THE UNIVERSITY OF NAIROBI

INVESTIGATING EFFECTS OF CLIMATE CHANGE ON AFLATOXIN CAUSING FUNGI ASPERGILUS DISTRIBUTION IN MAIZE OVER KENYA

BY

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2020

DECLARATION

I affirm that this dissertation is my unique work and has not been submitted elsewhere for examination, award of a degree or publication. Where other people's work or my own work has been consulted, this has been appropriately accredited and referenced in harmony with The University of Nairobi's guidelines.

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DEDICATION

I dedicate this dissertation to my family; my partner Stephen W. Njaramba, my sister Ruth W. Nying'uro, my Mother Agnes. W. Nying'uro and to the memory of my father Eliud O. Nying'uro for always supporting me and my work.

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ABSTRACT

Climate Change is currently the bane of human existence. From impacting food resources to threatening international security by weakening national defences, climate change has garnered the attention it rightfully deserves. Among the many anticipated changes, projected climate change will impact the agricultural sector and subsequently food security by influencing primary agricultural systems both directly by influencing yields and indirectly by impacting the safety of produced food. This study set out to investigate the effects of climate change on the distribution of the fungi causing aflatoxin – aspergillus- in maize in Kenya. This was achieved by first determining the spatiotemporal variability of past and future climate in Kenya, then determining the spatial distribution of aflatoxin under present climatic conditions and finally by simulating the effects of past and future climate on aflatoxin distribution using a species distribution model.

Past temperature and rainfall data was collected from Kenya Meteorological Department and passed through quality control. For future climate, Coordinated Regional Downscaling Experiment (CORDEX) data was used. The data was extracted for two Representative Concentration Pathways (RCP) namely RCP8.5 w/m^2 (RCP8.5) and RCP4.5 w/m^2 (RCP 4.5). Graphical and statistical analyses were used and the results presented in tables and charts. The rainfall and temperature data at various timescales was subsequently used as predictors and input into MaxEnt a species distribution model. MaxEnt model uses climate variables as well as environmental variables to probabilistically project distribution changes of different naturally occurring species.

Temperature and rainfall analysis show that climate has been changing across the years under investigation and will continue to change. Trends of the two variables show a rise in temperatures and a decrease in rainfall over the entire country. Notably, the rate of change of night time temperature is higher than daytime temperatures and rainfall. The results from MaxEnt, show that the distribution is expected to increase geographically under both RCP4.5 and RCP8.5 by the year 2050. This study recommends development of robust adaptation options to cushion the country in the future against the negative impacts of climate change within the agricultural sector such as, development of risk maps for aspergillus occurrence that will give rise to aflatoxin and infect maize.

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LIST OF ACRONYMS AND ABBREVIATIONS

AR4 - 4th Assessment Report

AR5 - 5th Assessment Report

CORDEX - Coordinated Regional Downscaling Experiment (CORDEX)

FAO – Food and Agricultural Organization

GHG - Green House Gas

GDP – Gross domestic product

GoK - Government of Kenya

IPCC - Intergovernmental Panel on Climate Change

KALRO - Kenya Agricultural and Livestock Research Organization

KNBS - Kenya National Bureau of Statistics

KMD – Kenya Meteorological Department

MAM – March April May

MaxEnt[2] - Maximum Entropy modelling software

MDG – Millennial Development Goals

OND – October November December

RCM – Regional Circulation Model

RCP - Representative Concentration Pathways

RCLIMDEX - Software packages for data homogenization and indices calculation.

SRES – Special report on Emission Scenarios

IFPRI – International Food Policy Research Institute

TFRCD - Taskforce for Regional Climate Downscaling

UN - United Nations

WCRP - World Climate Research Programme

CHAPTER ONE

INTRODUCTION

1.1 Background of the study

It is anticipated that climate change will have implications that have never been seen before on a global scale. These include impacts on regions that people can settle, the type of food they can grow as well as where to grow it, where they can build cities and settlements, and to a large extent whether or not existing ecosystems will remain functioning and provide essential services. In countless areas, temperature changes specifically in terms of rise and subsequent sea-level rise already are subjecting ecosystems to stress and affecting the well-being of people (IPCC, 2013).

Some of the expected effects of unmitigated climate change include a rise in global air temperature as well as changes in rainfall, both in spatial and temporal distribution as well as seasonal variability and shift in onset and cessation dates of rainfall. Within the agricultural sector, and especially in regions that depend solely on rainfall for agricultural production, these changes are expected to undoubtedly influence food production in various ways. These ways include directly influencing farming systems; these farming systems include plant and animal production and therefore directly impacting availability of food (Van der Fels-Klerx *et al* 2016.)

Depending on the region, and focusing on the agricultural sector, there are only two ways projected climate change effects are expected to go; either influence positively or influence negatively crop production and suitability of the land to cultivate specific crops. However, for most parts of the world the projected effects will largely be negative especially on agricultural production. Climate change effects provide complex problems that not only directly affect agricultural systems but indirectly as well through negatively affecting the safety of the food production chain, all the way from planting to storage. One of the effects of climate change within the agricultural sector due especially to an increase in temperature is the increase in occurrence of pests and diseases. The geographical extent of the occurrence of these pests and diseases is projected to shift in some cases and to increase in many others (Chattopadhyay *et al* 2019). With specific reference to mycotoxins of which aflatoxins are a subset, an increase in its main determinants namely moisture content as well as increasing temperatures determine the increase of aflatoxin distribution and concentration (Jaime-Garcia and Coty, 2003)

In Kenya particularly, cases of aflatoxin outbreaks have been reported in the recent past most of which occurred in semi-arid areas (Ongoma, 2013) as well as in relatively wetter areas of Central and Western Kenya where maize is predominantly grown. These outbreaks have led to food shortages and subsequent increase in food prices, the food security situation in the country has repeatedly been affected as the staple food for majority of low income households is maize and its derived products.

This research aimed to establish the current distribution of aflatoxin as well as the future distribution of aflatoxin in maize throughout the country under changing climate in terms of changing rainfall and changing temperature up to the year 2050.

1.2 Problem statement

Climate change is sure and associated impacts, though widely varied, include increased global air temperatures as well as reduced rainfall in some regions of the world. These impacts are expected to worsen the food security situation in the country and globally at large (IPCC, 2013)

Aflatoxin producing fungi widely occur in nature and have relentlessly tainted human food supplies as well as those of animals, resulting in health risks and even death in extreme but common cases (Kumar *et al.,* 2017) Climate directly affects the occurrence and distribution of these aflatoxin causing fungi aspergillus (Iqbal et al., 2016) However, the effect that climate change has on aflatoxin is extremely complex, and rightly so since the relationship is not necessarily linear. There is a proven rise in the mean global air temperature as well as change in how precipitation is distributed that is associated with climate change. In investigating the effects of climate change however, a rise in the variable nature of the weather, with increasing extreme events such as increased occurrence of subsequent days with very high temperatures, droughts and extremes in precipitation is of more concern in determining the impacts expected on growing plants and subsequently on food security globally as well as within our country Kenya. Additionally, these characteristics of changing climate are expected to have a direct impact on various stages of aflatoxin causing fungi.

1.3 Objectives

The principal objective of this study was to investigate the effects of climate change on aflatoxin distribution and probability of occurrence in maize in Kenya. The following specific objectives were used to achieve the principal objective**:**

1. To determine the spatiotemporal variability of past and future climate in Kenya.
2. To determine the spatial distribution of aflatoxin causing fungi aspergillus under present climatic conditions.
3. To simulate the effects of past and future climate on aflatoxin distribution

1.4 Justification

The agricultural sector is rightly recognized as the pillar of our country Kenya's economy. 24% of the Gross Domestic Product (GDP) is directly attributable to agriculture while indirectly 27% of GDP is from the sector in the form of interactions with other sectors such as with distribution, manufacturing, value addition and other sectors that are service related. The Government of Kenya derives roughly about 45% of its revenue from agriculture with this sector contributing more than 75% of inputs in the form of raw materials for use in industries (ASTGS, 2019) Agriculture also contributes to more than 50% of the export earnings by the country. Since many Kenyans are farmers, accounting for over 80% of the population of Kenya especially those not living in urban areas, we can therefore say that the agricultural sector is the greatest employer of people in the Kenyan economy, employing about 60% of the total employed citizens (IFPRI). It therefore goes without saying that for Kenya to achieve food security the, agricultural sector plays the biggest role especially in light of the fact that in Kenya food insecurity is unacceptably high with about 2.2 million people requiring food or food assistance (Food Security and Nutrition Working Group, 2017)

Maize is the primary food eaten in Kenya, and is consumed by many low to medium income households. In the past few years however, aflatoxin contamination of maize has threatened the food security situation in the country. Aflatoxin producing fungi widely occur in nature and they continue to severely contaminate human and animal food supplies, resulting in health risks and even death in extreme but common cases (Kumar *et al.,* 2017) Understanding the climatic factors affecting aflatoxin distribution and probability of occurrence are key to cushioning the country against their adverse effects in the future. According to projections, it is expected that global average surface temperature values will go up in the years leading up to 2100 under all greenhouse gas emission scenarios that have been assessed (IPCC, 2013).

Kenya has also launched a ten-year agricultural sector transformation strategy that aims to grow the Kenyan economy by increasing small-scale farmer incomes, increasing agricultural output and value addition as well as increasing household food resilience (ASTGS, 2019). This will be achievable by taking into account the various factors affecting food, maize production such as aflatoxin contamination. With this in mind it was imperative to study the effects that these climatic changes would have on aflatoxin distribution and probability of occurrence in the future and thus adapt to expected changes.

1.5 Area of Study

The geographical location of Kenya is such that it lies between longitudes 34E and 42E and latitudes 5N and 5.5S (Figure 1). The equator almost divides the country into two equal southern and northern halves.

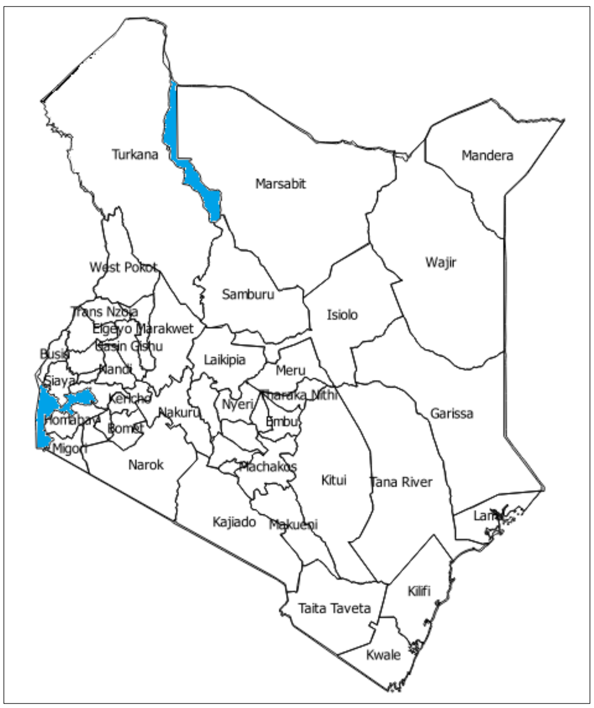

Figure 1: A map showing the area of study

1.5.1 Climate characteristics of the area of study

Kenya has a humid and warm tropical climate towards the east on its Indian Ocean coastline. Moving inwards and westwards from the Indian Ocean, the climate gradually cools into the savannah grasslands and further into the highlands before warming again and becoming hot and humid closer to Lake Victoria basin region which is on record as the largest fresh-water lake in the world naturally occurring within the tropics. Some of the cash crops grown within the highland regions as well as within the rift valley include coffee and tea. Moving towards the north-eastern regions along the border with both Somalia and Ethiopia we experience arid and semi-arid regions with near-desert lands. Maize is grown mainly and on a large scale within Western Kenya, rift valley and across the country by small scale farmers.

In Kenya, rainfall is the most sensitive climatic element. Rainfall information is, therefore, required in the planning and management of most socio-economic activities through its thorough investigation of past, present and future characteristics. Kenya, like many other parts of the tropics are prone to drought and floods, indicators of extreme climate events. These events have in the past had severe negative impacts on key socio-economic sectors. The recent impacts include the devastating severe 1997/98 floods and the 1999/2000 drought in the region that resulted into loss of life, damage to property and infrastructure, lack of food, deficient fresh water, energy and many other basic needs of society. Extreme climatic conditions have been around time in memorial and are here to stay.

The main synoptic scale systems that influence the weather and mainly the rainfall of Kenya include the Inter-Tropical Convergence Zone commonly referred to as the ITCZ, sea surface temperatures in various ocean basins, tropical cyclones, monsoon winds, sub-tropical anticyclones, ocean currents, jet-streams and easterly waves. Additionally, other regional factors influence and modify the weather of specific regions within the country. They include large lakes like Lake Victoria, and the lakes within the rift Valley which contribute to the intricate topography found in the Great Rift Valley, high mountains like Mt. Kenya and Mt. Elgon, smaller scale local influences like regional vegetation as well as land and sea breezes. These factors mainly affect the distribution of rainfall across the country and seasonally as well.

The temporal distribution of rainfall is such that there are two main rain seasons, March, April & May (MAM) is the long rains season while October, November & December (OND) is the short rain season. Some parts of the country mainly the Western regions and the coastal belt also experience another rainfall season, June to August which is quite significant for the two regions.

The climate of Kenya is complex in time and space. The region like many other parts of the tropics, is prone to extreme climatic episodes such as frequent floods and recurring droughts. These events have in years past had severe negative impacts on key socio-economic sectors. The recent impacts include the devastating severe 1997/98 floods and the 1999/2000 drought in the region that resulted into loss of life, damage to property and infrastructure, lack of food, deficient fresh water, energy and many other basic needs of society (Muhindi *et al.,* 2001). In terms of temperature distribution in time, the warmest months throughout the country tend to fall between January and February while the coolest months fall between June and July.

1.5.2 Maize farming in Kenya

Maize is grown throughout the country in different climatological and ecological zones (Figure 2). Kenya like many other countries and regions is subdivided into various agroecological zones, ranging from humid to very arid, with the variations based mainly on rainfall amounts and distribution, moisture availability and temperature regimes. For Kenya these zones are seven in total (Kabubo-Mariara and Kabara, 2015).

Most maize farmers are small scale farmers growing maize mainly for household use. The major maize growing regions for large scale farming are TransNzoia County, Nakuru County, Bungoma County and Uasin Gishu County. In other parts of the country mixed farming is more common where in maize is grown alongside other crops like beans, potatoes and bananas both for sale as well as for domestic subsistence use, these areas include South Nyanza, other parts of the Rift Valley, Western Province and parts of Central Kenya. In order to keep up with the rapidly changing climate the Kenya Agricultural and Livestock Research Organization (KARLO) has developed a new breed of maize that is hybrid in nature and is called Katumani. Katumani is adapted to drier conditions and is grown mainly in Eastern Kenya in the counties of Machakos, Kitui, Makueni, Tana River and Isiolo (Mbithi & Huylenbroeck, 2000).

Rainfall is the core source of water for this maize farming and the availability, amounts and distribution of this rainfall is influenced greatly by the location of Kenya. It is located between latitude 5^o in the North and 5^o in the South with the equator almost dividing it into two equal halves, and between longitudes 34^o and 42^o East. The total area is about 569,137 km^2. Annual rainfall follows a bimodal seasonal pattern with long rains occurring in March –April -May (MAM) while short rains occur in October-November-December (OND). There also exists another season June to August (JJA) which mainly impacts the coastal region and the Highlands west of the rift valley.

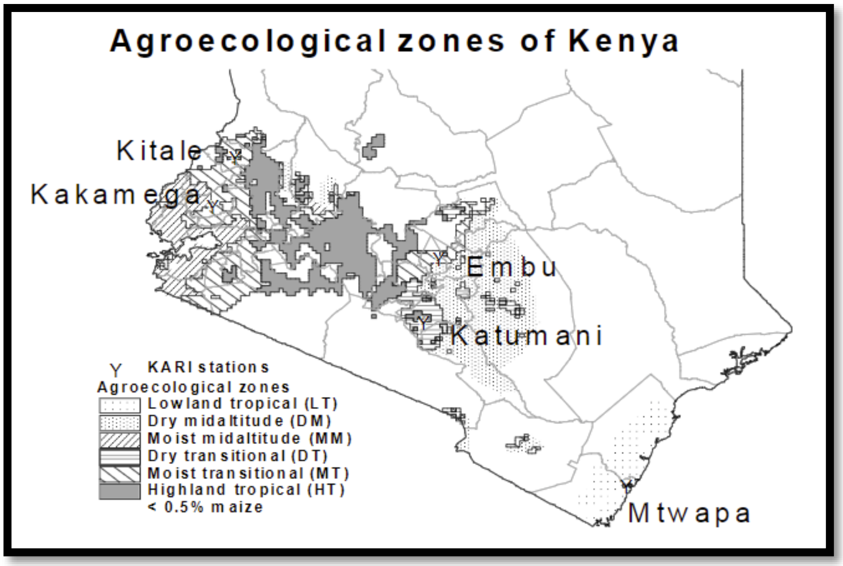

Figure 2: Maize growing Agroecological zones of Kenya (Source: Lutta *et al*, 2006)

CHAPTER TWO

2 LITERATURE REVIEW

This section looks at existing literature on the key and anchoring points of this study. From current findings on climate change, its impacts on agricultural production and organism phenology, to the various means of carrying out species distribution modelling as well as the history of aflatoxin contamination in Kenya the study area

2.1 Climate variability and change

The fact that the climate system has warmed is indisputable, and in recent years numerous documented changes are unmatched over hundreds to thousands of years. The atmosphere and the oceans have warmed, subsequently the amount of snow and ice has reduced and sea level rise has been witnessed. If emissions continue unabated, we are looking at more warming and long-term changes affecting all the constituents of the climate system as well as the interactions between them. These changes are anticipated to increase the likelihood of severe, overwhelming, universal and permanent impacts on both people and ecosystems. (IPCC, 2013)

On a global level the indicators of climate change include a global rise in the average temperature of the atmosphere as well as of the sea surface temperatures. Other indicators include, sea level rise, melting of glaciers and mountain glaciers. (IPCC, 2013)

On a more continental level, studies have concluded that Africa out of all the seven continents is the one that is most susceptible to changing climate owing to its higher exposure and lower adaptive capacity. Another factor is the continent’s great dependence on agriculture driven by rain as a main source of income (Awojobi & Oladayo, 2017). A study done by Amogne and others in 2018 examining the effects of climate change on temperature and rainfall in Ethiopia found out that both rainfall and temperature are anticipated to be negatively impacted by climate change. Night time temperatures are likelier to increase at a higher rate than day time temperatures at various RCPs by the year 2050 and even more by 2100. Rainfall is expected to be increasingly erratic as well.

On a more localized note, changing climate has been seen in the shifting of seasons in Kenya, more prevalent droughts within the great horn of Africa as well as increasing in incidents of extreme rainfall within the region.

2.2 Climate Projections

In order to effectively investigate the impacts of climate change scientists use different scenarios to simulate varying futures. Data at the global level is developed by different modelling teams, then a round the world downscaling is done to better simulate local circumstances. The importance of projections of future climate cannot be overstated; they provide important information for risk assessment, adaptation as well as mitigation planning. In order to develop relevant and highly effective adaptation strategies as well as targeted global greenhouse gas emissions reduction goals such as those outlined in individual country Nationally determined contributions, as well as inform emission reduction at more localized scales accurate climate change projections prove to be important.

Currently the most common way projections are made available is in the form of socio-economic and emission scenarios (IPCC, 2013). These are used in climate research to provide reasonable descriptions of various future outcomes or evolutions based on a range of variables. These variables include but are not limited to energy and land use, change in global and regional socio-economy, change in technologies in use and change in emissions of greenhouse gases, aerosols and air pollutants. They are used as input for climate model runs and as a basis for assessment of possible climate impacts and mitigation options and associated costs.

