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The Climate Change Impact on Crop Yield in Sub-Saharan African Countries Production Function Approach

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DEDICATION

My dissertation is dedicated to my late grandmother (Aisha), my mother and my late father; and to my siblings and their children. I also dedicate it to my friends (Bouchra and Elnazier) and to all people in Africa who have been seriously impacted by the negative aspects of climate change.

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ABSTRACT

The issue of climate variability has received only limited attention in the empirical literature. There are no clear results on the link between variability in crop yield to weather variability. The purpose of the first part of this analysis is to fill this gap in the empirical literature of climate change.

Some major studies have shown that climate change have negative impact on crop yield and crop production in general. Understanding the dynamics of climatic variables impact on the mean and variance of crop yield functions is important step towards developing an optimal poli**cy** to deal with climate change. The first part of this study examines the effect of climatic variables and crop area on crops yield as Maize and Millet in the context of Sub-Sahara African (SSA) countries.

The production function approaches were used in estimating the first model. The Cobb-Douglas and quadratic functional forms were used to estimate the first model. The first model results suggested that the variability of climatic variables have significant impact on Maize and Millet yield functions. The result has indicated further that temperature and precipitation impact on Maize mean is non-linear, meaning that there is always an optimum level of climate that will help in achieving the highest yield. Maize and Millet in SSA respond non-linearly to excessive temperature and precipitation. The generally negative coefficients of the squared precipitation or temperature variables indicate that the relationship between crop yield and climate is inverse U-shaped. Many major studies confirmed that, extreme temperature that is higher than 32 degree Celsius is found to be harmful for Maize and other crops yield. This result is consistent across all yield model specifications.

In the second part of this study the Panel Autoregressive Modeling (P-var) has been used to estimate the model. P-var model is traced from the traditional vector autoregression (VAR) introduced by Sims (1980). Panel-var used mostly in dynamic macroeconomics analysis and proved to be more flexible, traces individual heterogeneity and improve asymptotic results (Rymaszewska 2012).

The second part of the study finds that, for the baseline model there is a significant positive effect from temperature and significant negative effect from precipitation to agriculture production index in the short run. The result shows that the use of fertilizers and machinery both have negative significant impact on agriculture production index, whereas, Livestock has positive significant effect on agriculture production index for SSA countries.

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CHAPTER 1 INTRODUCTION

A noticeable increase in average global temperature of 0.85 degree Celsius occurred between the years 1880 to 2012, according to the Intergovernmental Panel on Climate Change (IPCC) fifth report. The report suggests that the main reason for this increase in global average temperature is the increased emission of carbon dioxide and other greenhouse gases (IPCC, 2013).

Climate change is one of the most serious problems the international community faces over the next century. Many analysts believe that the overall economic impact of climate change is likely to be much more damaging than any other economic issue of the size of the recent global financial crisis and that the consequences will accordingly be felt by every human being and by many other species living on earth. To put the size of the problem in perspective, the Intergovernmental Panel on Climate Change (IPCC).this is a United Nations (UN) scientific body, deals with climate change with a staff of more than 1300 scientists from the United States and other countries, projects that a global temperature increase of 2.5 to 10 degrees Fahrenheit will occur by the beginning of the next century (IPCC, 2007)

IPCC report predicts that, between 75 and 250 million of Africans will suffer a serious water shortage by 2020. Major rain-dependent crops in Africa are expected to lose half of their yield by 2020. The report indicates that food in many African countries will be severely impacted ("AR4 SYR Synthesis Report - 3.3.2 Impacts on regions17," 2007).

The Stern Review is a famous report on the economic impact of climate change. It was funded by British government and issued by British economist Nicolas Stern in 2006. The Stern

Review calls for immediate decisive action to stabilize greenhouse gases because, as stated by the review, the benefits outweigh costs if early and strong actions are taken to deal with climate change (Stern, 2006).

The Stern Review explains that immediate action would be considerably beneficial and that immediate action will cost less than it will in the future. The report indicates that around 5% of the world GDP could be lost yearly because of climate change; moreover, it suggests that the loss could be even larger and may reach more than 20 percent of global GDP (Stern, 2006). Many economists and policy makers agree that the accumulation of greenhouse gases will cause the earth to warm (IPCC, 2007). However, the disagreement apparently concerns what are the most effective policies to handle climate change with the least cost to economic growth.

Prof William Nordhaus, Sterling Professor of Economics at Yale University, advocates a more balanced mitigation approach that starts slowly and becomes faster over time (Nordhaus, 1991). Others, such as Nicolas Stern (head of the Stern Review on the economics of climate change, published in 2006), advocate a more aggressive mitigation policy that starts immediately.

