.

APPENDIX 2: SEMI-STRUCTURED INTERVIEW QUESTIONNAIRE USED FOR FIELD WORK

A Spatial Analysis of Climate Change Effects on Maize Productivity in Kenya

The questions in this form will help the researcher to collect data about locations' suitability to growing maize as well as people's knowledge, attitudes and practices regarding climate change in Kenya.

NB: Note-taking form provided separately.

Background question: For how long have you been growing maize in this area?

1. What is your general impression of the ability of this area to produce maize?

   Probe: Why is this so?

2. What factors affect maize productivity in your area?

   Probe: How have each of them maize cropping?
   Probe: Have your neighbours also faced a similar problem

3. Overall, on a scale of 1-5, how would you rate suitability of this area for maize production?
   Probe: Why is this so? Physical or other factors?

4. What weather conditions are you familiar with? Generally, are there any noticeable changes in their patterns over time?

   Probe (has the area become too hot or too cold, or is it the same? Has the rainfall become too much, too little or is it the same amount received over the years? Why do you say that?)
5. If you said yes to (5) above, please share with me if and how this change has affected your maize yields

   Probe: How do you know this?
6. How have you been adapting to and mitigating the effects of the changes?
   Probe: did you consider planting other crops? Which ones? What other methods did you apply?

Thank you very much for answering these questions. Your time to take part in this is highly appreciated. Should you have any questions about the project or how this information will be utilized, feel free to contact me using the contact info on your consent form.

APPENDIX 3: RAINY SEASON AVERAGE STARTING MONTH IN KENYA