Based on an Intergovernmental Panel on Climate Change (IPCC) expert meeting a total of 4 Representative Concentration Pathways (RCP) radiative forcing levels were chosen. These four are outlined in Table 1 including a short description of the model characteristics.

Table 1: Overview of representative concentration pathways (RCPs)

Name	**Radiative Forcing**[1]	**Concentration**[2]	**Pathway shape**
RCP8.5	>8.5 W/m^2 in 2100	> ~1370 CO_2-eq in 2100	Rising
RCP6	~6 W/m^2 at stabilization after 2100	~850 CO_2-eq (at stabilization after 2100)	Stabilization without overshoot
RCP4.5	~4.5 W/m^2 at stabilization after 2100	~650 CO_2-eq (at stabilization after 2100)	Stabilization without overshoot
RCP3-PD[3]	peak at ~3W/m^2 before 2100 and then decline	peak at ~490 CO_2-eq before 2100 and then decline	Peak and decline

These RCP projections are for a global scale. Further research and studies have been carried out to find better regional representation of future climates. One such experiment is Climate model output from Coordinated Regional Downscaling Experiment (CORDEX). CORDEX was created in 2009 by The Taskforce for Regional Climate Downscaling (TFRCD) with the purpose of generating relatively lower scale (regional) climate change projections for all terrestrial regions of the globe within the timelines of the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC) and beyond.

In order to effectively analyse or document climate change impacts scientists or researchers carry out scenario analysis. The climate change research community employs the use of scenarios in order to improve understanding of how the future is likely to look like based on various suppositions. These scenarios take into account the interactions within the climate system, ecosystem interactions as well as human socio-economic activities that modify the climate system. It is noteworthy that the outputs of the generated scenarios are not true predictions; rather they provide probable descriptions of what may happen.

Latest research incorporates the use of Representative Concentration Pathways (RCPs) as opposed to previously used SRES scenarios. The name "Representative Concentration Pathways" rightfully underscores the basis for their use. They are termed emission pathways to underscore the fact that their main purpose is to provide projections of atmospheric greenhouse gas (GHG) concentrations at various time steps. In addition, the term is also meant to emphasize the trajectory or path that is taken over a given time to reach a certain outcome (Moss *et al.*, 2008). Based on this, four RCPs were produced from Integrated Assessment Modelling Scenarios; the first pathway is a high one in which radiative forcing reaches just over 8.5 W/m^2 by the year 2100, thereafter the forcing continues its upward trajectory for some amount of time. There are two intermediary pathways, appropriately dubbed "stabilization pathways" which are characterized by stabilization of radiation at approximately 6 W/m^2 and at 4.5 W/m^2 after year 2100; the final pathway is one in which radiative forcing peaks at 3W/m^2 before the end of the century then declines to a radiative forcing of either 2.9W/ m^2 or 2.6W/m^2. Both of these scenarios are overshoot scenarios with peaking radiative forcing followed by declining where the peak and decline of 2.6W/m^2 is more pronounced than the 2.9W/m^2 one. RCP2.6 scenario had some concerns as it requires very rapid investments in mitigation quite early in the century and increasing use of negative emissions technology later in the century and this appears to have been passed by time and almost unachievable (Moss *et al.*, 2008)

There's caution to be taken when using scenarios for research so as to avoid misapplication. These include but are not limited to the fact that they are not forecasts i.e. they are reasonable alternative scenarios for possible future outcomes and that they are not policy-prescriptive i.e. they are meant to support scientific research without making any judgment as to which one is most desirable.

The data used in the development and generation of the RCPs is found in research that is subsequently peer-reviewed and published in literature. Various Integrated Assessment Modelling (IAM) teams developed each RCP. Their respective published scenario papers were consistent with the base criteria for each particular RCP. Different stakeholders then repeatedly reviewed the surveyed and synthesized data sets from available representative studies. The final consensus set of RCPs was then published. Table 2 highlights the outputs from the different modelling teams in various institutions.

Table 2: CORDEX models used for the projections

	Model Name	Institute	Institution Name
1	CCCma-CanRCM4	CCCma	CCCma (Canadian Centre for Climate Modelling and Analysis, Victoria, BC, Canada)
2	CNRM-ALADIN52	CNRM	Météo-France / Centre National de Recherches Météorologiques
3	CSIRO-CCAM	CSIRO	Commonwealth Scientific and Industrial Research Organisation
4	IPSL-WRF311	IPSL	Institut Pierre-Simon Laplace
5	MOHC-HadRM3P	MOHC	Met Office Hadley Centre
6	MPI-CSC-REMO2009	MPI-CSC	Helmholtz-Zentrum Geesthacht, Climate Service Center, Max Planck Institute for Meteorology
7	ICHEC	ICHEC	Ireland
8	MIROC-AGCM	MIROC-ESM	Japanese research community -
9	NorESM	NCC	Norwegian Climate Center
10	NOAA	NOAA	NOAA

2.3 Maize Production

Maize is the paramount cereal crop grown for consumption in Kenya and is the main food that about 90% of the Kenyan population now numbering about 45 million depends on (World Bank, 2015). The bulk of maize production is carried out by small holder farmers all over the country. However medium to large scale farming is done mainly within the Highlands West of the Rift Valley as well as within the Rift Valley and some parts of Central Kenya (Luziatelli. et al 2012)

Since maize is the primary food consumed in Kenya, it has varied uses. Dried maize grains are ground to make maize flour which is in turn cooked as 'Ugali' a local delicacy. The maize can also be consumed as a grain. It is consumed in various states namely; fresh, dried, ground into flour, boiled or mixed in with other foods. The remnants of the post harvested maize crop namely the stalks, the leaves, and others such as maize cobs are used as feed for household domestic animals including dairy cattle which we will later see is crucial for our study. Other uses for the stalks and cobs include their use as household fuel particularly in rural areas. They are also put back into farms as organic manure.

Maize grains are also a key component in manufacture of vegetable (corn) oil and also in manufacture of food for animals, hence maize is an important raw material for industrialization. Typically, maize is harvested during the dry season. This prevents rotting of the harvested maize grains due to moisture contamination both in the field and in the stores. The husks are removed and the maize is stored. It is then dried spread under the sun so that the grains are completely dry if the intended use is as flour or as input for manufacture of animal feeds.

On larger tracts of lands for farming, the maize plants are cut and heaped in several places across the field. This gives time for the grains to partially dry while still in the farm. The maize cobs are then manually separated from the plants and from the husks after which shelling or deseeding is done by machines. The grain is sorted and packed in preparation for transport to markets or to marketing agencies.

According to the National Farmers Information Service of Kenya there are ecological and climatic conditions that are favourable to maize growth. These include, suitable soils mostly loam soils, well drained and having good air flow with a pH of 5.5 to 7. Altitude also plays a pivotal role in determining maize production in terms also of the variety to grow. Moderately higher altitudes are better suited and give rise to higher yields while very low altitudes and very high ones result in poor yields. This explains why the Western regions of Kenya are the main maize growing regions for the country. Despite this, maize is grown throughout the country (0 – 2200m above sea level) with corresponding varied results. Optimum temperature for optimum yields stands at 30^{o}C. Cold conditions prolong the maturity period whereas high temperatures lower the yields. Generally warm temperatures above 15°C are suitable for maize growing and these can be found in most parts of the country. Rainfall amounts that are conducive to maize production vary between upwards of 1200mm to about 2000mm. The rain is required to be well distributed throughout the growing season, to be useful to the production since various developmental stages require different amounts of rainfall or none at all. Additionally, activities are carried out depending on the rainfall amounts and availability. Flowering and silking stages require proper rainfall which critically influences pollination. At harvesting time, dry conditions are desirable as they facilitate drying of the grain. In some cases, some maize species can do very well under different rainfall regimes and at times can even grow with seasonal rainfall totals between 635mm and 1145mm. Maize crop has been known to even adapt to semi-arid regions with rainfall totals of below 380mm. The ideal topography required for maize production is described as undulating, with gentle curves or slopes. This allows for use of machines in farm activities to reduce the work load. The landscape of Trans Nzoia and Uasin Gishu counties in Kenya are good examples and as such the regions are among the largest scale of producers of maize. (Du Plessis, 2003)

As with most endeavours, maize farming in Kenya is faced by various challenges. These challenges include, the current high cost of production from expensive farm inputs, fluctuating prices of maize in the markets as well as vulnerability to climate hazards such as prolonged droughts and extreme rainfall events among many others. Pests and diseases also pose a threat to maize production throughout the whole growing process, as does competition within markets, cheaper imports and lack of protection mechanisms for small scale farmers. Soil exhaustion is also a challenge that arises from monoculture, in some regions, perhaps due to lack of knowledge, farmers year in year out only plant maize. Finally, poor or lack of marketing strategies move farmers to sell their crop at pitiable prices due to lack of markets occasioned by poor or lack of marketing.

On their own, these challenges pose a threat to maize farming and subsequently to food security in the country. However, when one or more of these challenges interact with each other, more compound issues arise that further threaten production and availability of maize for consumption.

In Kenya maize is grown mainly in the southern half of the country in suitable agroecological zones. The maize growing agroecological zones are as highlighted in Figure 2.

2.4 Climate change and Food security

Every human being has a right to access food. However, 11% of people around the world which roughly translates to 805 million go hungry every day in our time (FAO, 2014). World leaders expressed commitment to reducing by up to half, the number of people with no access to food between the years of 1990 and 2015 guided by the global Millennium Development Goals (MDG). These efforts are also supported by others such as those outlined in the Paris agreement as a direct outcome of COP21, it opened the door for more adaptation and mitigation in the agriculture sector. Additionally, the ambitious sustainable development goals (SDG) address food security issues. Goal 2 of the SDGs to achieve zero hunger particularly seeks to address food security by the year 2030. Interestingly and rightly so this goal is directly impacted by goal 13 on Climate Action.

Humans' food security is achieved when people have availability and suitable regular access to satisfactory, nontoxic and nutritive food to maintain a healthy and vibrant life. The various facets of food security include food availability which is determined by the availability of ample amounts of food of adequate quality, supplied to people through local, in-country production or through imports by buying or as aid. It is about food supply and trade, not just the quantity but also the quality and wide range of needed foods to cater to the nutritional aspects or needs of human beings. Availability is hinged on enhanced productivity which in turn is a direct consequence of sustainable productive farming systems, proper management of existing natural resources, as well as development and implementation of relevant policies. Availability of food is expected to be impacted by changing climate in various ways by impacting the factors that influence availability such as infrastructure for transportation of farm produce to markets (Chaudhari, 2018). The interplay between these various components of food security and other extenuating circumstances is highlighted in figure 4. Food access the other component of food security relates to whether factors are met that allow for people in need to get the food they need both physical access as well as economic access. Markets play an important role in this aspect and questions that can be asked include; is the smallholder farmer able to access market for his produce? Is the person in need able to travel to markets to get the food needed? Are the roads safe? Is it too far? Is there political goodwill that allows food to be available at the market? Food that is nutritious? Does the person have enough money to purchase the food? Utilization of food is concerned with how equipped the body is to utilize the many nutrients ingested in food. Factors influencing utilization and subsequently nutritional intake include the state of an individual's health, his /her feeding regimen, how the food is prepared, and the diversity of their diet and the distribution of food within the household. In order to improve how ingested food is utilized, nutrition and food safety must also be improved, post-harvest losses should be reduced, produce should be preserved and value added. There should also be an increase in the diversity of diets. Food stability the other aspect of food security is dependent on whether a population, a particular household unit or an individual can access suitable food when needed and at all times regardless of whatever external factors exist. Food insecurity can be transient based on a number of factors such as, as an impact of one bad season, a change in employment status of the main breadwinner, conflict within the region or country or household, or a rise in food prices. Those most impacted negatively when prices rise, are very frequently the poor who are most vulnerable because the bulk of their income is spent on food.

For this study availability of food is the component of food security being investigated. Availability of food is directly connected to food production through agriculture and as such is prone to negative influence from, among other factors, climate change. Food quality and safety also is crucial in influencing food availability. Food safety is a paramount concern for all, as it introduces complexities we would rather avoid. Food related ailments may result from ingestion of contaminated food including contamination by Aflatoxins (Chaudhari, 2018) In light of this, safeguarding food safety is increasingly important in light of shifting food consumption habits as well as the globalization of food supply. Globalization of food supply necessitates strengthening food safety systems within and between all countries.

In the context of this study therefore, all the maize production chain stages need to be safeguarded to ensure growing stage is safe, so is storage and transportation to markets.

In recent years Kenya has suffered impacts of drought and reduced rainfall during the main growing seasons leading to food insecurity in the country. Low crop productivity coupled with post production losses due to poor post production management, high moisture levels or pests and contamination have contributed to food losses in turn leading to higher food prices due to low supply.

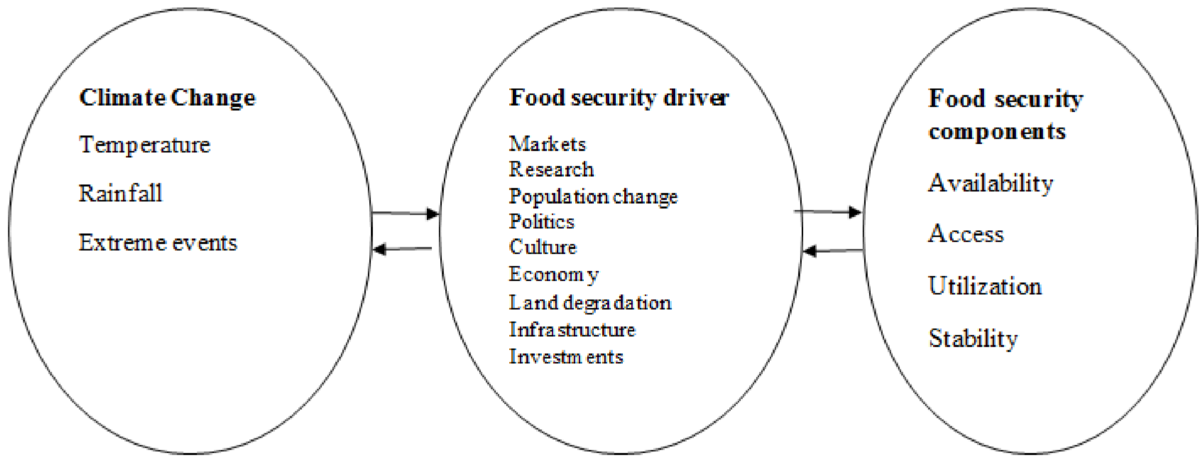

Figure 3: Relationship between climate change and food security

2.5 Climate change and Mycotoxin Contamination

Aflatoxins are a type of mycotoxins that have acute and chronic toxicity which causes cancer as well as inhibition of the immune system (Shekar *et al.,* 2018) Due to this, the concentration of these fungi in agricultural food, feed and their commodities is controlled worldwide to meet acceptable standards. Aflatoxins are metabolites that are toxic that belong to the Fungi aspergillus parasiticus and aspergillus flavus families which live in soil. These toxins are dangerous carcinogens which pose a grave threat to both humans and domestic animals once they consume contaminated agricultural produce. Long-term exposure to these toxins is believed to increase the risk of blood cancer in humans (Marcel & Wild, 1995; Julia, 2005).

Most research into aflatoxin contamination focuses on the post-harvest aspects, however at the production level, aflatoxin contamination is also a risk. Aflatoxins present themselves in a number of feed and food crops, cereals like maize, inn nuts and in milk. Regions between 40N and 40S latitude popularly referred to as tropical and subtropical, where Kenya lies, are the most likely to be infected by *Aspergillus* as well as most likely to be contaminated by aflatoxin (Van der Fels-Klerx *et al.*, 2016). And just like any other living organisms, these fungal species occur or prefer a very specific range of optimum environmental conditions particularly related to rainfall, temperature, RH, for crop infection, colonization, toxin production, spread and survival. Research has shown that the ideal conditions for aflatoxin development in terms of moisture content is between 18 and 20%, in terms of pH a range of 3.0 to 8.5. Favourable ambient temperature sits at between 12°C and 40°C with an optimum range of between 25°C and 30°C (Iqbal *et al,* 2016)

Therefore, changes in these environmental conditions influenced by a change in global climatic conditions are expected to lead to an alteration in the fungal population and patterns of occurrence from region to region. Many studies have been done to develop models that predict probability of mycotoxin contamination at the harvest stage in a variety of crops using weather data as the main input or as the only input. Most of those studies concentrated on occurrence of *Fusarium* head blight in wheat (Leggieri *et al.,* 2013) as well as a model for maize *A. Flavus* was developed (Chauhan *et al.* 2015; Battilani *et al.,* 2013)

Climate change effects are expected to undoubtedly impact how and when crops are infected by fungi as well as aflatoxin production. As previously mentioned, the most significant climatic factors to aflatoxin contamination are temperature, rainfall and relative humidity since these factors directly impact fungal growth and fungal infection (Nazari *et al.,* 2014) In a study conducted in Europe by Medina *et al.* (2014), it was discovered that since the 2000s the occurrence of *Aspergillus Flavus* and consequent aflatoxin contamination has increased and even more notably, coinciding with hot and dry summers. Typically, *Aspegillus* is seen in regions in which drought and high temperatures are common, of which the tropics and subtropics ideal. This study showed that an increase of temperature in a specific area will directly impact the presence and the copiousness of this particular aflatoxin species in the crops grown in those regions. Kenya being right in the tropics, astride the equator, is thus highly prone and vulnerable to contamination by aflatoxin and even more so as temperatures increase due to climate change.

In a study done in Norway for occurrence of Mycotoxins at the various phenological growing stages of oats, Hjelkrem, 2018 and others discovered that cool and humid conditions, coupled with moderate temperatures during the booting stage, were linked to increased mycotoxin buildup in harvested oat grains. On the other hand, during stem elongation and during florescence emergence warm and humid weather, or cool weather and lack of rain during booting was found to reduce the risk of mycotoxin buildup. Warm and humid weather occurring just after flowering multiplied the risk of buildup, while moderate to warm temperatures and no rain during dough development, reduced the risk of mycotoxin buildup in the oat grains under investigation. Their overall research discovered that weather conditions both before and after flowering influenced mycotoxin contamination in oats not only in post-harvest as many more studies have shown.

Mycotoxin contamination is a direct risk to food safety and quality and hence food security on an overall level. Currently, the climate experienced in tropical Africa including Kenya is advantageous for the growth of fungi and subsequent mycotoxin production (Gacheru *et al* 2015)

Droughts as well as heat stress during the time that maize crops mature are the main factors contributing to aflatoxin contamination of maize and other grains. Climate change is causing insecurity about future temperature and rainfall regimes which in turn affects distribution of aflatoxin into areas that in previous years without the threat of climate change were safer for crop production. (Lagogianni & Tsitsigiannis, 2018) Further studies have shown that the main stages affected by fungal contamination are the ripening stage, harvesting stage and in the first phases of storage of the maize crop. This is owing to the fact that in these stages the ambient temperatures as well as the water activity of the grains are high. Therefore, poor weather conditions coupled with, poor drying conditions as well as climate change, result in fungal contamination of grains and subsequent mycotoxin production. (Gomez *et al*, 2017)

Studies have shown that as our climate changes and temperatures increase we can expect that more insect pests will occur, which are an important factor in the contamination with mycotoxigenic fungi. More insects may also increase the number of birds that feed on insects, possibly resulting in more damage to crops caused by them as they forage for insects, which will in turn contribute to higher synthesis of mycotoxins. Changes in crop phenological stages, such as when flowering occurs and maturation of cereals, are also foreseen as temperatures keep rising. Climate change is also projected to change the range of regions that various crops can comfortably occur as well as amounts of produce from the crops. (Nesic, 2018) With this in mind therefore it is vital for future safety to study the possible effects that Climate change will have on aflatoxin contamination in Kenya.

2.6 History of Aflatoxin Contamination in Kenya

Aflatoxin is a highly carcinogenic and toxic mycotoxin and has as a result been classified under Group I in the carcinogen classification by the International Agency for Research on Cancer (IARC). The IARC classifies compounds or physical factors into four groups based on evidence from science on their carcinogenicity. Group one into which aflatoxin falls is described as being Carcinogenic to humans, not probably, not possibly but definitely carcinogenic. This is because studies have shown that among all mycotoxins, aflatoxin has the utmost severe and chronic toxicity (Zhang *et al* 2018).