There is a general consensus among economists that African economies are expected to suffer more from the climate change than other parts of the world. The structure of African economies, their overreliance on agriculture and their weak adaptive capacity are the most-often cited reasons to expect that climate change will impact Africa more seriously.

1.1 Research Description and Motivation

Climate variability represents a serious challenge for African economies because African economies are mainly rain-dependent agriculture economies. According to the International Water Management Institute (IWMI), in sub-Saharan Africa (SSA), more than 95% of farmed land is rain-fed (IWMI, 2007). On average, agriculture accounts for 35% of the gross domestic product (GDP) and, employs70% of the population in sub-Saharan Africa (World Bank, 2000).

In Africa, more than 95% of the agricultural area is rain-dependent agriculture; the main cereals—such as maize, millet and sorghum—are mainly rain-dependent crops. In sub-Saharan Africa the cultivated area for major crops has doubled since 1960 according to FAO report, same report indicates that yield per unit of land has been stagnant for these crops (FAOSTAT, 2005). The above-listed facts are alarming indeed and require that some serious action is taken before it is too late.

The first part of this study seeks to analyze the impact of climate variability on agriculture productivity for selected Sub-Saharan African countries (SSA) covering the period of 1961-2006. The study uses production function approaches by incorporating temperature and precipitation variables as proxies for climate change (variability) along with some other control variables used in the production function. The countries selected (28 countries) and the variables used for this study are based on data availability (See the appendix).

Climate variability is defined by the World Metrological Organization (WMO) as, "variations in the mean state and other statistics of the climate on all temporal and spatial scales, beyond individual weather events" (WMO, 2011). According to this definition, variability is the deviation of climate variables from their long term mean (average).

Climate variability can include but is not limited to changing patterns of rainfall, changing patterns of temperature and other variables on a timeframe ranging from a few weeks to a few decades (WMO, 2011).

IPCC defines “climate variability” as, “a variation in the mean state and other statistics (such as standard deviations, the occurrence of extremes, etc.) of the climate on all temporal and spatial scales beyond that of individual weather events” (IPPC, 2007). According to the IPPC definition, climate variability can be an internal process resulting from natural internal processes or what is termed (internal variability), or it can be an external process caused by variations in natural or anthropogenic external forces (external variability) (IPPC, 2007).

Based on the IPCC 2007 report, climate change refers to any change in climate over time, whether due to natural variability or as a result of human activity. On the other hand the United Nations Framework Convention on Climate Change (UNFCCC), defines "climate change" as

“a change of climate which is attributed directly or indirectly to human activity that alters the composition of the global atmosphere and which is in addition to natural climate variability observed over comparable time periods"(IPCC, 2007).The United Nations Framework Convention on climate change (UNFCCC) makes a distinction between "***climate change***" attributable to human activities altering the atmospheric composition, and "***climate variability***" attributable to natural causes. According to UNFCCC, the main difference between ***climate variability*** and ***climate change*** [1] is in the continuation of ***"anomalous"*** conditions - when events that used to be rare occur more frequently, or vice-versa- (UNFCCC, 1992).The United Nations

[1] According to IPCC the 5th report, climate variability and climate change are contributing to the modern climate. Consequently, climate variability is "superimposed" on the climate change long-term evolution and makes the detection of its impacts over a short time period difficult. Chapters 8 and 10 of the 5th IPCC report.

Framework Convention on Climate Change (UNFCCC) makes this clear distinction to highlight the importance of human activities in causing the recent change in climate. Figure 1.1.shows the global annual temperature anomalies computed from land and ocean data.