The first report of aflatoxins in Africa was in 1961. It was found in animal feed that had been contaminated by Aspergillus parasiticus in studies done in India, French West Africa, Uganda, Gambia, Tanzania, Nigeria, and Ghana (Sargent et al., 1961).

Closer home in Kenya, from studies that have been done over the years, it emerges that aflatoxin contamination in maize especially has some hotspots within Kenya. These hotspots include Central Kenya, Nairobi, Eastern and Western parts of Kenya. More often than not then, the aflatoxin contamination in maize consumed by Kenyans in flour and grains is slightly higher than the internationally accepted limit of concentration of 5ppb (Nduti & Njeru, 2017). Kenya has however a regulatory limit of 10ppb.

Every year reports of poisoning by aflatoxin consumed in contaminated maize come up especially within the Eastern parts of Kenya, with the worst report having occurred in 2004 (Obade *et al*, 2015[a]). Contamination levels of up to 376 times beyond 10 ppb which is the regulatory limit of Kenyan have likewise been reported in South Nyanza predominantly within nut growing areas, 40% of these nut samples got from farmers in the region had aflatoxin levels way beyond 10 ppb. (Mutegi *et al,* 2007). The region of Kenya that's most notorious for frequent recurring cases of aflatoxin contamination is usually the Eastern region of Kenya ranging from Machakos county, southeast towards Kitui, however studies have shown that averaged aflatoxin levels of up to 54ppb have been found in maize in other regions in western Kenya such as Homa Bay and Rongo compared to 21ppb in Makueni and 44ppb in Mbooni East, indicating that even higher levels of aflatoxin still occur in foods in Nyanza region (Obade *et al*, 2015[b]).

This exposure to aflatoxin contamination has had adverse health effects on members of society who are chronically exposed. In recent years, cancer continues to afflict more and more Kenyans and is the third highest killer, accounting for 7% of all reported deaths annually. Additionally, aflatoxin exposure leads to liver cancer which is reportedly one of the most prevalent types of cancer observed in Kenyan men (NCCS, 2016). Kang'ethe *et al* 2017 did a study in Makueni and Nandi counties to investigate the extent of exposure of residents of those two counties to aflatoxin contamination. Their rationale for selecting these two regions was that there is documented history of human acute aflatoxicosis in Makueni and high incidences of cancer of the esophagus in Nandi. Maize is consumed in the form of *Ugali*, porridge, *Muthokoi* and *githeri* within these study regions. This diversifies the extent of expected contamination to include babies and the elderly in society who take porridge as well as the rest of the adult population. Some of the results their study uncovered included the fact that the exposure of people to aflatoxins (or mycotoxins) starts early in childhood and continues into adulthood. Most babies were infected from breastmilk of mothers who themselves had consumed contaminated produce.

Maize contamination by aflatoxins in Kenya has been reported by a number of researchers including Muthomi et al. (2012), Lewis et al. (2005), Strosnider et al. (2006), Muture and Ogana (2005), Probst et al. (2010), Daniel et al. (2011), among others. Human poisoning or contamination from consumption of milk obtained from cattle and goats that were fed with aflatoxin contaminated fodders has been reported by both Kang'ethe et al. (2007) and Kang'ethe and Lang'at (2009) in their studies.

It is therefore of high importance that studies on risk monitoring, risk assessment and early risk prediction of aflatoxin contamination in all the affected produce such as maize, peanuts, milk and other agricultural products be considered as an essential ground for effective aflatoxin contamination control.

Some of the impacts of human exposure to aflatoxin include stunted growth, which is a key indicator of malnutrition in early childhood. When growing children are exposed to contaminated food through breast milk as well as directly after being weaned, they experience stunted growth. Children also end up being underweight**,** not putting on the recommended weight for their respective age groups due to consumption of affected food. Some of these adverse impacts are highlighted in figure 4.

Figure 4: Aflatoxin in Kenya's food chain from occurrence to impacts on various consumers Adapted from ILRI: An overview of what researchers are doing to combat the threat to public health

(a) Management of Aflatoxin Contamination

Robust adaptation options are needed and are employed in most cases to manage aflatoxin contamination. Since this study mainly concentrated on aflatoxin at growth stage, the management strategies considered are for this as well.

Application of proper agricultural practices during all the vulnerable stages including cultivation, as well as during handling, storage, processing and distribution, as well as risk analysis and critical control point procedures will ensure that fungal infection and mycotoxin formation are as low as possible (Nesic, 2018)

Various strategies/approaches are in place to manage aflatoxin contamination in farm produce, some are here under discussed.

Use of atoxigenics – these work by reducing aflatoxins all the way from crop development in the farm to post-harvest storage, and thereafter throughout the value chain. Atoxigenic strains that occur naturally are introduced to the crops to surpass their aflatoxin-producing relatives, they are the same kind of fungus that produce aflatoxin, but in this case they do not and cannot ever produce the toxin. The friendly fungal relatives are applied onto ordinary maize grain, which acts as a useful means to help them get established and can easily be transmitted onto fields. The International Institute of Tropical Agriculture (IITA) has developed Aflasafe a popular type of atoxigen to solve the problem of aflatoxin.

Use of fungicides – Several previous field trials in Europe have demonstrated that fungicides, including organophoshorus fungi-cides, thiabendazole, triadimefon, propiconazole, tol-clofos-methyl can be used to control mainly Fusarium mycotoxin formation, with the timing of pesticide treatments being particularly important for control-ling mycotoxin production (Lagogianni & Tsitsigiannis, 2018) However care needs to be exercised with the use of Fungicides since some of them can promote aflatoxin production. Even if fungal growth is reduced, aflatoxin production could still be promoted. Thus, the best fungicides are those that prevent or reduce fungal growth as well as mycotoxin production at the same time. Additionally, these complications associated with use of fungicides have led to decreased use and advocacy on use of biological pest control as discussed in the next point.

Use of Biological pest control – Use of plant essential oils to combat fungi has in recent years gained more popularity. This is in part owing to the fact that too much application of synthetic chemical fungicides has been shown to have increasingly negative impacts to humans, animals, and plants in recent years. Moreover, fungal species have become more resistant due to the haphazard use of chemical fungicides for controlling among others aflatoxin. Most essential oils (EOs) derived from plants are relatively nontoxic to laboratory fish and animals and they meet the criteria for being lower risk pesticides. Many essential oils show that they can act to protect against plant fungi and have long been used in the protection of stored produce (El-Mohamedy, 2017).

Researchers at Wageningen University have in the recent past been researching alternative means of fighting fungi such as mycotoxins as a direct result of increased demand for non-chemical pest control. Without crop protection while using pesticides up to about 85% of the crop harvest is prone to loss, additionally pesticides pose a serious danger to bees which are indispensable as pollinators in agriculture and horticulture as well as to water sources. Pests also in the long run become resistant to pesticides; therefore, biological pest control offers a very timely and welcome alternative.

Use of Risk Maps – these when specifically developed for aflatoxin and toxigenic fungi risk could be used by stakeholders and farmers as a communication or information tool. They could be made readily available inform scientific research and supervision, decision making and support and governments' policy-development and implementation, as well as prioritization of a more effective intervention strategies and targeted approaches, especially in high-risk regions as shown by research (Battilani *et al* 2016).

(b) Species Distribution Modelling

Mapping all the biodiversity in the World is important for various studies. However, it is a very challenging responsibility due to the fluidity of species and ecosystems. It becomes even more challenging to effectively predict how current species' distributions inferred from the mapping will change under threats such as habitat destruction and others driven by climate change.

One way scientists attempt to map biodiversity is using species distribution modelling (SDM). Species distribution models (SDMs) are used for modelling the geographic distributions of various species based on correlations between known occurrence records and the non-random but specific environmental conditions at occurrence localities. Applications of SDMs include in macro-ecology, bio-geography and bio-diversity research (Hefley & Hooten, 2016)

In recent years use of SDM in conservation and ecological research has become more and more popular owing partly to the fact that there's a growing availability of geo-referenced species records and corresponding environmental data available on the internet, together with the easy to use characteristics of some of the modelling methods.

There are various types of data used in species distribution modelling, the three most common being Count data, Presence-Absence data and Presence only data.

- **Count Data** - Count data models have a dependent variable that is counts (0, 1, 2, 3, and so on). Most of the data are concentrated on a few small discrete values. Examples include: the number of rain days in a month for a specific region, the number of dentist visits per year a person makes, and the number of trips per year that a person takes. An example of a model that uses count data is the Poisson Regression Model typically employed in R-statistical software

- **Presence-Absence data** – Presence-absence data in most cases is usually count data that has been reclassified in to binary (1,0) format where 1 signifies the presence of at least one individual while 0 signifies absence or that there was no detection at a given location. A key issue which doubles up as a limitation of models that use presence-absence data is that a species may be deemed absent simply due to not being spotted or detected using the prescribed sampling methods while that may not necessarily be the case. Therefore, parameter estimates are likely to be biased.
- **Presence only data** – Presence only data are usually collected accidentally. This is quite unlike the preceding two data sets, which are usually collected systematically at preselected locations and specified times. Common sources of presence only data include museum specimens, records and voluntary contributed sightings of a particular species. Normally, presence-only data are reported in terms of metadata of the location and time that an individual sighting of a species collected. This study utilizes presence only data collected by scientists carrying out work on aflatoxin within the country as well as data from Government bodies mandated with ensuring food safety. Therefore, this data type and its use in SDM is most described and investigated for justification of use.

Based on the collection method of these presence only data, there's a wide gap of knowledge on how to determine the types of observational errors and how these errors can be taken into account in modelling. This presents an opportunity for research. From what is currently known, three popular or common types of observational errors that likely arise include, location error, sampling bias and non-detection.

In modelling presence only data many analytical approaches have been used by researchers, some inappropriately. (Pearce & Boyce, 2005) In using species distribution modelling we aim to estimate the resemblance of the environmental conditions at any other site within a study region to the conditions at the locations of known occurrence (and perhaps of non-occurrence) of a species. A common application of this method one that is also used in this study is to predict the range of species using only climate data as the predictors (Hijmans & Elith, 2017).

Species distribution modeling starts by first compiling the locations of occurrence of the species under investigation, then environmental predictor variables at these same locations are extracted from existing spatial databases. Thereafter, the environmental predictor variable values are then used to fit a model to estimate correspondence to the documented presence sites, or another measure such as estimated abundance of the species. Finally, the model is used to predict across the region of interest, the variable of interest perhaps for a future or past climate). This study uses this method to predict for a future climate.

There are various software or models that can be employed in manipulating data for investigation of species distribution, including R statistical software package. One of the most commonly used SDMs and which is used for this study is MaxEnt, which in recent years has become increasingly popular with researchers since its introduction. MaxEnt is run using presence-only data and this enables researchers to avoid the expensive costs of species sampling throughout all their regions of occurrence. Records of presence data are readily available, but absence data are relatively harder to obtain. To overcome the lack of absence data, MaxEnt uses a background sample to contrast the distribution of presences along environmental gradients against the distribution background points, randomly drawing from the study area (Gomes *et al*, 2018)

Maximum entropy modelling uses environmental data sets in raster format to model species distribution as well as probability of occurrence. Studies have been done on the use of ecological niche models to determine species distribution. These ecological niche models use species presence records in form of point locations (longitude and latitude data) with environmental layers in spatial format to calculate the distribution of species (Masuoka *et al* 2010). A similar approach is used in this study.

MaxEnt model uses the maximum entropy (uniform distribution) principle to define the comparative probability of each environmental or climatic predictor on its own, to define the characteristics of sites at which the species already occurs compared to the features of the whole study environment (Pirathiban *et al*, 2015)

2.7 Conceptual framework

Figure 5 outlines this study's conceptual framework, a short summary of how the work is expected to be carried including various inputs out as well as expected results based on the study's hypothesis. Aflatoxin causing fungi is hypothesized to be directly impacted by climatic changes, therefore these climate variables are modelled onto the distribution data to investigate how future distribution will be affected. This study concentrated on sighting data as a proxy for distribution, there's however room for investigating concentration in the light of climate change

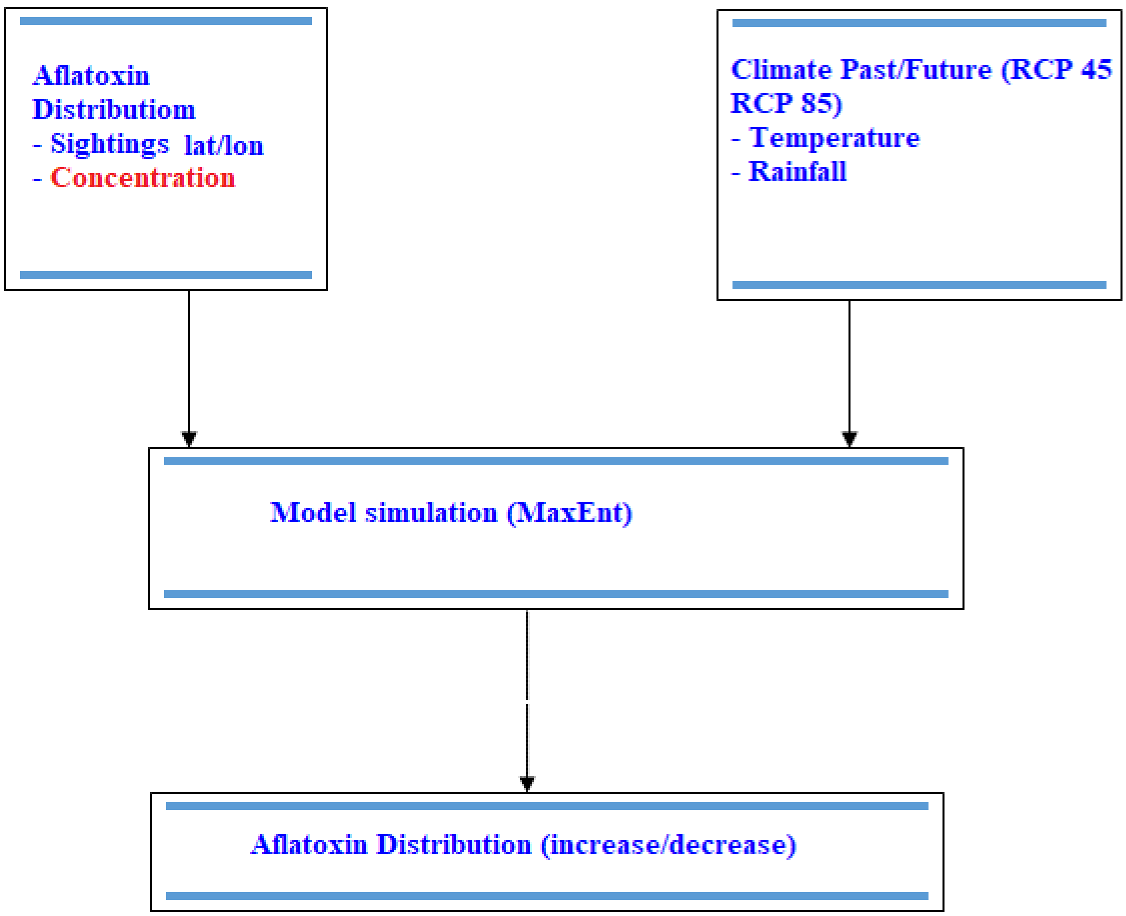

Figure 5: Conceptual framework

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CHAPTER 3

DATA AND METHODOLOGY

This chapter highlights all the data that was used for the study as well as the methods that were employed in order to achieve the objectives of the study.

3.1 DATA

3.1.1 Climate Data

Climate data which includes temperature and rainfall was used in this study. Observed climate data was sourced from the Kenya Meteorological Department (KMD). The rainfall data is from 1961 to 2017 while the minimum and maximum temperature is from 1975 to 2017. Quality control was done on the two data sets using a package called rclimdex in R to ensure good quality high standard data. Table 3 highlights the metadata of the stations used.

Table 3: Stations for which rainfall and temperature data was obtained

STATION	LONGITUDE	LATITUDE
DAGORETTI	36.8	-1.3
KAKAMEGA	34.8	0.3
KERICHO	35.3	-0.4
KISII	34.8	-0.7
KISUMU	34.8	-0.1
KITALE	35.0	1.0
MACHAKOS	37.2	-1.6
MAKINDU	37.8	-2.3
MERU	37.7	0.1
MOMBASA	39.6	-4.0
MTWAPA	39.7	-3.9
THIKA	37.1	-1.0
VOI	38.6	-3.4

This study used Climate model output from Coordinated Regional Downscaling Experiment (CORDEX) for projection of temperature and rainfall. Projection on rainfall and temperature was done up to 2050. For this study ten model outputs from the suite of models available on CORDEX were used. The projection data was downloaded from the site for individual models then ensembled. The data was downloaded at the daily timescale then converted into monthly totals for rainfall and monthly averages for temperature for seasonal analysis. Yearly data was also used for trend statistics using Makesens.

For this study two future climate Representative concentration pathways (RCPs) were used, RCP4.5 W/m^2 and RCP8.5 W/m^2. The rationale for using these two scenarios for this study and not the RCP2.6 is that with RCP2.6 W/m^2 the mitigation measures to be employed to attain it are very aggressive and not entirely consistent with the nationally determined contribution for Kenya. The RCP8.5 W/m^2 scenario is the scenario that illustrates what would happen in a world with very minimal mitigation measures. Therefore, this scenario is useful to move to action. The worst case scenario is represented by RCP8.5 and assumes generally undiminished emissions, in this scenario greenhouse gas emissions increase over time, leading to high GHG concentration levels by 2100. For this reason, this RCP was chosen to show the impacts of unmitigated climate change. RCP4.5 on the other hand is a stabilization scenario. Shortly after 2100 total radiative forcing is stabilized without overshooting the long-run radiative forcing target level and emissions are generally stable throughout the century. Its forcing pathway is analogous of a number of climate policy scenarios as it leads to lower emissions, it also corresponds to several low emission reference scenarios such as the previously used SRES B1 (Wayne, 2013). RCP4.5 was selected to show the impacts of climate change if some effort is put to mitigate.

Studies into the capability of the CORDEX regional circulation models (RCMs) to adequately mimic the present day climatology of Africa have been carried out by various researchers including Nikulin and others in 2012, who showed that most of the regional models capture the core details of the climatology of rainfall, although individual models may show significant biases. After that study, several others investigated the suitability of future projections of temperature and precipitation based on CORDEX-Africa RCMs. These include Misiani, who also found out in his 2015 study that the individual RCMs do not perform very well in capturing the rainfall over Kenya especially but perform better with temperature. However, an ensemble of 8 to 10 RCMS is able to tame the RCMs that overestimate as well as the ones that underestimate rainfall.

In another research, (Endris *et al*, 2013) researchers focused on the Great Horn of Africa in determining how well the RCMs simulated rainfall climatology as well as interannual variability. Their findings included the fact that the multimodel ensemble average adequately simulates eastern Africa rainfall. This therefore gives confidence in using the ensemble of models to assess future climate projections for the great horn of Africa region.

These findings influenced the choice to use an ensemble of all models for this study so as to minimize noise and get an average of the projected future.

3.1.2 Aflatoxin distribution data

Afaltoxin sighting data in the form of longitudes and latitudes was obtained from a team at the Kenya Meteorological Department that carried out research between 2015 and 2017 on aflatoxin contamination in Kenya on maize and milk. The KMD team collected their data from farmers who participated in the study. Additional data for the period between 2015 and 2017 was obtained from KARLO scientists working on a similar project for parts of Coastal Kenya.