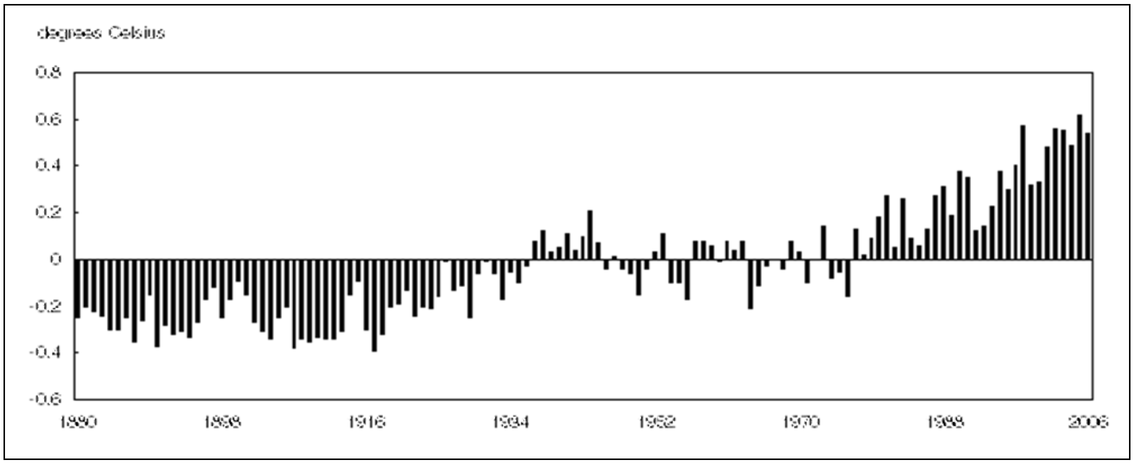

Figure 1.1.Global annual temperature anomalies computed from land and ocean data.

Source(s): Hansen, J.E., R.MRuedy, M. Sato, and K. Lo, 2007, NASAGISS Surface Temperature (GISTEMP)

Analysis, http://cdiac.ornl.gov/ftp/trends/temp/hansen/gl_land_ocean.dat

within the context of sub-Saharan Africa, many previous studies have shown that clear evidence links the change in mean temperature and cumulative precipitation to fluctuations in crop production and crop yield. The issue of climate variability has received only limited attention in the empirical literature. There are no clear results on the link between variability in crop yield to weather variability.

The purpose of the first part of this study is to fill this gap in the empirical literature of climate change. Some major studies have shown that climate change has a negative impact on crop yield and crop production in general. Understanding the impact of climatic variables on the crop yield functions is an important step towards developing an optimal policy to deal with climate change.

The first part of this study examines the effect of climatic variables and crop area on the yield of major crops like maize and millet in the context of sub-Saharan Africa. In the second part of this study, panel autoregressive modeling (PVAR) has been used to estimate the model. The PVAR model is traced from the traditional vector auto-regression (VAR) introduced by Sims (1980).

Panel VAR is mostly used in dynamic macroeconomics analysis and has proven to be flexible. It traces individual heterogeneity and improve asymptotic results (Rymaszewska 2012). Following Raddatz (2007), this study employs a P-VAR approach to estimate the response of a country's agriculture output (as represented by the agriculture production index and other variables) to climate-change variables (temperature and precipitation) along with some other control variables usually used in agriculture production such as, land, machinery, fertilizers and livestock. Panel VARs are used to capture the dynamics of the relationship between variables in a multiple equations setup.

1.2 Economic Impacts of Climate Change

Climate change can affect economies in many different ways; the impact of climate change can be studied on microeconomic, sectoral and overall macroeconomic levels. Some economists have focused more on studying the microeconomic aspects of climate change to address the issue of how climate-change impact can alter supply, demand and consumers' decisions. Other economists are more interested in targeting certain industries or in analyzing the climate impact on small scale communities.

It is evident from the literature that certain sectors of the economy will be harmed more seriously than others. The agriculture sector in the developing world, where agriculture is the major economic activity, will be subject to more crises due to climate change. Some evidence shows that the service sector in many countries will be seriously affected by climate change—especially in tourists attractions and coastal cities—, as these areas are under frequent attacks by extreme weather events such as floods and hurricanes (Harvey in Texas is a recent example) — and are expected to be under more serious future climate threats than other areas.

Major studies on the impact of climate change have reported that impacts of climate change on the industrial, energy and transportation sectors. Labor productivity and political stability are affected the most by the climate change, as some studies have reported.

The impact of climate change on the overall macro economy can be seen from the important report the World Bank published in 2003. This report lists the costs associated with natural disasters in the African continent. According to this report, the drought in Zimbabwe in the early 1990s cost the country an approximately 11 percent loss of GDP; the floods of 1999 in Mozambique cost an estimated 23 percent reduction of the GDP (World Bank, 2003).

The World Bank estimates that economic losses from natural disasters, including floods and droughts have increased three-fold between the 1960s and 1980s; and ten-fold between the 1950s and 1990s.

1.3 Channels of Climate-change Impact on the Agriculture Sector

Based on a recent UN population report, the world's population is projected to reach around nine billion people by 2050 (UN report 2013). As the world population grows and becomes more affluent, global calorie intake is expected to increase by 60 percent between 2000 and 2050, according to report by Deutsche Bank (Deutsche Bank, 2009). These trends require significant increases in food production despite more constrained resources. In the developing world, 29 percent of the gross domestic product (GDP) comes from the agriculture sector (See the appendix).