3.2 METHODOLOGY

The methodology used follows and is informed by the objectives

3.2.1 Data Quality Control

Quality control was done on the rainfall and temperature data sets using the extraqc function of Rclimdex to ensure good quality high standard data. Rclimdex is a script run in the software R that looks at climate change using 27 predetermined indices. The extraqc function is an extra quality control step that flags suspicious data sets based on the climatology of the respective regions derived from long-term data input into the software. Some of the tests imposed on the data include flagging out duplicates, jumps from one small value to another very large consecutive one, very large diurnal temperature range as well as flatlines. These methods include validating, replacing or set to missing in case of lack of another data set to compare with. The documentation for the quality control done using Rclimdex is as illustrated in table 4**.**

Table 4: Documentation of quality control

Station Name	
WMO code	
Year	
Month	
Day	
Variable	"**RR**" for precipitation / "**Tx**" Maximum Temperature / "**Tn**" Minimum Temperature
Original value	Raw data
Value replaced with	Value for which we change
Detection test	Internal consistency / tolerance test / temporal coherency
Type of error	Transcription / Data source error
Procedure adopted	Validated / Corrected / Set to missing

The extraqc package of RClimdex produces graphs as part of its output.

3.2.2 Determine the spatiotemporal variability of past and future climate in Kenya.

The temperature and rainfall data was used to determine the climatic spatiotemporal variability of the areas affected by aflatoxin contamination (hotspots). Representative stations from all the 12 climatological zones within Kenya were used. For areas that are aflatoxin hotspots more than one station per zone was used.

3.2.2.1 Temporal variability of climate

To determine temporal variability, trend analysis was used. Both statistical and graphical approaches were used. Graphical approaches involved plotting of line graphs on the software excel. The statistical approach utilized the Makesens method which resulted in a trend test as well as generation of the magnitude of the trend. This temporal variability was done for both past and future (RCP4.5 & RCP8.5) climate.

In Makesens analysis the two-tailed test is used at four different significance levels namely; at 0.1, at 0.05, at 0.01 and at 0.001.

The significance level 0.001 indicates that the existence of a monotonic trend is very probable and that there is a 0.1% probability that the values are from a random distribution and with that probability we make a mistake when rejecting the hypothesis that there’s no trend in the data. Respectively the significance level 0.1 means that there is a 10% probability that we make a mistake when rejecting the same hypothesis.

Additionally, the Z value serves to evaluate the presence of a statistically significant such that if the Z value is positive (negative) it indicates an upward (downward) trend. The statistic Z is assumed to have a normal distribution. Table 5 highlights the symbols for the four tested significance used in the template

Table 5**:** Representation of the different significance levels in the Makesens test

Symbol	**Significance**
***	if trend at $\alpha = 0.001$ level of significance
**	if trend at $\alpha = 0.01$ level of significance
*	if trend at $\alpha = 0.05$ level of significance
+	if trend at $\alpha = 0.1$ level of significance
++	if trend at $\alpha > 0.1$ level of significance

Percentage change per year is calculated using the formula below

%change = ((Sen's slope * length of period) / mean) *100

3.2.2.2 Spatial Variability of climate change and aflatoxin distribution

To determine spatial variability, maps were generated using the software ArcGIS. For climate change, both past (1961-2005) and future (RCP 4.5 & RCP 8.5) *(2021 – 2050) climate data sets were used. For aflatoxin distribution the location data was simply plotted using ArcGIS as well.

The data that was spatially represented was for the two main rainfall seasons namely, October to December and March to May as well as total annual rainfall. For temperature, annual average temperature maps were also generated for both maximum and minimum temperature.

3.2.2.3 Simulate the effects of climate change on aflatoxin distribution and probability of occurrence.

The Maximum entropy method was used to model the aflatoxin distribution. The model used is (MaxEnt[2]) and it is open source software. For the modelling part, projected rainfall and temperature data was input into the software together with location data for the aflatoxin occurrence.

MaxEnt uses as input environmental data in raster layer format as well as species metadata in text format to produce probability maps that predict the potential range of a species. (Royle J.A *et al* 2012). Other environmental factors typically used include NDVI, land use change, and elevation. But for this study all these were assumed to be constant, this was because the study aimed to isolate and investigate mainly the impacts of changing rainfall and changing temperature. Table 6 and figure 7 show the input into the model and expected outputs as well as the progression of the research.

Table 6**:** Illustration of inputs and expected output from MaxEnt

INPUT	**PAST/PRESENT**	**FUTURE**
Climate (Rainfall & Temperature)	**X**	**Y**
Aflatoxin distribution	**X**	**?**

X – Assumed to remain Constant

? – To be determined

Y - To be varied based on projection

Environmental datasets input into the model included, rainfall, maximum temperature and minimum temperature. These datasets were, extracted in raster format that MAXENT takes and input into the model. When running the model, we input the number 30 when designating the percentage of data to be used for random testing. This is important as it allows the program to perform simple statistical analysis on the data set. The analysis used a threshold to make a twofold prediction, with favourable conditions predicted above the threshold and unfavourable ones below the threshold.

CHAPTER 4
RESULTS AND DISCUSSION

This section outlines the results from the various proposed analysis of data as well as a discussion of the results and subsequently linked to the hypothesis

4.1 Data quality Control

The results of data quality control from select stations within the study are represented

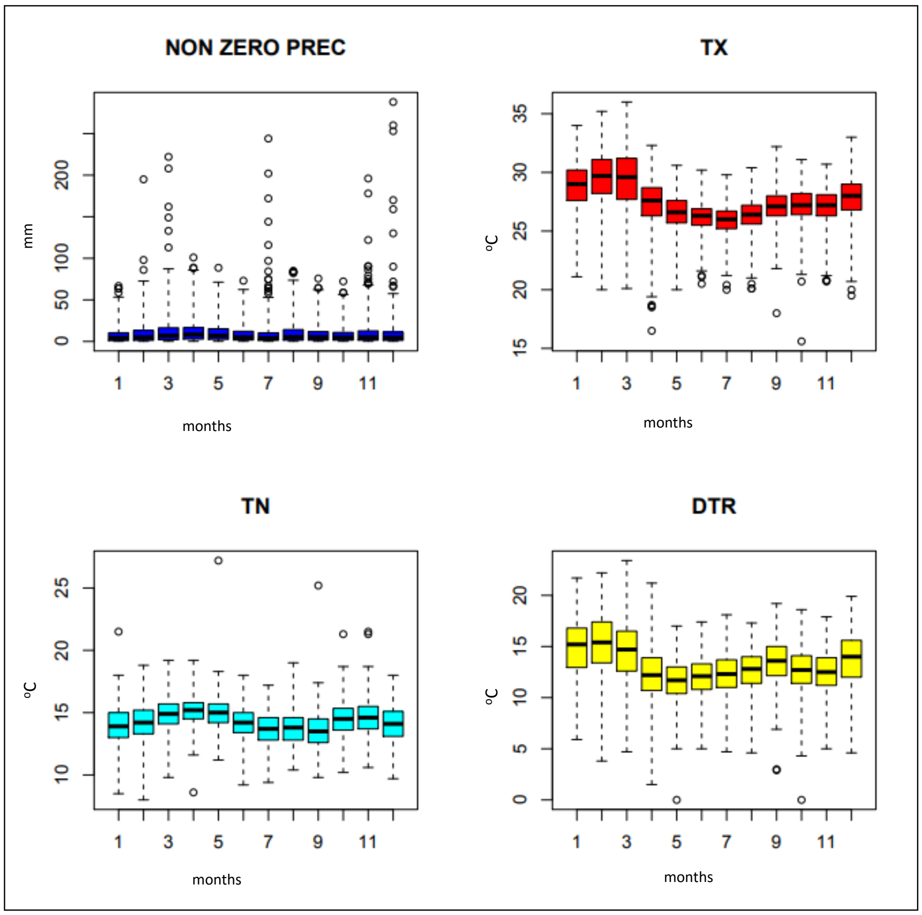

Figure 6: Output from quality control test done on Kakamega Meteorological station

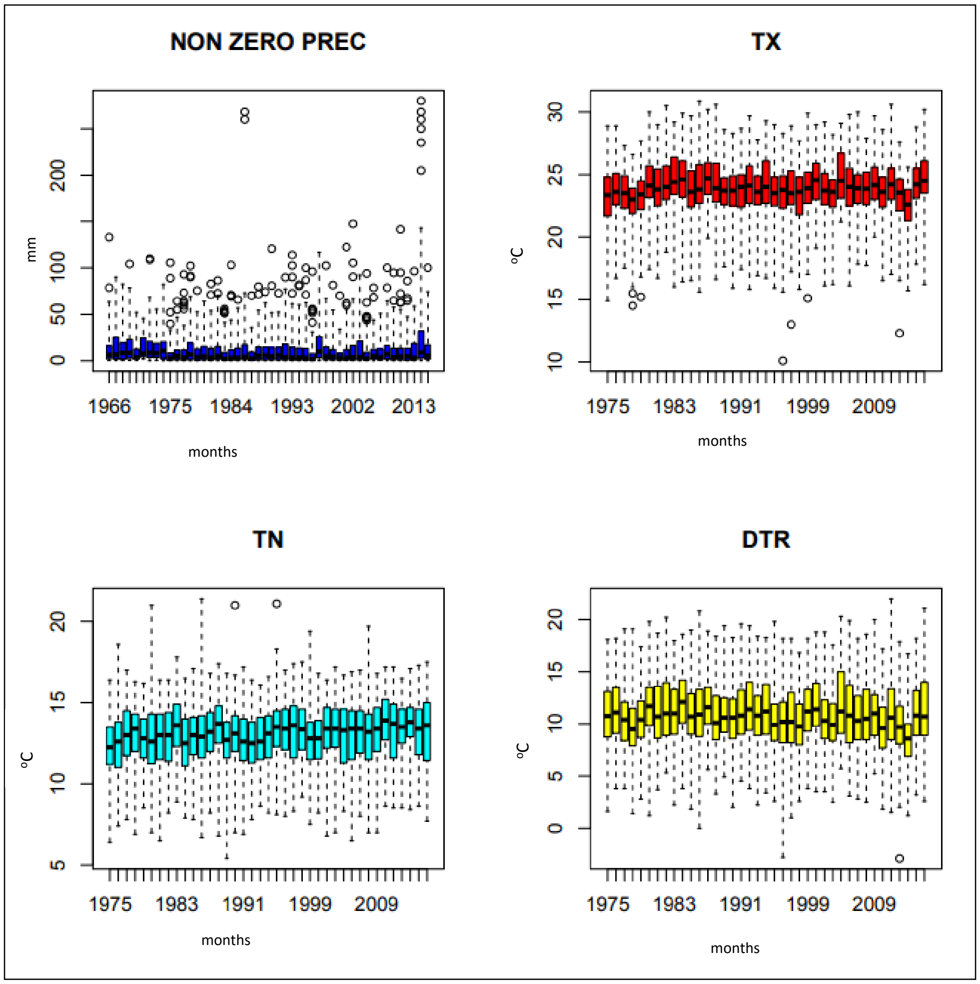

Figure 7: Output from quality control test done on Meru Meteorological station

The graphs in figure 6 show the variation of precipitation above 0mm, variation of maximum temperature as well as of minimum temperature and trend in diurnal temperature trend for each station across the 12 months in a year. On the other hand, figure 7 shows the variation of precipitation above 0mm, minimum and maximum temperature as well as trend in diurnal temperature trend for each station across the test years with one average value per year.

Figure 6 and 7 both show a sample of the graphical representation of the quality control done on the data across the years as well as across months. The quality control run flagged out a number of errors within the data which were then corrected before using the data set in MaxEnt and for analysis. The most common error that recurred repeatedly was flatline, where up to 5 consecutive days had the same data value. For some stations this was validated by checking the original rainfall recording cards and the raw data, while for the majority it was found to be erroneous reporting and was subsequently corrected. The non-graphical output of the extraqc test was generated in comma separated values. After thorough crosschecking of the data that underwent quality control with similar data from other sources, the data was deemed to be useful for further analysis

4.2 Spatiotemporal variability of past and future climate of Kenya

The results are discussed separately under temporal and spatial variability and represented by graphs and maps respectively.

4.2.1 Temporal distribution of annual and seasonal rainfall and annual temperature

The following graphs show the average annual rainfall per station for select stations derived from data from 1981 to 2010 as the climatological period. These graphs serve to illustrate seasonality or the bimodal nature of rainfall within most parts of the country.

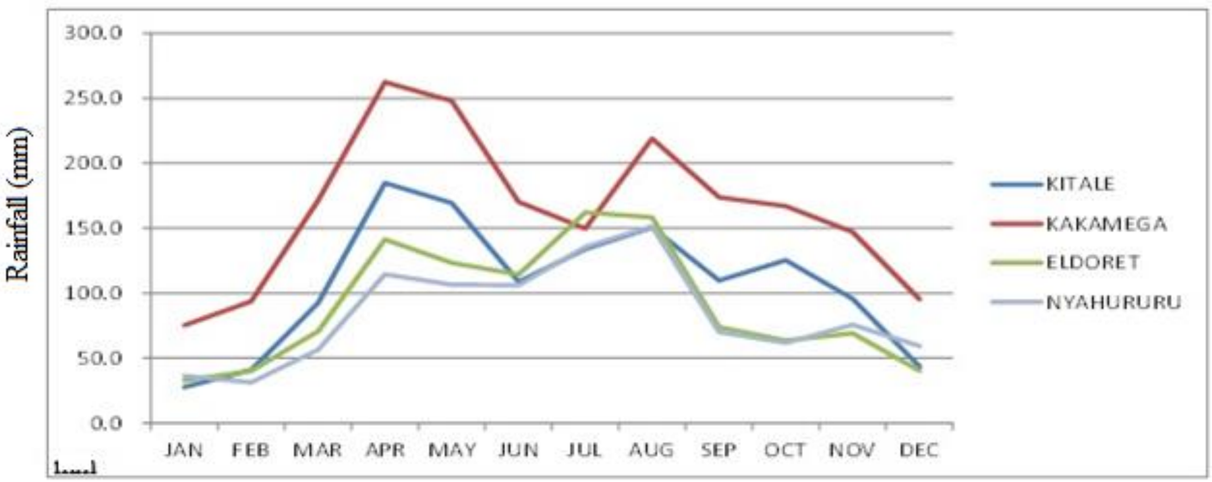

Figure 8: Rainfall (mm) distribution across the year for stations west of the Rift Valley

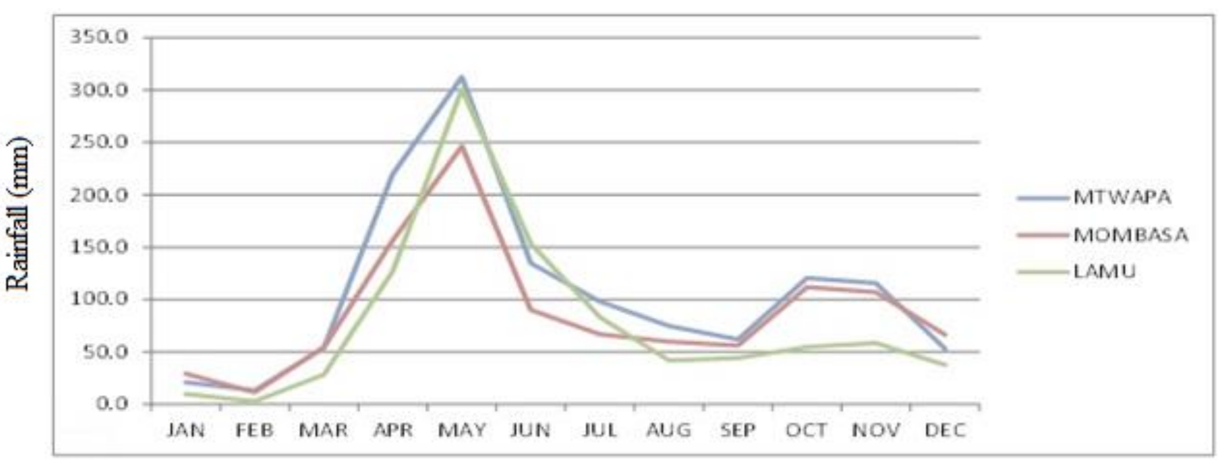

Figure 9: Rainfall (mm) distribution across the year for stations within the Coastal strip

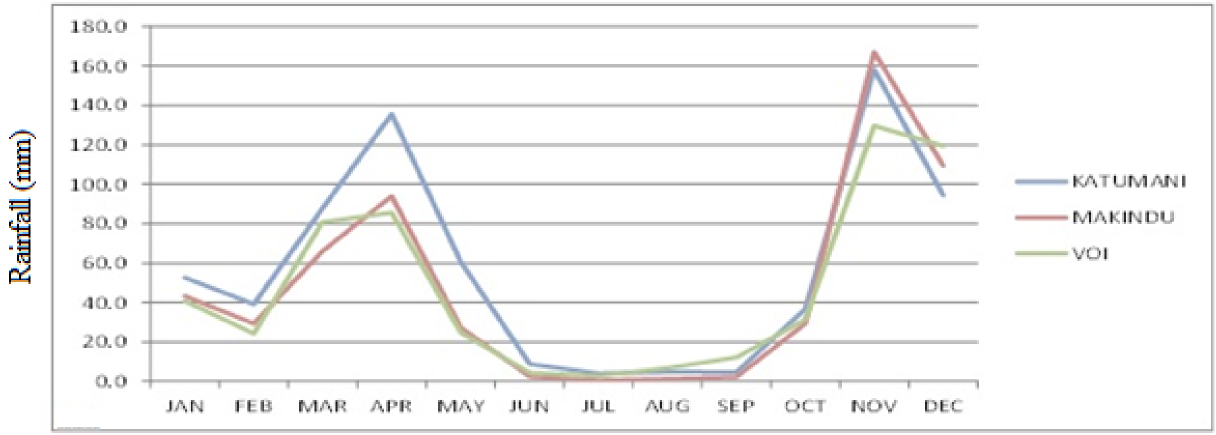

Figure 10: Rainfall (mm) distribution across the year for stations within the East and Southeast lowland regions of the country

Figures 8 to 10 clearly illustrate the seasonality of rainfall within the country which in turn corresponds to the various maize growing seasons across the country. Parts of Western Kenya and the Coast clearly exhibit tri-modal rainfall with rainfall falling additionally between the months of June and August (JJA). Other studies concur with this assessment, that Kenyan rainfall is mainly bimodal. This includes the work done by Muhindi *et al (*2001).

For the coastal regions the short rains season of March to May (MAM) has its peak in the month of May which then extends into June, July and tapers off in the month of August. On the other hand, for the western regions including counties of Kakamega, Kisii, Kericho, Kitale among others, the March to May rainfall exhibits a peak in April then a gradual drop during the month of May and transitions into the June to August season with a peak in July.