About 20 percent of the world population and 65 percent of developing countries' populations are employed in the agriculture sector. Based on the above mentioned statistics, the impact of climate change on agriculture represents a serious threat to the livelihoods of millions of people, food production and overall economy of some countries particularly those with agriculture-based economies in the developing world (Padgham, 2009).

The fourth assessment report of the Intergovernmental Panel on Climate Change (IPCC) suggests that, the agriculture sector will be greatly affected by both long-term trends in mean temperature, precipitation and winds and, more seriously, by increasing climate variability associated with increased frequency and severity of extreme events such as droughts and floods (IPCC, 2007). According to the IPCC report, at least 22 percent of the area responsible for the most important crops in the world is expected to suffer seriously from climate-change impact by 2050.

1.4 The Research Area

New studies confirm that Africa is one of the most vulnerable areas to climate variability and climate change because of its low adaptive capacity (IPCC, 2007a). Sub-Saharan Africa in particular is the most vulnerable region to climate change, and yet it contributes the least in terms of greenhouse-gas (GHG) emissions such as carbon dioxide (the principal greenhouse gas responsible for global warming) (IPCC, 2007b). The African region is responsible for only 2-3% of global CO_2 emissions from energy and industrial sources (UN, 2006; World Bank, 2006). The diverse physical features of sub-Saharan Africa present opportunities and constraints for agricultural development.

Sub-Saharan Africa is endowed with many physical natural resources which are expected to sustain the region's growing population and help fuel economic development if these natural resources are well utilized and well managed (Lelo and Makenzi, 2000).

1.5 Crops Selected for the Study

According to the Food and Agriculture Organization (FAO), maize is the most important food source in many African countries. Maize has the highest production of all cereals. Its production reached around 817 million tons in 2009. Maize is used both as animal food and in many industrial applications (FAOSTAT, 2013) (See appendix section). Millet is the most widely grown crop in Sub-Saharan Africa. The region produces 56% of the world's millet. Around 99.9% of African millet is produced in sub-Saharan Africa. India is the top world producer of Millet, followed by Nigeria, Niger and Mali. 70% of sub-Saharan Africa's production is from these three African countries alone. Sudan cultivates large areas of Millet, but yields are relatively low (0.3 tons/ha compared to 1.8 tons/ha in Nigeria) (FAOSTAT, 2013).

1.6 Graphic Statistics for Climate Variability

Descriptive statistics such as the mean, standard deviation and coefficient of variations (CV) are used to examine the regional variability of climate variables. Since the first objective of this study is to examine inter-district or inter-regional variations in climate, the relative variability expressed by the CV and climatic anomalies are more appropriately measured than the standard error (Alauddin and Tisdell 1). (See appendix section).

The term temperature anomaly refers to a departure from a reference value or long-term average. A positive anomaly indicates that the observed temperature was warmer than the reference value, while a negative anomaly indicates that the observed temperature was cooler than the reference value. According to this definition, the figure 1.2 clearly indicates that there is a departure from the long-term mean temperature in sub-Saharan Africa from the period of 1990 to 2010. According to Hulme et al. (2005), the 1980s and 1990s are considered to be the warmest decades and the years 1987 and 1998 are considered to be the warmest years during that period.