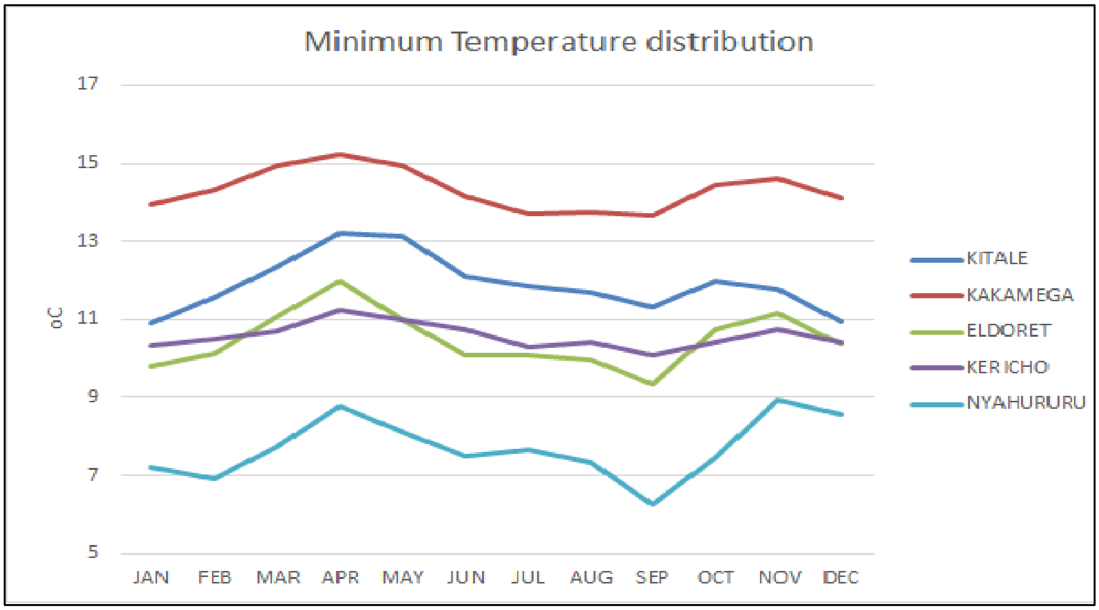

Figure 11: Minimum temperature distribution for stations within the Highlands west of the Rift Valley

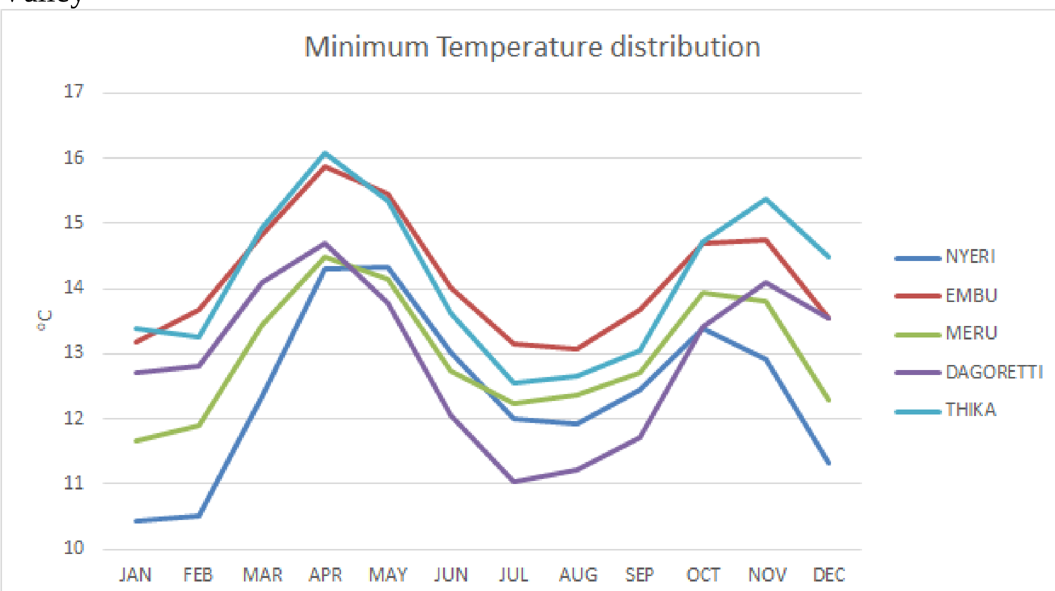

Figure 12: Minimum Temperature distribution for stations within the Highlands East of the Rift Valley

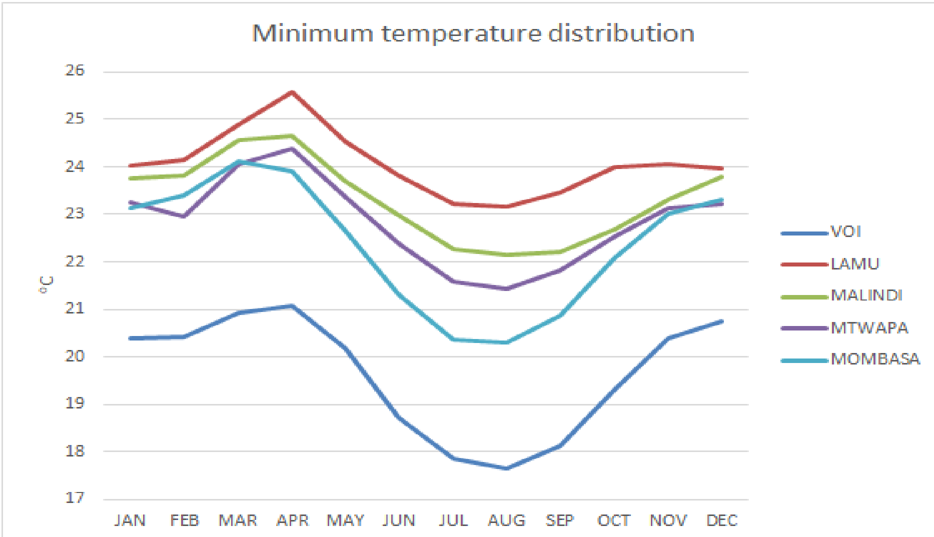

Figure 13: Minimum temperature distribution for stations within the Coast

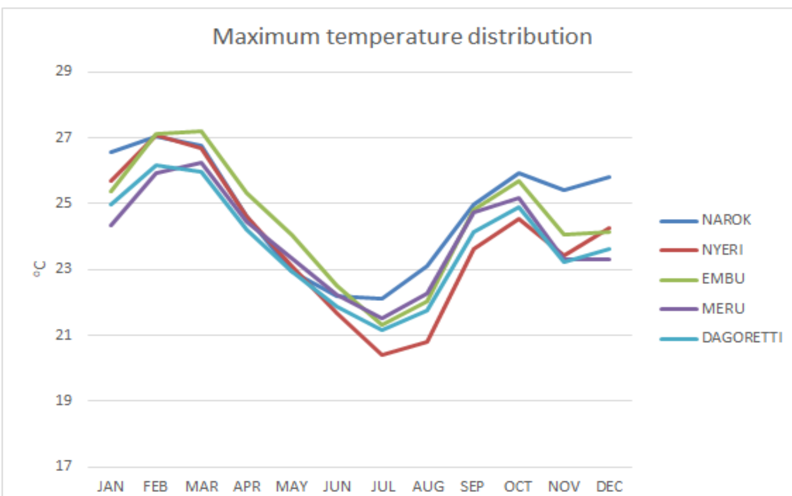

Figure 14: Maximum temperature distribution for select stations

Figures 11 to 14 show the distribution of both maximum and minimum temperatures across the year. All the graphs clearly show that the months with the coolest temperatures fall between June and August while the months with the warmest temperatures fall between December and March

4.2.2 Statistical Analysis of past and future rainfall data

The table below summarizes the results of the test for all the 13 stations for annual and seasonal rainfall data.

Table 7: Statistical trend analysis past rainfall data

	ANNUAL RAINFALL					MAM RAINFALL				OND RAINFALL			
Stations	**n**	**Z**	**Sig.**	**Q**	**%change**	**Z**	**Sign.**	**Q**	**%change**	**Z**	**Sig.**	**Q**	**% Change**
Mombasa	56	-1.27	++	-3.120	-16.554	0.33	++	0.558	7.01245	-0.76	++	-0.783	-14.9703
Makindu	56	-1.63	++	-3.196	-30.551	-1.14	++	-0.716	-21.2771	-1.42	++	-1.66	-29.4084
Machakos	56	-0.81	++	-1.380	-11.3316	-0.36	++	-0.400	-8.02464	-0.74	++	-0.556	-10.7033
Thika	56	0.01	++	0.063	0.373345	-0.37	++	-0.747	-9.41882	1.1	++	1.195	18.88649
Kisumu	56	-0.49	++	-0.857	-3.48217	-1.31	++	-1.391	-14.5205	-0.08	++	-0.089	-1.41631
Kakamega	56	-0.53	++	-1.400	-3.94923	0.41	++	0.572	4.6920	1.21	++	1.506	20.34153
Kericho	43	-1.05	++	-3.773	-8.08487	-0.83	++	-1.481	-9.3248	2.01	*	4.555	45.318
Kisii	54	0.07	++	0.144	0.371219	0.90	++	1.308	10.14961	-0.19	++	-0.272	-2.7609
Dagoretti	56	-0.80	++	-1.524	-8.23514	-0.40	++	-0.688	-7.8094	0.54	++	0.464	8.1455
Voi	56	-0.70	++	-1.158	-11.2924	-0.60	++	-0.463	-13.3769	0.28	++	0.315	6.137787
Mtwapa	56	-0.47	++	-1.384	-6.03968	0.73	++	1.682	16.18655	0.94	++	0.915	17.25253
Embu	51	-1.14	++	-4.100	-15.7369	-1.54	++	-2.467	-27.5501	0.04	++	0.071	0.5209
Kitale	38	0.83	++	3.600	10.70171	0.23	++	0.368	3.1661	2.39	*	4.036	57.962

Based on the Z-Test, stations like Mombasa, Machakos, Mtwapa, Kakamega and Kisumu all indicate negative trend at both the annual and October to December season level. This supports the fact that rainfall has been decreasing over the years as is also outlined in other studies such as one by Ayugi *et al* (2018). It is important to note however that according to the Senn's slope estimate the significance level is greater than 0.1 for all of the data. More than 10% of the data was not well captured within the line of best fit. This can be directly attributed to the variable nature of rainfall from year to year as well as the influence of systems such as El Nino and Lanina as well as the Indian Ocean Dipole (IOD).

Table 7 also highlights the percentage change of rainfall across the years. Total annual change of rainfall is quite significant for most regions, an example is Makindu with a -30% change indicating a significant reduction is expected on the annual level. Kitale on the other hand shows a slight increase of 10% on the annual level. The predominant change is negative within the region however some stations indicate slight increases. Using Mombasa as an example, it is evident that March to May rainfall has a positive change while October to December season has a negative change resulting in an annual overall negative change. The following graphs also show the trend of rainfall for select stations. Figure 15 shows the decreasing trend of rainfall over Mombasa across the years. From the peaks and valleys it is evident also that in recent years there’s greater variability of the rainfall. Figures 27 to 29 in the annexes provide further evidence of the trend of rainfall for various stations across the country at both the seasonal and annual level.

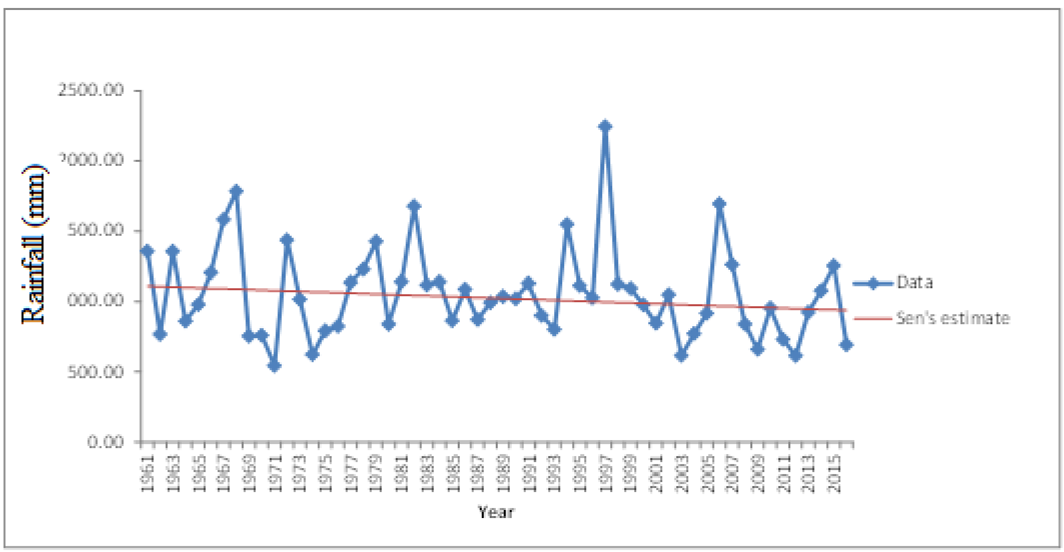

Figure 15: Mombasa annual rainfall trend

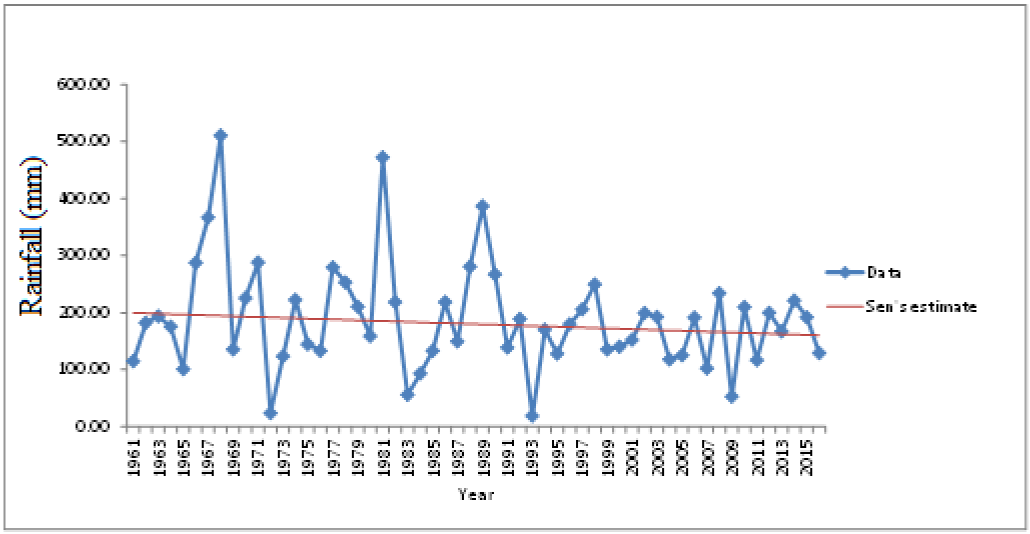

Figure 16: Makindu MAM rainfall trend

Table 8: Statistical trend analysis for future rainfall at RCP 4.5 and RCP 8.5

		ANNUAL RAINFALL RCP 45					ANNUAL RAINFALL RCP 85				
Stations	**n**	**Test Z**	**Signific.**	**Q**	**%change**	**Mean**	**Test Z**	**Signific.**	**Q**	**%change**	**Mean**
MOMBASA	31	0.88	++	1.403	6.238165	697.25	1.97	*	3.781	18.66334	627.95
MAKINDU	31	0.61	++	1.802	4.683074	1193.00	2.65	**	6.625	18.45542	1112.82
MACHAKOS	31	1.29	++	1.600	9.298613	533.41	2.45	*	3.170	19.44121	505.47
KITALE	31	0.92	++	2.107	4.076008	1602.22	1.46		4.629	10.12322	1417.65
KISUMU	31	-0.31	++	-0.362	-1.9678	569.65	2.75	**	3.500	20.22574	536.45
KAKAMEGA	31	-0.61	++	-1.550	-3.53053	1361.31	1.84	+	4.716	11.91552	1226.84
KERICHO	31	-0.75	++	-0.723	-4.73821	472.93	2.69	**	2.727	19.80953	426.68
KISII	31	-0.75	++	-1.114	-5.6969	605.99	3.74	***	4.313	24.13526	554.03
DAGORETTI	31	0.41	++	1.089	2.202521	1533.41	1.90	+	5.145	10.50175	1518.84
VOI	31	0.61	++	1.029	5.384173	592.51	2.86	**	4.154	24.12626	533.77
MTWAPA	31	0.88	++	1.403	6.238165	697.25	1.97	*	3.781	18.66334	627.95
MERU	31	1.50	++	1.799	13.25685	420.68	2.72	**	2.795	23.21715	373.17

Table 8 shows how annual rainfall is expected to change with time and at different emission levels. The change is greater and predominantly positive under RCP 8.5 compared to RCP 4.5 a probable explanation for this is the expected increase of more frequent and more severe extreme events projected under radiative forcing of 8.5W/m^2 (IPCC, 2013). This could result in higher total rainfall amounts but not useful for farming activities among other economic activities and leading to more floods due to reduced infiltration. Figures 30 and 31 offer additional proof of the changing characteristics of rainfall in the future under different RCPs.

4.2.3 Statistical Analysis of past and future temperature data

Temperature is less variable compared to rainfall over most parts of the world (Asfawo *et* al 2018). Average temperatures vary strongly between the narrow coastal strip, the arid regions, semi-arid regions and the highland plateau. The temperature over Kenya varies geographically from the coastal lowlands where high temperatures are recorded and cools as we move to the central highlands of Kenya. Towards the western parts of the country the temperature rises again and even further towards the North of the country.

January, February and March are typically the hottest months during the year with the highest temperatures being recorded during these months through the country.

Table 9 shows how the temperature has changed over the years over the various regions across the country. Consistently across all the regions the average temperature exhibits an increasing trend albeit at different magnitudes. The highest range of change is seen over the coastal strip with change of up to 2°C

Table 9: Temperature changes within Kenya over the years from 1975 to 2017

REGION	TREND	MAGNITUDE
Western	Increase	0.5 – 2.1°C
Northern	Increase	0.1 –1.3°C
Northeastern	Increase	0.1 – 1.3°C
Central	Increase	0.1 - 0.7°C
South Eastern	Increase	0.2 - 0.6°C
Coastal strip	Increase	0.2 - 2.0°C

Table 10: Statistical trend analysis for past annual temperature data

		TMIN				TMAX			
Stations	**n**	**Test Z**	**Signific.**	**Q**	**% change**	**Test Z**	**Signific.**	**Q**	**% change**
MOMBASA	56	1.70	+	0.005	1.310367	4.45	***	0.013	2.412207
MAKINDU	56	5.59	***	0.018	6.07	5.19	***	0.025	4.948639
MACHAKOS	29	3.98	***	0.042	9.132129	3.62	***	0.037	4.265066
THIKA	29	1.44		0.016	3.315152	4.92	***	0.072	8.074372
KISUMU	56	7.41	***	0.025	8.133205	4.34	***	0.014	2.733268
KAKAMEGA	35	3.38	***	0.025	6.052378	5.30	***	0.044	5.546945
KERICHO	49	7.10	***	0.052	24.10246	6.44	***	0.056	11.7188
KISII	35	3.72	***	0.018	4.126177	3.95	***	0.022	2.950909
DAGORETTI	56	8.40	***	0.041	17.80991	4.05	***	0.017	3.933602
VOI	56	7.17	***	0.026	7.389228	3.53	***	0.012	2.147792
MTWAPA	29	3.96	***	0.046	5.807645	1.97	*	0.020	1.947188
MERU	43	3.83	***	0.017	5.732115	1.76	+	0.013	2.254115
KITALE	56	5.50	***	0.027	12.6019	6.50	***	0.037	7.950866

Based on the Z-Test, all the stations subjected to the analysis clearly show an increasing trend in both maximum and minimum temperatures. These results are consistent with studies done in various other parts of Africa including a study by Asfaw *et al* (2018) for Ethiopia. The study found out that temperature within their study region was increasing more than rainfall. The test also showed that the rate of increase of minimum temperatures as evidenced by percentage change, is higher than in the maximum day time temperatures. This therefore drives the increase in annual average temperature and reduces the diurnal temperature range. These results are also consistent with results from other studies (Asfaw *et al*, 2018). Figures 32 to 37 in the Annex additionally illustrate how both minimum and maximum temperatures have evolved over the years.

Table 11: Statistical trend analysis for annual maximum temperature data at RCP4.5 and RCP8.5

RCP 45 Tmax						RCP 85 Tmax			
Station	n	Test Z	Signific.	Q	% CHANGE	Test Z	Signific.	Q	% CHANGE
MOMBASA	*31*	4.45	***	0.013	1.273	4.28	***	0.029	2.878
MAKINDU	*31*	5.19	***	0.025	2.997	5.54	***	0.031	3.698
MACHAKOS	*31*	3.62	***	0.037	4.471	5.98	***	0.035	4.267
KITALE	*31*	4.92	***	0.072	8.050	5.95	***	0.034	3.775
KISUMU	*31*	4.34	***	0.014	1.493	5.81	***	0.033	3.423
KAKAMEGA	*31*	5.30	***	0.044	4.911	5.88	***	0.034	3.854
KERICHO	*31*	6.44	***	0.056	6.014	6.25	***	0.035	3.705
KISII	*31*	3.95	***	0.022	2.237	6.02	***	0.032	3.287
DAGORETTI	*31*	4.05	***	0.017	2.439	6.25	***	0.038	5.553
VOI	*31*	3.53	***	0.012	1.217	4.62	***	0.031	3.142
MTWAPA	*31*	1.97	*	0.020	1.968	4.28	***	0.029	2.878
MERU	*31*	1.76	+	0.013	1.412	6.36	***	0.035	3.960
THIKA	*31*	6.50	***	0.037	6.019	6.36	***	0.038	6.239

Table 11 highlights how future annual maximum temperature varies across the years from 2020 to 2050. The results indicate that at RCP 8.5 by the year 2050 the percentage change in temperature is higher than at RCP 4.5 for all the regions sampled. These findings are consistent with the 2013, 5th assessment report of the IPCC.

These results are very important to take into consideration because temperature is the other important climatic parameter in Kenya and it affects evapotranspiration, soil moisture and water availability among other effects especially on crop production, as well as modifying the photoperiod response especially in non-stressful conditions (Svystun *et al* 2019).

4.2.4 Spatial distribution of seasonal and annual rainfall and temperature in the past and in the future and aflatoxin

Results are divided into rainfall comparisons separate from temperature comparisons and seasonally and annually as well.

4.2.4.1 Spatial distribution of seasonal and annual rainfall in the past and in the future

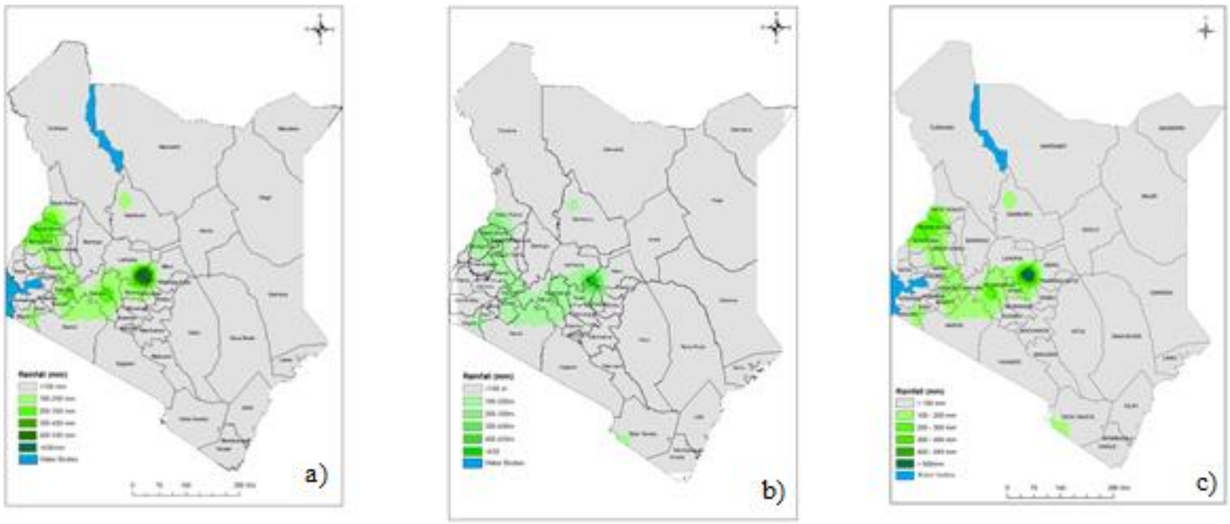

Figure 17: Spatial distribution of annual rainfall across Kenya for (a) the past (b) RCP4.5 and (c) RCP8.5

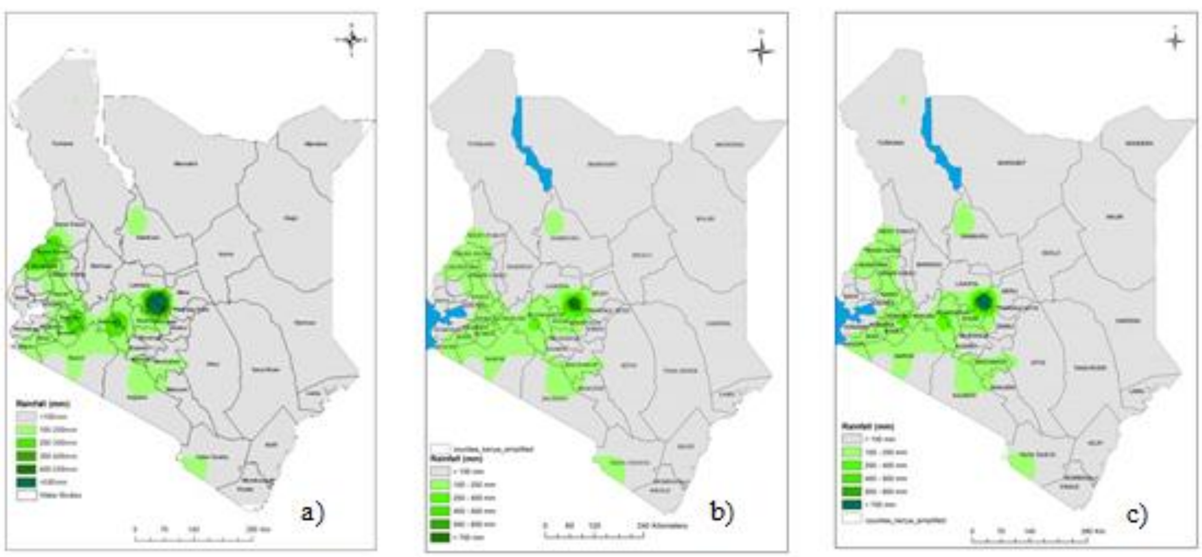

Figure 18: Spatial distribution of rainfall between March and May (MAM) for the **a)** past **b)** RCP4.5 **c)** RCP8.5 in Kenya

A comparison of the three panels in figure 17 and 18 from past to 4.5 and 8.5 futures it is apparent that the spatial extent of both annual and March to May rainfall is changing. Under RCP 4.5 fewer areas within the country are expected to continue to have high rainfall amounts during the long rains season of March to May as well as during the entire year. The graphs use the same scaling in order to compare the spatial extent. Under RCP 8.5 similarly the extent is reduced but not as significantly as with the RCP 4.5 case. A probable explanation for this is the expected increase of more frequent and more severe extreme events projected under radiative forcing of $8.5W/m^2$ (IPCC, 2013). This could result in higher total rainfall amounts but not useful for farming activities among other economic activities.

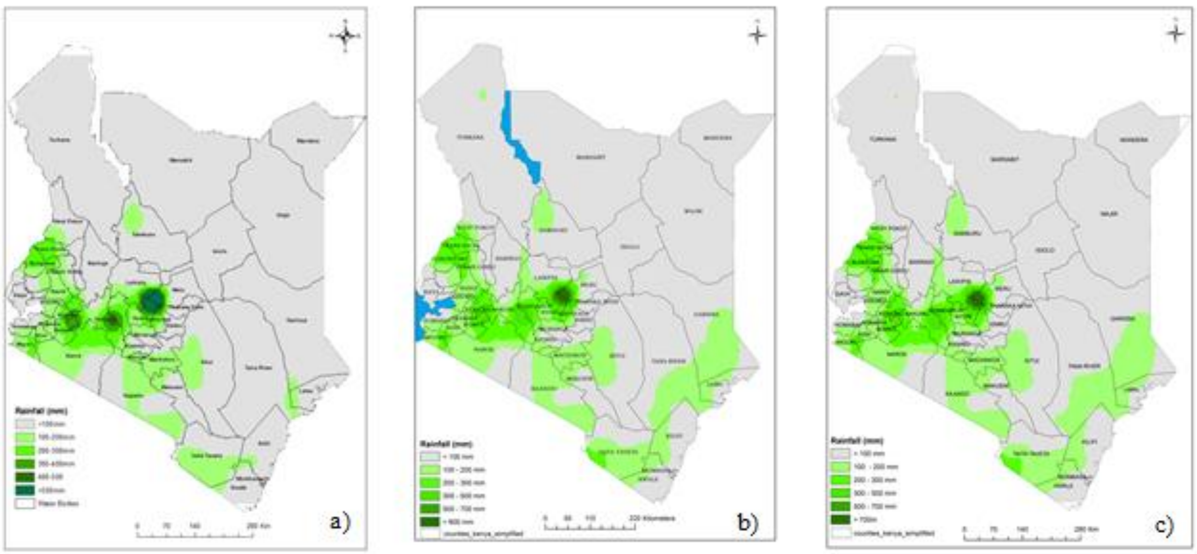

Figure 19: Spatial distribution of rainfall between October and December (OND) for the **a)** past **b)** RCP4.5 **c)** RCP8.5 in Kenya

A comparison of the three panels of figure 19 describes a similar narrative to the situation for March to May and annual rainfall in the 2050 future under the two scenarios under investigation. Rainfall amounts for the OND season are expected to reduce over most parts of the country. The coastal region however is expected to see an increase in spatial extent of areas with significant rainfall while the rest of the country reduces.

4.2.4.2 Spatial distribution of annual minimum and maximum temperature in the past and in the future.

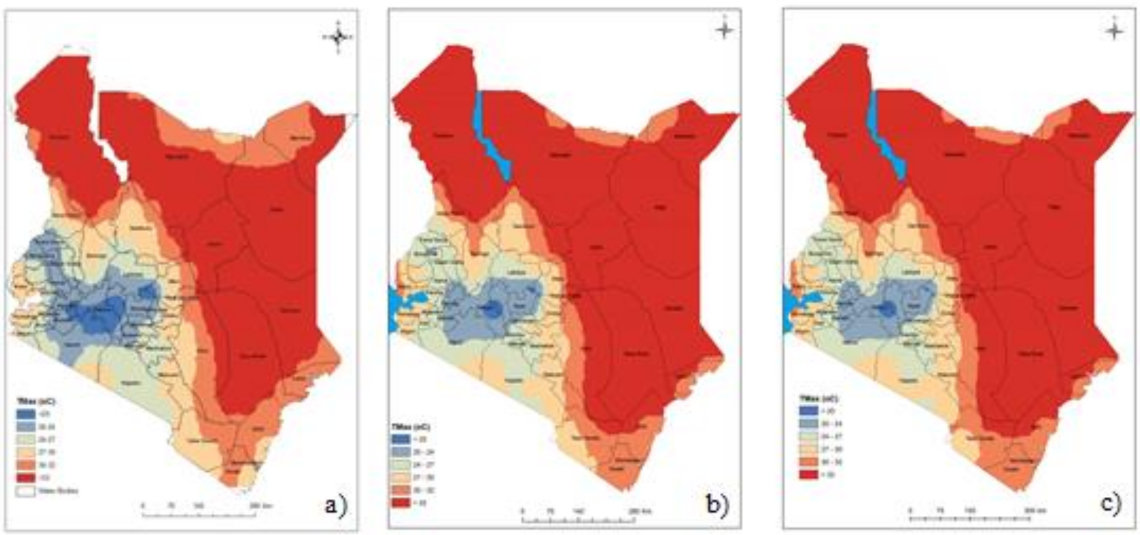

Figure 20: Annual maximum temperature distribution for **(a)** the past future under **(b)** RCP4.5 and **(c)** RCP8.5

From figure 20 (a,b,c) The extent of warming within the country is clearly seen from the past and extending into the future used in this study of 2050 under the two scenarios 4.5 and 8.5. The already warmer regions of the country are expected to be even warmer up to 2050 at both radiative forcing level of 4.5w/m^2 as well as at radiative forcing level of8.5 w/m^2 are warmer under RCP 8.5 using the same temperature scale. This is consistent with literature that shows that under RCP 8.5 temperatures globally are expected to be warmer (IPCC, 2013).

Using temperature data from the past (1975-2005) and spatially representing it shows us that mainly the highlands of Kenya extending to parts of the rift valley and parts of western are relatively cooler compared to the rest of the country. At radiative forcing of 4.5w/m^2 the geographical extent of cooler regions significantly is expected to reduce with higher temperatures experienced in regions with previous cooler climates. The situation is replicated under radiative forcing of 8.5w/m^2 with an even greater geographic extent.

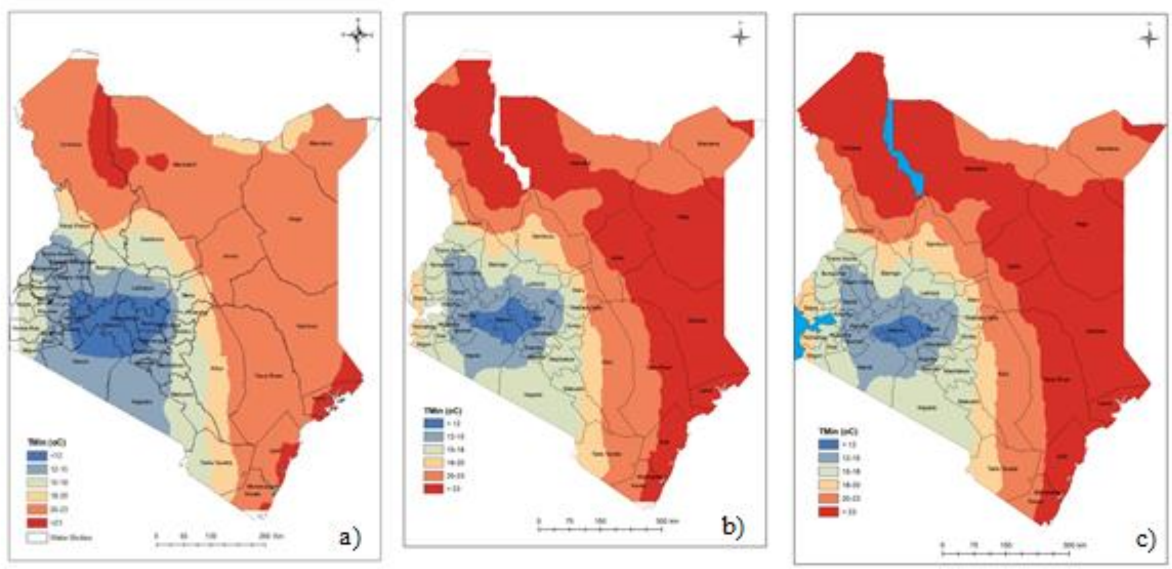

Figure 21: Annual minimum temperature distribution for **(a)** the past future under **(b)** RCP4.5 and **(c)** RCP8.5

Figure 21 (b,c) illustrates a similar tendency of increase of minimum temperature in the 2050 future as was observed for maximum temperature relative to figure 22 (a) which illustrates the past average minimum temperature.

Under the two RCPs; RCP4.5 and RCP8.5 significant warming will have taken place by the year 2050. Larger tracts of land especially within the eastern parts of the country are warmer compared to the climatological period up to 2005, however, warming under RCP8.5 is relatively higher compared to RCP4.5.

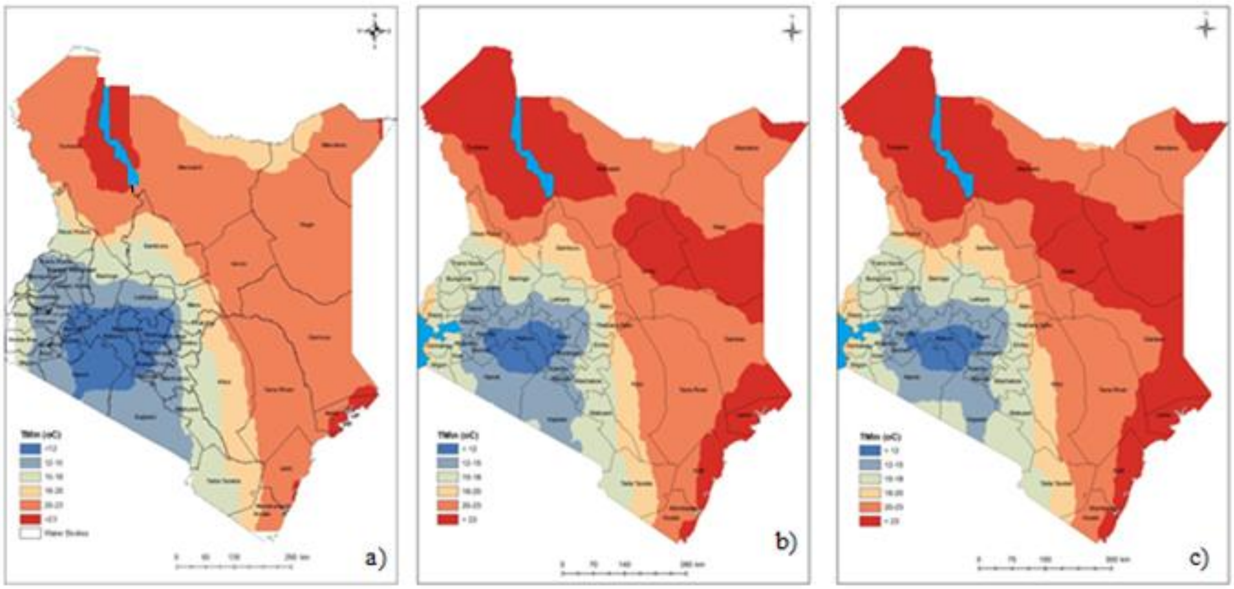

Figure 22: June to August minimum temperature distribution for **(a)** the past, **(b)** RCP4.5 and **(c)** RCP8.5 up to 2050

The three panels in figure 22 serve to illustrate the change in temperature during the current cool season for June, July and August. It is evident that up to 2050 the minimum temperatures will have risen significantly over especially the Eastern, Coastal and Northeastern parts of the country. This is consistent with assessments by the IPCC in AR5.

4.3 Assessment of the spatial distribution of aflatoxin under present climatic conditions

The Figure 23 below shows the hotspots within the country for only maize infestation. The data is in point data representing the longitudes and latitudes of sightings. Figure 23 shows the regions that are most commonly associated with aflatoxin contamination within Kenya. Most of these regions experience the optimum climatological conditions that are favourable for the aspergillus fungi development. Several other researchers have identified these regions as being aflatoxin hotspots in Kenya, including (Nduti & Njeru, 2017) and (Obade *et al*, 2015[a]). In both their studies they identified parts of Central Kenya, Nairobi, Eastern and Western parts of Kenya as being worst afflicted especially because these are predominantly maize growing regions.

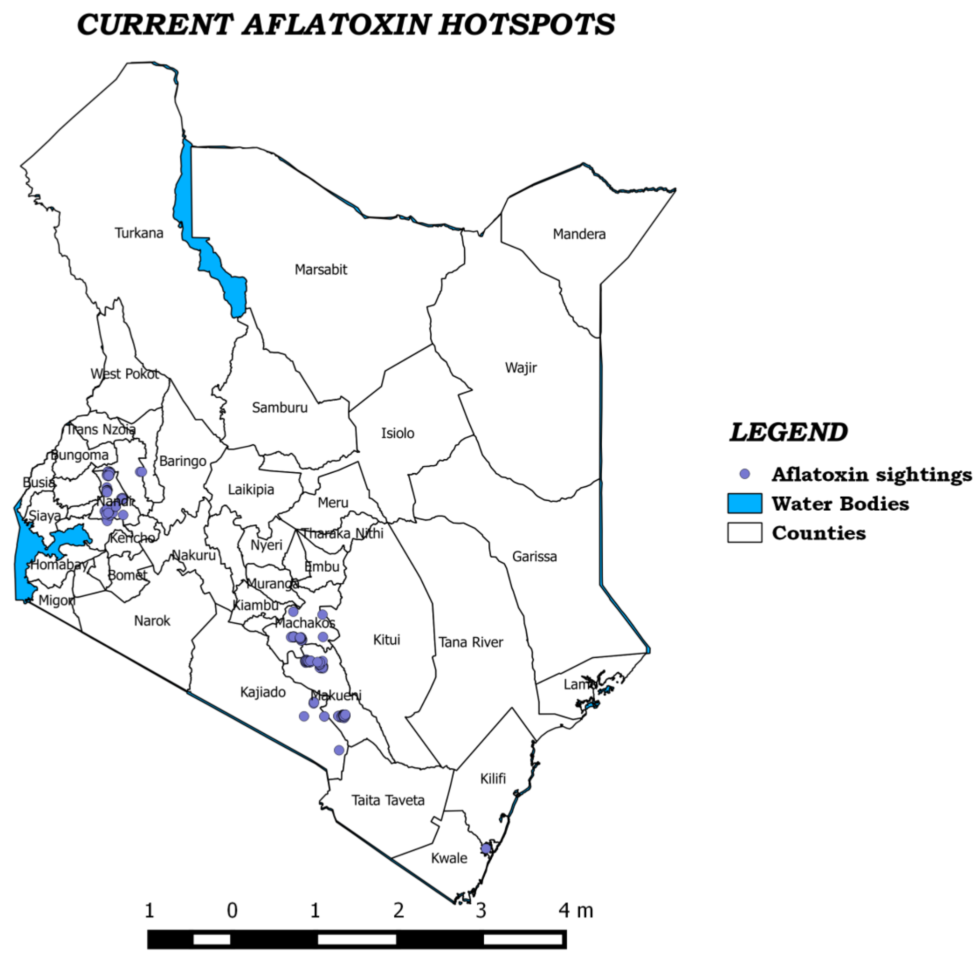

Figure 23: Aflatoxin sightings in Kenya.