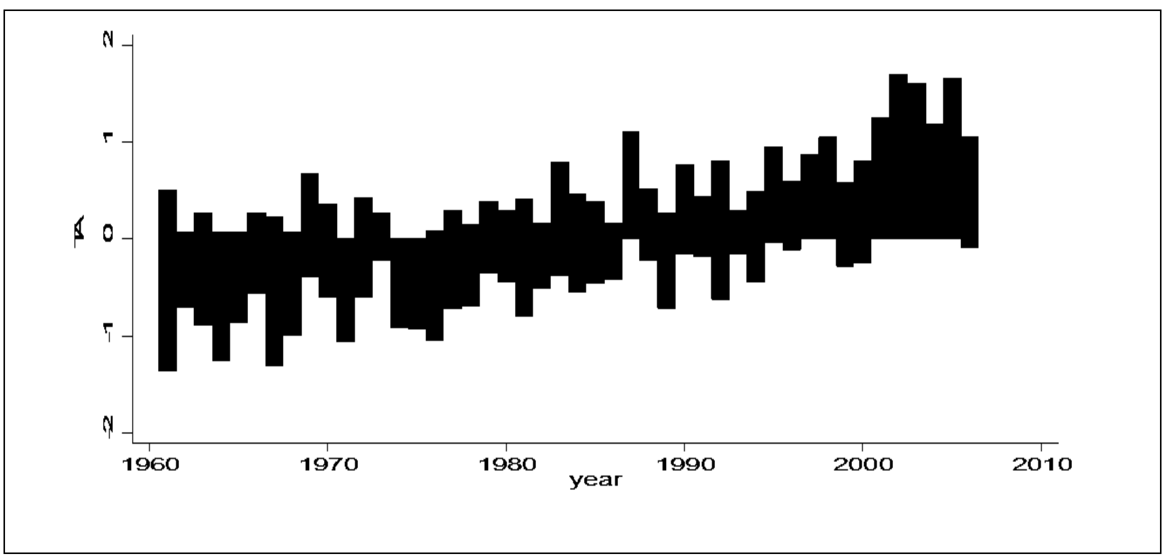

Figure 1.2.Temperature Anomalies in SSA

Projected results of other study show that, for all seasons, the average temperature will increase by the end of this century by between 0.3 and 4 degree Celsius; by the year 2099, temperatures will have increased to around 1.5 times the mean global temperature (Boko et al. 2007).

The term precipitation anomaly refers to a departure from a reference value or long-term average. For precipitation anomalies, the reference value is average precipitation over the period 1970-1999. The figure 1.3 shows a negative anomaly, which means that the rainfall trend in sub-Saharan Africa was less than the long-term mean between 1980 and 2000.

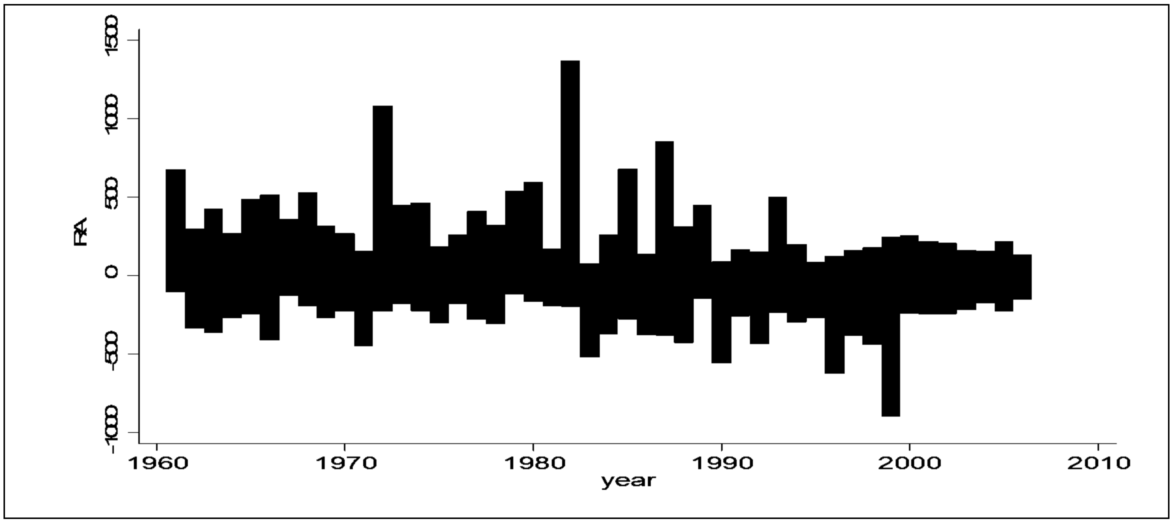

Figure 1.3.Precipitation Anomalies in sub-Saharan Africa

The Met Office Hadley Centre reports that, in the last 25 years, a trend towards reduced rainfall in Southern Africa has been observed. Two or three serious droughts occurred in southern part of Africa during the early 1990s, (Vogel and O'Brien 2003). However, a more reliable parameter clearly projects relative wetting in eastern part of Africa, drying in southeastern Africa, and a poorly specified outcome for the Sahel (Met Office Hadley Centre 2006).

1.7 Objectives and Contribution of the Study

The main objectives of this study are to analyze how climate variability and related risks can affect the crop yield in sub-Saharan Africa and to test whether climate change will indeed have a persistent impact on overall agriculture output (Agricultural Production Index) in general and on major crop yield in particular.

1.7.1 General Objectives

Given the above situation, the main objective of this study is to increase our understanding on the effects of climate change on crop production—specifically on maize and millet— production and food security in sub-Saharan Africa. The specific objectives of the study are as follows;

1. To trace variabilities in crops yield and climatic variables in sub-Saharan Africa.
2. To determine the effects of temperatures and rainfall variabilities on major crops' yield variabilities (maize and millet) in sub-Saharan Africa.
3. To estimate the impact of non-climatic variables (such as area planted, machinery fertilizers and livestock) on crop yield and agriculture output.

1.7.2 Specific Objectives

The objectives of the study can be summarized more precisely as follows:

1. The prime objective is to provide a rigorous qualitative and quantitative analysis of the potential impacts and economic costs of climate change, the risks of increased climate variability, the cost of inaction, and the potential costs of climate change on sub-Saharan African agriculture.
2. Quantify the impacts of climate change on sub-Saharan African economic performance especially in the most dominant sectors, such as the agricultural sector.
3. Identify the channels of transmission from climate change to economic growth in some selected sub-Saharan African countries.

4. To develop scenarios and recommendations for policy making within sub-Saharan Africa and to explain how sub-Saharan Africa could continue to work on issues of environment and climate in relationship with the process of economic integration in a more cooperative manner.

This study will contribute to the literature in many important ways. First, there are few empirical studies about the impact of climate change on crop yield (Chen et al. 2004; Isik and Devadoss 2006; Kim and Pang 2009). Second, earlier studies using panel data have been using average temperature and cumulative rainfall as the two main climate variables (Chen et al. 2004; Isik and Devadoss 2006; Kim and Pang 2009), this study is the first that uses climatic variables designed to precisely capture the impact of climate change (variability) on crop yield. Third, most major studies in the past have one crop or a group of crops as a whole (Chenetal. 2004; Schlenker and Roberts 2006; Deschenes and Greenstone 2007; Guiteras 2007); in this study, the impacts of climate variables are assessed by using two major crops (maize and millet) in sub-Saharan Africa in more comparative manner.

The dataset gathered for the purposes of this study is unique—especially the use of new climatic variables that are quite different from average annual temperature and precipitation, which are traditionally used in climate- change analyses—. A full description of climatic variables is presented in the data section of this study. Second part of this study considers per-capita GDP, the agriculture output index, and agriculture value added as dependent variables. Although we estimate the short-run impact of changes in rainfall and temperature, our main interest is to assess the long-run economic effects of the climate.

1.8 The Research Question and Hypothesis

The literature on climate change and economic impact provides clear evidence of a serious gap in the literature that needs to be covered. In this context, this study investigates the issue by asking the following questions:

1. Does annual climate variation affect overall agriculture production in in sub-Saharan Africa?
2. Does annual climate variation affect the yield of major crops in in sub-Saharan Africa?
3. Does annual climate variation affect crop yield in different climatic zones in in sub-Saharan Africa?
4. Does annual climate variation affect level of overall agriculture output in in sub-Saharan Africa?
5. Does annual climate variation affect the growth of overall agriculture output in in sub-Saharan Africa?

To answer the above- mentioned research questions, empirical analysis of the present study seeks to investigate the following hypotheses:

Hypothesis 1: The relationship of climate change and overall agriculture output in in sub-Saharan Africa

Under this hypothesis, we seek to test the following null and alternative hypotheses:

H0: Climate change has no significant effect on overall GDP agriculture output in some sub-Saharan African countries.

Ha: Climate change has significantly negative or significantly positive effect on overall GDP agriculture output in some sub-Saharan African countries.

More precisely, in symbolic terms, H0, $\beta3=0$ and Ha, $\beta3<0$ OR $\beta3>0$

Hypothesis 2: The relationship of climate change and crop yield in SSA

Under this hypothesis, we seek to test the following null and alternative hypotheses:

H0: Climate change has no significant effect on crop yield in some sub-Saharan African countries.

Ha: Climate change has a significantly negative or significantly positive effect on crop yield in some sub-Saharan African countries.

More precisely, in symbols terms H0 $\beta3=0$ and Ha, $\beta3<0$ OR $\beta3>0$

1.9 Organization of the Study

This study is organized as follows. Chapter Two reviews the theoretical and empirical literature on climate-change impact on agriculture production in general and on crop yield in particular. Chapter Three is about the theoretical framework. Chapter Four describes the data and methodology used in the study. Chapter Five discusses the results of the baseline model (Model One), which concerns the climate-change impact on crop yield.

The second model is about the climate-change impact on overall agriculture output in sub-Saharan Africa. A number of extensions and robustness checks on the benchmark models will be introduced at the end of the chapter. Chapter 6 discusses the summary of research findings, recommendations and conclusions.

Conclusions

Climate change is one of the most serious challenges facing the international community now and over the next century. Many analysts believe the overall economic impact of climate change is likely to be much more damaging than any other major economic issues. Climate variability represents a major threat to African economies because African economies are mainly rain-dependent agriculture economies.

The fourth-assessment report of the IPCC has indicated that the agriculture sector will be greatly affected both by long-term trends in mean temperature and, precipitation and, more seriously, by increasing climate variability associated with the increased frequency and severity of extreme events such as droughts and floods (IPCC, 2007).