4.4 Effects of climate change on aflatoxin distribution

Figure 24 (a, b, c) shows the distribution of aflatoxin after running location data with climate predictors at RCP4.5 and RCP8.5 for the year 2050.

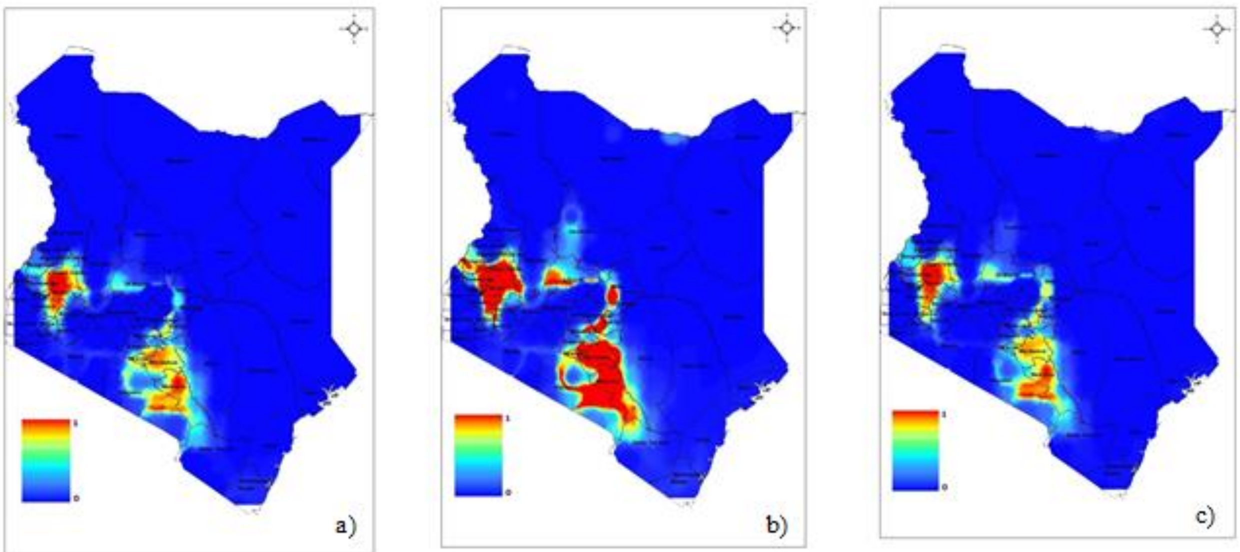

Figure 24: Aflatoxin distribution **(a)** currently and at 2050 under **(b)** RCP4.5 and **(c)** RCP8.5

Warmer colours indicate regions with better projected conditions favouring occurrence of aflatoxin. The image uses a colour scale to indicate projected likelihood that conditions for occurrence are favourable, with the colour red signifying highest likelihood of favourable conditions for the aflatoxin species, green colour signifying conditions characteristic of those where the aflatoxin species exists. Paler shades of the colour blue indicate regions with low projected likelihood of favourable conditions.

It is evident that changing climatic conditions will have an impact on suitability of regions to host aflatoxin fungi. Temperatures are expected to be significantly warmer as evidenced by analysis and corroborated by other studies. Rainfall is expected to be more erratic with more extremes and reduced average amounts within the growing regions and the regions that are current aflatoxin hotspots. Figure 24b shows a wider geographical region coloured red indicating that a larger region is expected in the future to be at risk of aflatoxin contamination, failure to mitigate these circumstances. Figure 24c also shows a comparable situation though with slightly less spread of probable distribution

The locations wherein the species were present provide the random sample for the test points. The same random sample is used each time MaxEnt is run on the same data set.

Figure 25 is a plot showing how the choice of cumulative threshold affects both the testing and training omission and predicted area. The omission on test samples indicated by the light blue line is proven to be a good match to the predicted omission rate highlighted in black, the omission rate for test data drawn from the MaxEnt distribution itself. This therefore indicates that MaxEnt can be reliably used to give an accurate picture of species distribution under different environmental conditions.

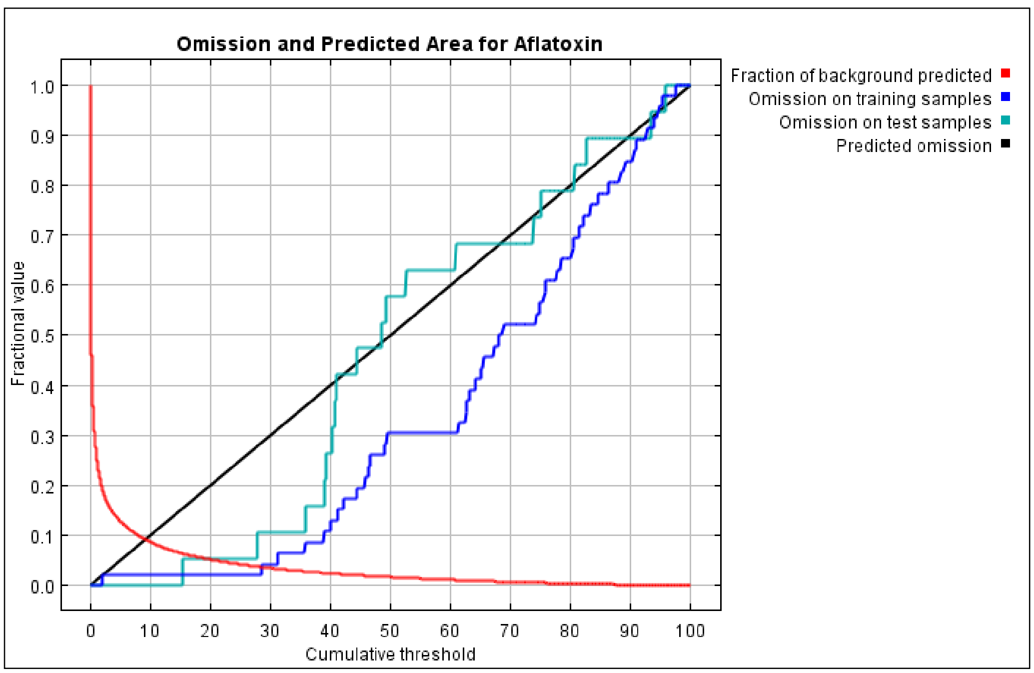

Figure 25: Predicted and omission area for aflatoxin

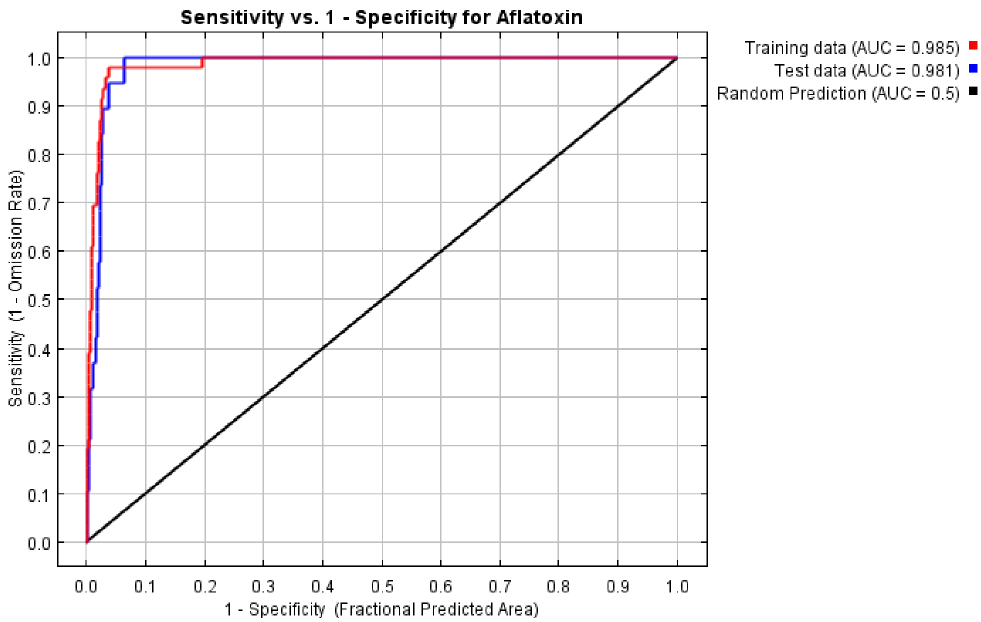

Figure 26: Sensitivity vs. 1- specificity for aflatoxin

Figure 26 shows that the area under the curve (AUC) for the aflatoxin model based on the climatic variables associated with radiative forcing of 8.5 at 2050 was 0.99 for training data and was 0.98 for test data. These values indicate that the model developed by MaxEnt for aflatoxin prediction is applicable, and can be trusted to accurately predict future geographical distribution.

CHAPTER FIVE
CONCLUSION & RECOMMENDATIONS

This study set out to investigate the impacts a changing climate will have on aflatoxin contamination at the growing stage. The study hypothesized that climate will change and therefore lead to an increase in aflatoxin cases due to increase in aflatoxin causing fungi, aspergillus.

5.1. Conclusion

Based on the outcomes from the study, the geographical scope of the distribution of aflatoxins in Kenya is expected to increase under climate change by the years 2050. Larger regions of maize growing areas are likely to be affected by aflatoxin contamination due to an increase in the aflatoxin causing fungi aspergillus. The study also established that by 2050 climate characteristics will have changed. Rainfall is expected to reduce in some regions and increase in others albeit due to increased extreme events. Minimum and maximum temperatures are also expected to increase with a greater increase expected for night-time or minimum temperatures. Additionally, this study has also showed that the model MaxEnt can be used to reliably simulate the effects future climate on aflatoxin distribution.

5.2. Recommendations

In view of the findings of this study, urgent adaptation options are required to cushion against future impacts of climate change

This study recommends that several adaptation measures can be put into place to cushion the country and other regions from the expected increase in distribution of aflatoxin. Additionally, diversifying the crop production within the country could be a useful way to adapt to changing climate and its impacts on food production. On an individual and large scale level, mitigation should be done to slow the rate of change of climate.

For future similar studies, there's room to use projection at a nearer time level, 2030 as well as to further this research into 2070 and up to the end of the century 2100. This study only investigated the distribution of aflatoxin projected up to 2050. This study also used climate data as the primary input for MaxEnt. However more environmental data can be used such as land use change, vegetation index and others to simulate future distribution.

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ANNEXES

APPENDIX 1: Trend of seasonal and annual rainfall for stations within the aflatoxin locations

The data used was primarily from 1961 for various stations, while a couple other stations had a shorter time series but were subjected to the same analysis. The figures below show the results of annual and seasonal rainfall trends for select stations.

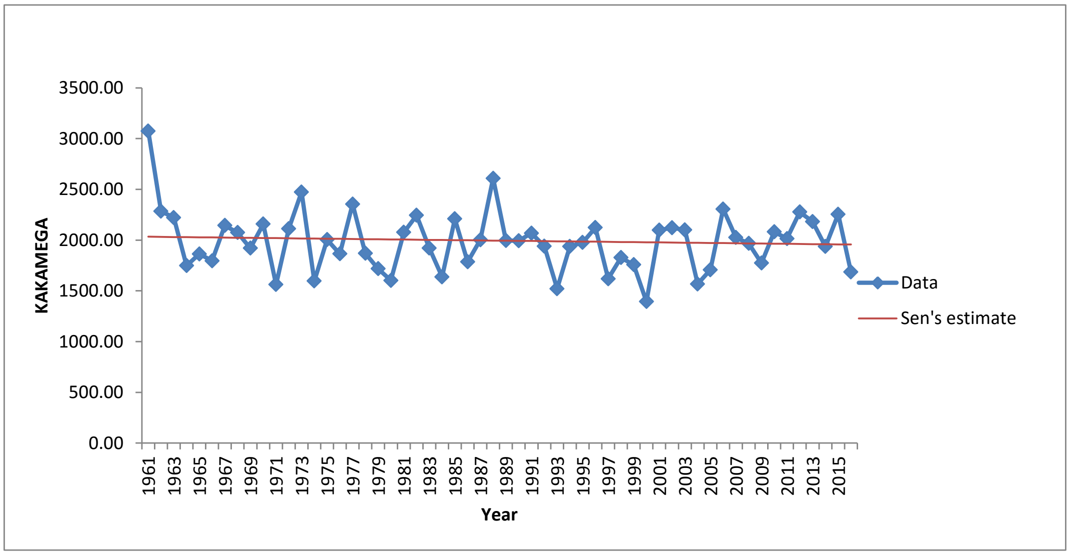

Figure 27: Kakamega climatological past annual rainfall trend

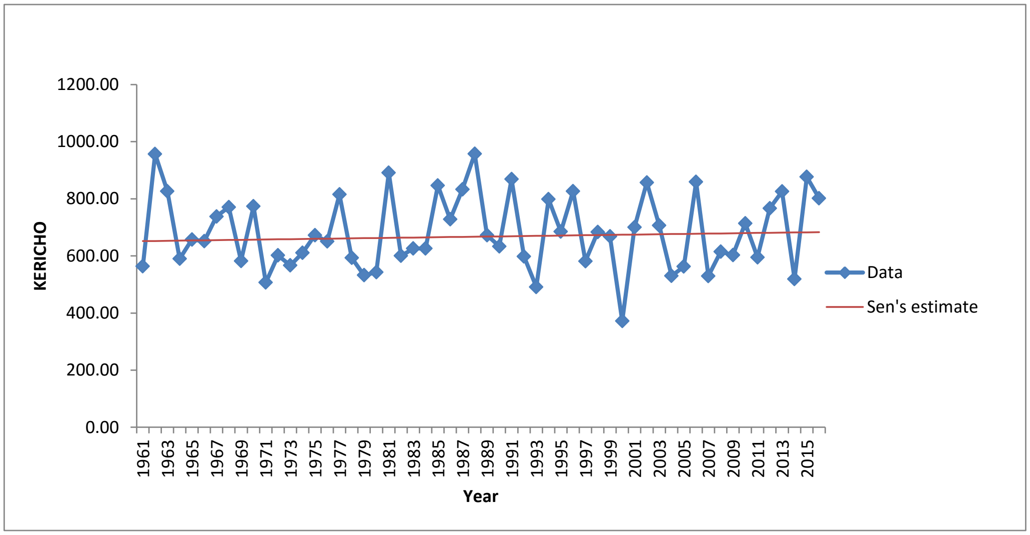

Figure 28: Kericho MAM rainfall trend

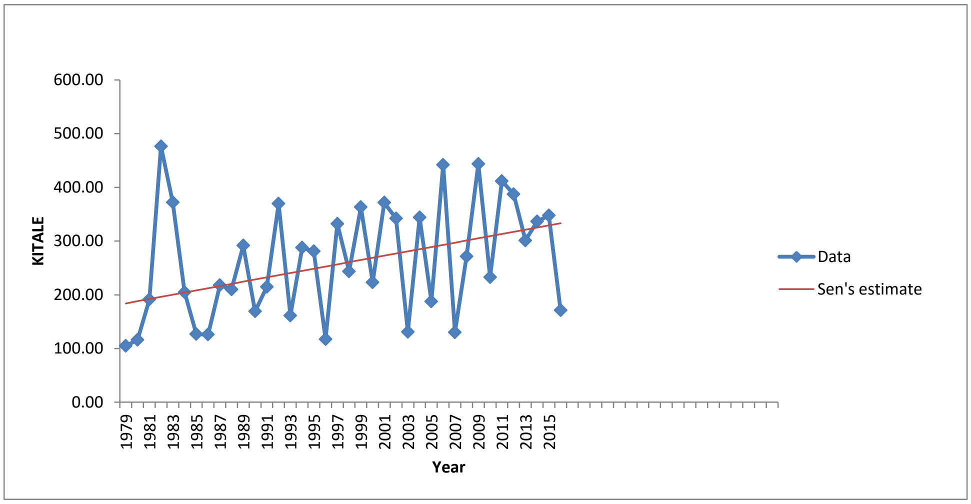

Figure 29: Kitale past OND rainfall trend

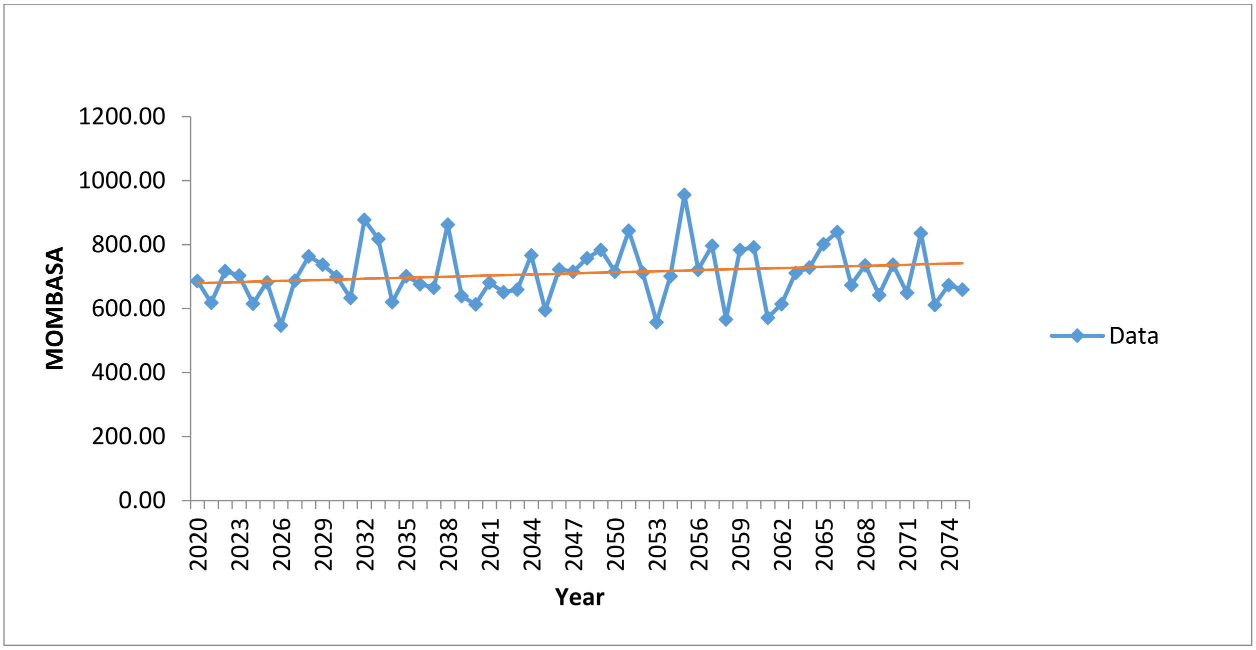

Figure 30: Mombasa OND future rainfall trend

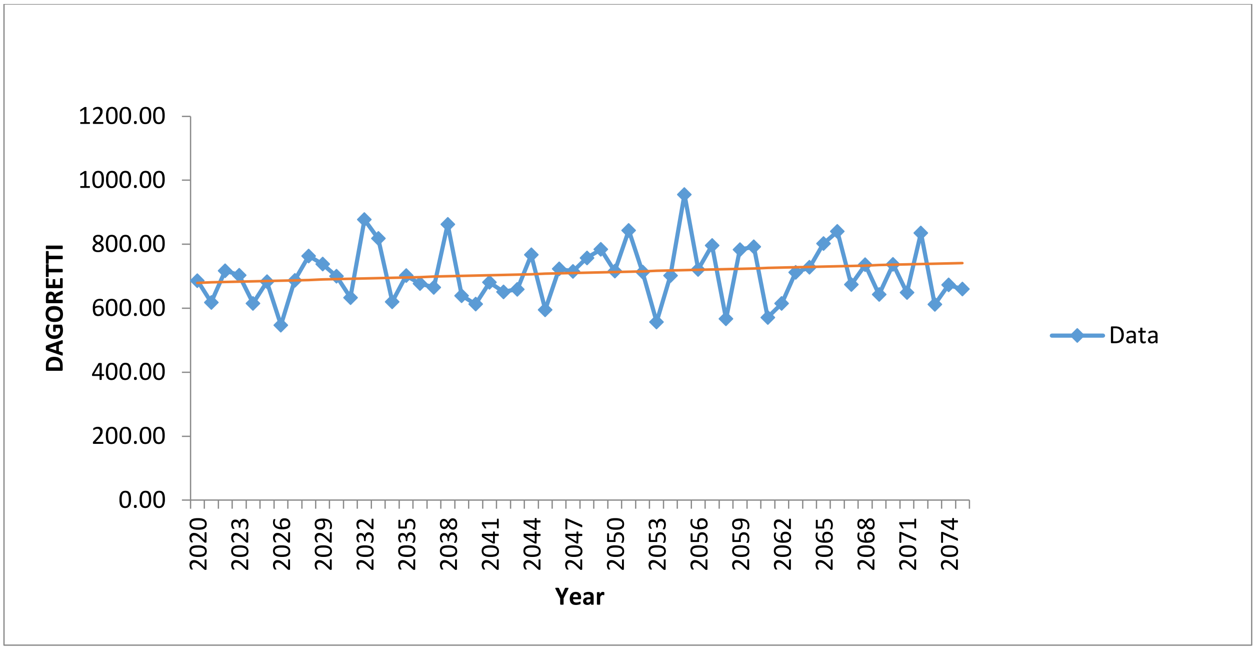

Figure 31: Dagoretti MAM future rainfall trend

APPENDIX 2: Trend of seasonal and annual TMax & TMin for stations within the aflatoxin locations

The following time series plots of select stations illustrate the trend in temperature through the years.