Given the above situation, the main objective of this study is to intensify our understanding on the effects of climate change on crop production—especially on the production of maize and millet— and food security in sub-Saharan Africa.

This introductory chapter has identified the research problem, defined the area of the study, defined the basic terms related to the study, and identified the overall and specific objectives of the study. How this study will contribute to the current debate over the topic is also explained in this section.

CHAPTER 2 THE LITERATURE REVIEW

Climate change and its economic impact have become among the most important issues of this century and many centuries to come. It is a critical issue for the world economy today and in the future. Climate change recently captured the attention of individuals and institutions such as governments, businesses, research institutions and social media. It is evident now that, climate change will bring serious risks to many regions of the world.

This study has raised the following critical question: How will climate change and climate variability impact the production and yield of major crops in sub-Saharan countries? This part of the study will focuses on reviewing theoretical and empirical literature on the economic impact of climate change and on trying to answer this question and many other related questions.

Extensive literature has been written on the economic impact of climate change. Some of this literature focuses on the link between climate change and economic growth based on a regional classification of the world; other literatures look at the sectoral level. Most of these writings have some limitations, but they still can provide a good start for further research.

Recently, many scholars in the fields of science, economics, business and public policy have started to write more about climate change. This section introduces a thorough review of the current and historical literature on the economics of climate change; this review includes literature on the historical development of the issue of climate change. Major works written by scholars in the field are presented and analyzed. Published materials from reliable sources such as books, papers of international conferences, peers-reviewed papers, and articles from well-recognized journals are analyzed.

The literature review section has three sub-sections. Section 2.1 covers historical studies about the historical development of the climate-change issue. Section 2.2 examines studies that analyze theoretical models of the economic impact of climate change. Some of these studies have analyzed the influence of climate change on a microeconomic level; while others focus on using macro-level integrated- assessment models to link the overall impact of climate change on GDP growth. Section 2.3 is devoted to the empirical literature. Finally, section 2.4 offers the conclusion of the chapter.

2.1 The Historical Literature

Classical economists like David Ricardo, Thomas Malthus, Adam Smith, John Stuart Mill, and Jean-Baptiste Say do not mention climate change directly within their major works for simple reason that during theirs times climate change had not yet emerged as a political issue. Most of their writings were mainly about ethical concepts of rights, justice and freedom. These; great historical writings in some way are mainly about the basic principles of equity, fairness and social justice. These issues are at the forefront of the current debate on climate change.

The current debate on economic analysis of climate-change basically focus on how to weigh the mitigations costs of current climate risk against the expected benefits future generation should enjoy. This debate is an essentially ethical one. Intergenerational fairness is one of the major ethical issues of the discussion of what proper discount rate to use in the cost-benefit analysis of climate change.

Adam Smith, for example, never directly addressed the problem of climate change in his famous book "*An Inquiry into the Nature and Causes of the Wealth of Nation*" (1776), but his book in many respects shows evidence of market and government failures. At the center of his work are these questions: How can a fully liberal system be formed? How those systems can works within a social system driven by a human nature of self-interest (Smith, 1776).

Adam Smith uses the term "invisible hand" to mean that when every individual in society naturally acts in self-interested manner this eventually will lead to unintended social benefits with little or no government intervention. For this system to function well, Adam Smith, suggested a minimum role of government and less regulation (Smith, 1776). This idea might not be accepted by climate-change advocates who have more or less prescribed heavy regulations on major emitters of greenhouse gases.

In his book, "*The Theory of Moral Sentiments*" (1759), Adam Smith describes human nature and how such human nature can play role in forming social institutions that are based on moral principles (Smith, 1759). "Human happiness" to Smith, comes from our feeling about other people around us and their acceptance of our self-interested actions. This is what Smith called a share for "mutual sympathy". To Smith, this kind of behavior is basic human nature, and it will eventually lead to the rise of moral society, Smith's Ideas of self-interest, invisible hand and moral judgment are well presented in the ethics of climate change and highlighted in some way or another in the current discussion around the "**conflict *of interest***" [2] between two groups, the developed world (emission producers) and the developing world (the recipients of the damage from climate change).

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[2] At the United Nations Framework Convention on Climate Change Conference in Cancun, in November 2010, the Heads of State reached an agreement on the aim of limiting the global temperature rise to 2 °C relative to preindustrial levels. They recognized that long-term future warming is primarily constrained by cumulative anthropogenic greenhouse gas emissions that deep cuts in global emissions are required, and that action based on equity must be taken to meet this objective. However, negotiations on emission reduction among countries are increasingly faced with difficulty, partly because of arguments about the responsibility for the ongoing temperature rise (UNFCC, 2010).