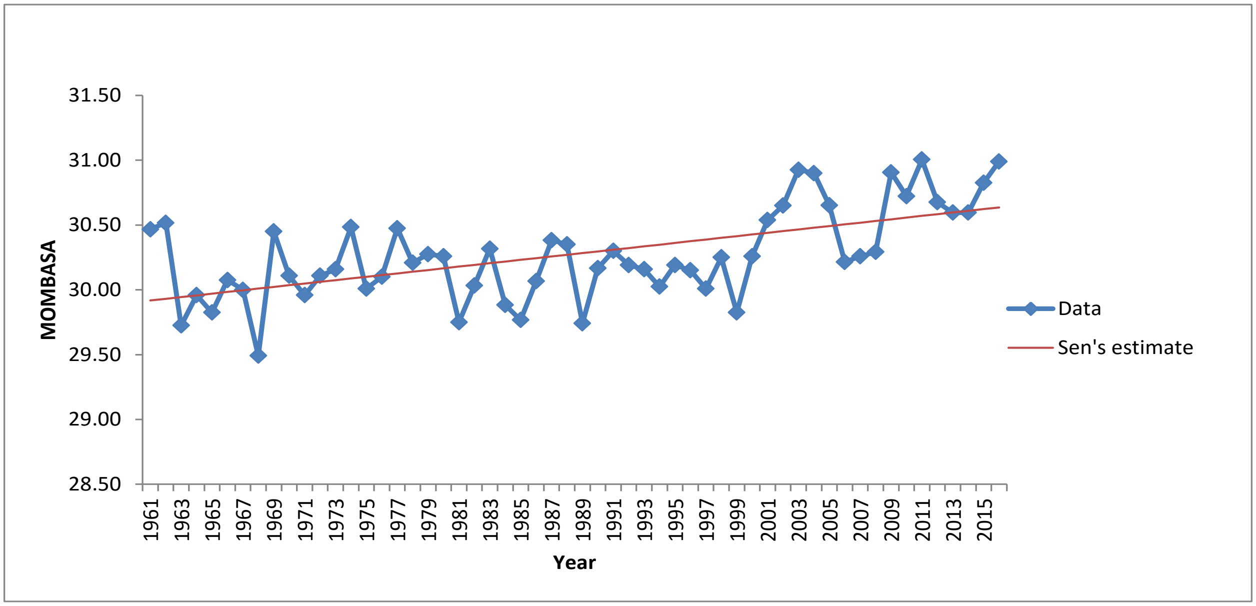

Figure 32: Maximum temperature trend throughout the years for Mombasa

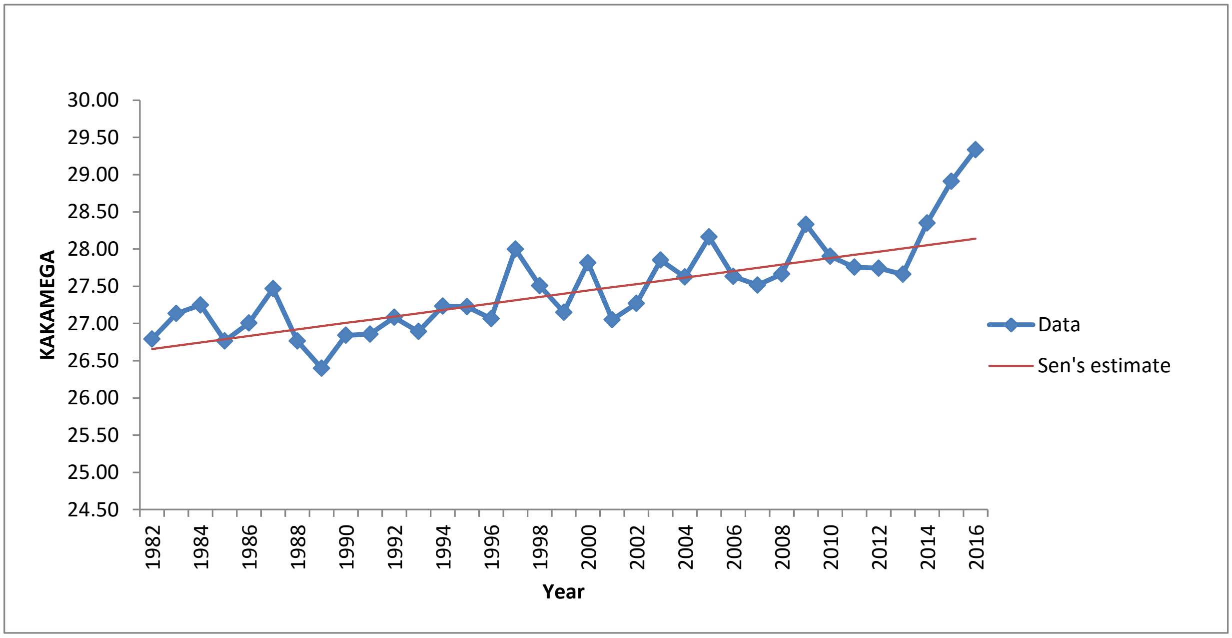

Figure 33: Maximum temperature trend throughout the years for Kakamega

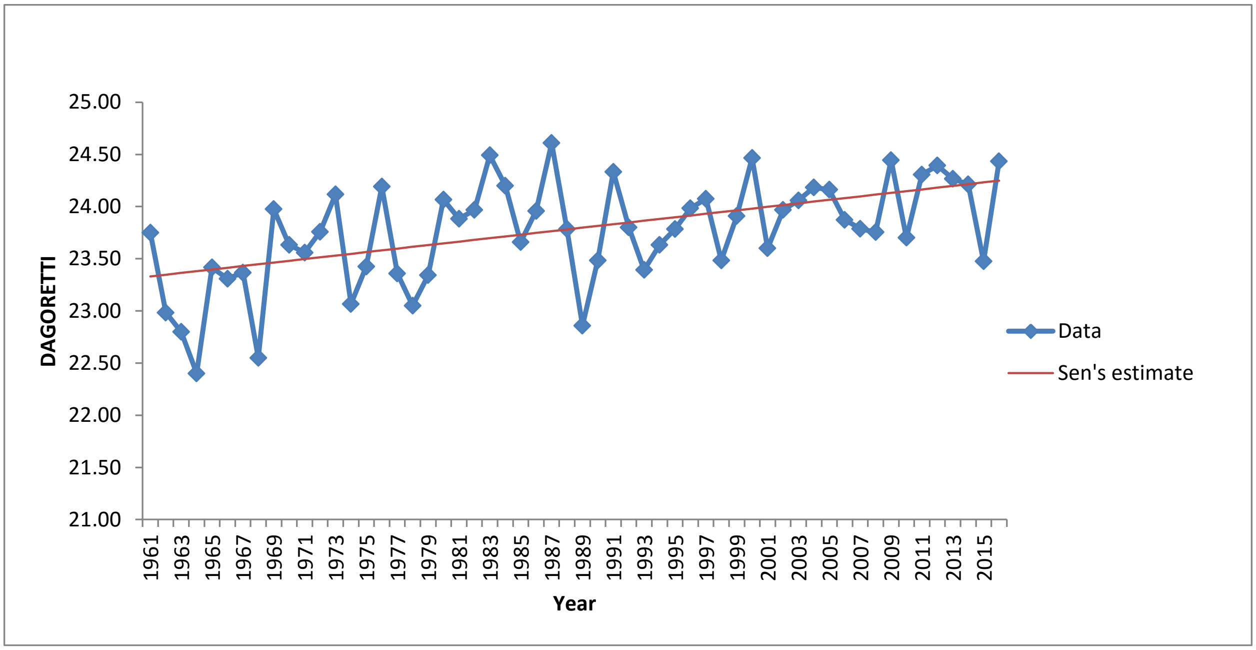

Figure 34: Maximum temperature trend throughout the years for Dagoretti

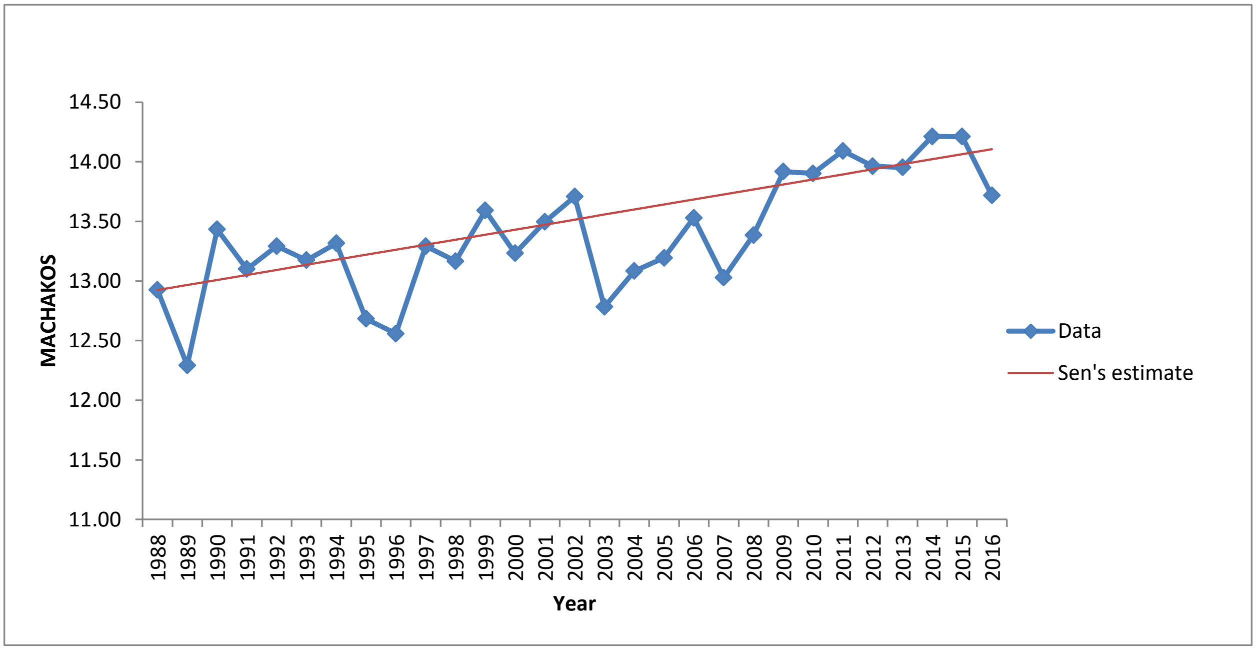

Figure 35: Minimum temperature trend throughout the years for Machakos

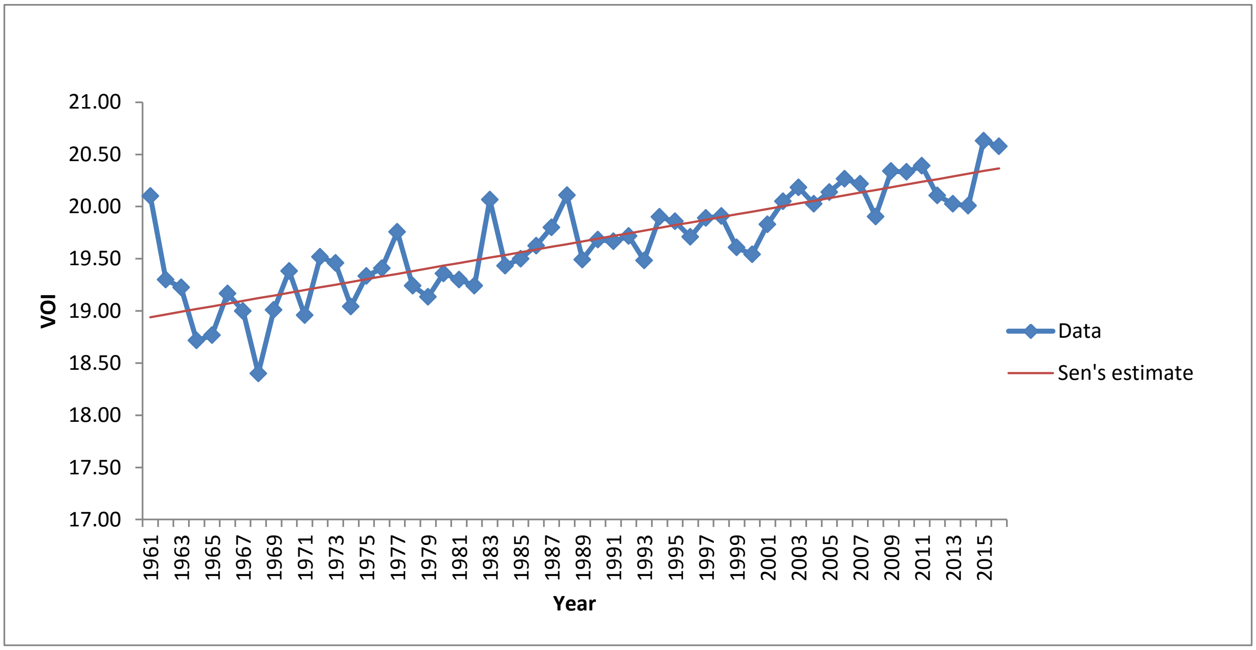

Figure 36: Minimum temperature trend throughout the years for Voi

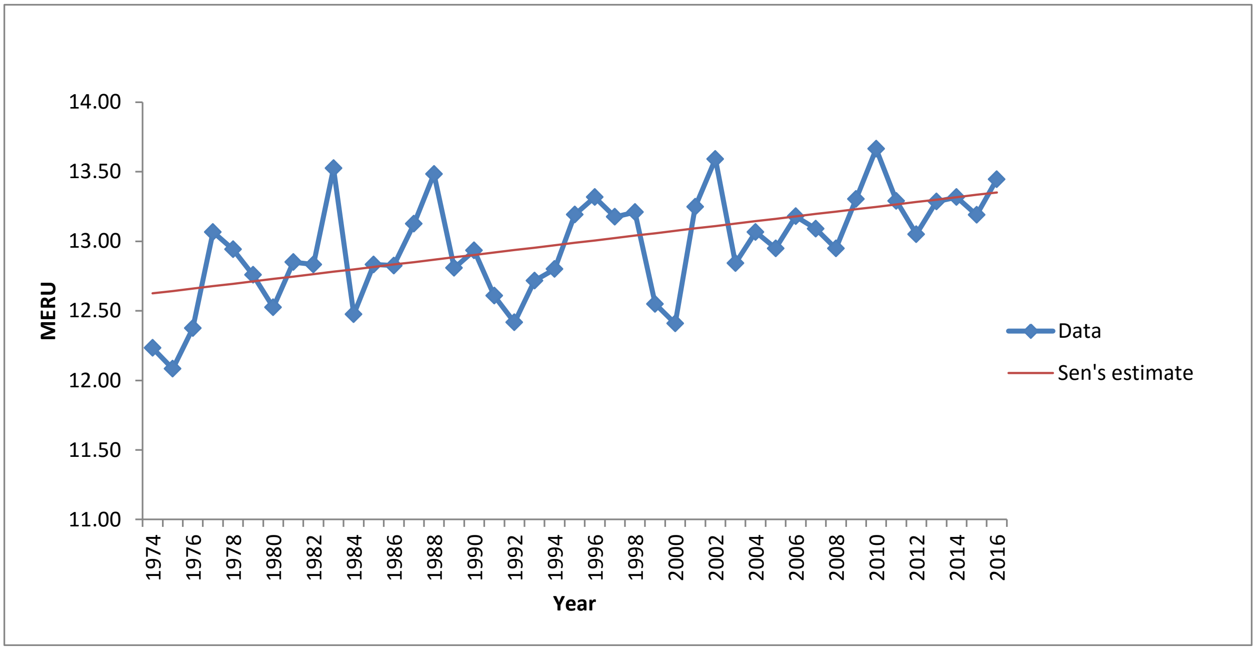

Figure 37: Minimum temperature trend throughout the years for Meru

Annex 3: Predictors generated and used in MaxEnt for modeling aflatoxin distribution

Table 12: List of predictors generated and used in MaxEnt

SCENARIO	Rainfall	Temperature	Rainfall	Temperature
YEAR	**RCP 4.5**		**RCP 8.5**	
2021-2050	pp452050ann	tn452050m1	pp852050ann	tn852050m1
	pp452050mam	tn452050m2	pp852050mam	tn852050m2
	pp452050jja	tn452050m3	pp852050jja	tn852050m3
	pp452050son	tn452050m4	pp852050son	tn852050m4
	pp452050ond	tn452050m5	pp852050ond	tn852050m5
	pp452050djf	tn452050m6	pp852050djf	tn852050m6
		tn452050m7		tn852050m7
		tn452050m8		tn852050m8
		tn452050m9		tn852050m9
		tn452050m10		tn852050m10
		tn452050m11		tn852050m11
		tn452050m12		tn852050m12
		tx452050m1		tx852050m1
		tx452050m2		tx852050m2
		tx452050m3		tx852050m3
		tx452050m4		tx852050m4
		tx452050m5		tx852050m5
		tx452050m6		tx852050m6
		tx452050m7		tx852050m7
		tx452050m8		tx852050m8
		tx452050m9		tx852050m9
		tx452050m10		tx852050m10
		tx452050m11		tx852050m11
		tx452050m12		tx852050m12