John Stewart Mill was another great philosopher of the 19th century; On Liberty is Mills' landmark work on supporting individuals' moral and economic freedom from the government and society at large. Mill's early economic philosophy advocated free markets principles. In his major book *"Principles of Political Economy, Essays on economics and society" (*1967).

John Steward Mill's view differs from Smith and strongly supports the idea of imposing taxes on alcohol (active role of the government in the economy); if doing so would benefit the economy (we can see that the idea behind the carbon tax is similar). Another example of the idea of social welfare Mill's philosophy is that, he accepted the principle of government intervention for animal welfare. Based on the above mentioned background, climate change and environmental concerns might be at the center of Adam Smith's and John Stewart Mill's writings.

In this part of the literature review, major historical developments of climate science are introduced. Important early works in the area of climate science were started by Joseph Fourier in the year 1824.These are; followed by works by Pouillit, who did some good works in 1836 and 1859.

John Tyndall produced some noticeable results in (1861). But Svante Arrhenius (1896) was the first who found the link between greenhouse gases and glacial advances and retreats. Callendar (1938) mathematically proved the connection between greenhouse gases and climate change. He found that increases of carbon dioxide concentration can lead to a two degree Celsius increases in the mean global temperature with noticeable warming at the poles. Callendar in 1938 linked increasing fossil-fuel combustion with a rise in (CO_2) and discovered that this will cause greenhouse effects.

In the 1990s, researchers started to study the connection between climate change and economic activities (Tol R. S., 2009).

2.2 The Theoretical Literature

Climate change does not have a standalone economic theory to explain it, but most disciplines, in the economic and other sciences have touched one or more aspects of climate change. For example, climate change represents a major externality and a market failure; these issues are major concerns for modern microeconomics.

Climate change is in fact an issue which can be embedded in most branches of economics, such as macroeconomics analysis, cost-benefit analysis (CBA), welfare economics, the theory of pubic choice, economic development and urban and international economics. Concepts such as market failure, opportunity cost, Pareto optimality, willingness to pay (WTP), willingness to accept (WTA), intergenerational fairness, social discount rate, and equity and fairness, are at the heart of the climate change theoretical literature.

The most important source of the official literature about climate change is the (IPCC's) annual reports. The official IPCC website, defines the organization as follows;

"The Intergovernmental Panel on climate change was created in 1988. It was set up by the World Meteorological Organization (WMO) and the United Nations Environment Program (UNEP) to prepare, based on available scientific information, assessments on all aspects of climate change and its impacts, with a view of formulating realistic response strategies" (IPCC, 2007).

The Intergovernmental Panel on Climate Change (IPPC) defines climate change as,

"a change in the state of the climate that can be identified (e.g. using statistical tests) by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer. It refers to any change in climate over time, whether due to natural variability or as a result of human activity" (IPCC, 2007a; p.30).

The most important models used in climate change analysis are; the DICE and RICE model, the fund model, and the PAGE model. The rice and dice models are integrated economic and geophysical models of economics of climate change. They were developed by William Nordhaus, David Popp, Zili Yang, Joseph Boyer, and their colleagues, at Yale University. DICE stands for (dynamic, integrated climate-economy) model. The DICE model was presented in its modern form by Prof Nordhaus (1992a, b). In 2010, Nordhaus introduced the most recent version of the RICE model, which explicitly counts damages that came as result of sea level rise (Nordhaus, 2010).

The second climate model is (PAGE) which stands for (policy analysis of the greenhouse effect) PAGE simulates different economic and environmental policies to address climate change. PAGE was first intended to study trends in global mean temperature (GMT), (Hope, 2006). PAGE was developed by Chris Hope, John Anderson, Paul Wenman and Erica Plambeck in 1991 at the University of Cambridge (Hope, 2006).

The third model is the climate framework for uncertainty, negotiation and distribution (FUND). It is an integrated-assessment model of climate change. FUND was originally developed to evaluate the role of international-capital transfers in climate policy; FUND was, later used as a test model for studying the dynamic impacts of climate change. FUND is now mostly used to conduct cost-benefit and cost-effectiveness analyses of climate-change economics. FUND was originally developed by Richard Tol; it is now co-developed with David Anthoff (Tol R. S., 2009).

The disagreements in all these models can be seen in the estimation of the social cost of carbon (SCC), which is, according to the US Environmental Protection Agency defined as, "an estimate of the economic damages associated with a small increase in carbon dioxide (CO_2) emissions, conventionally one metric ton, in a given year" (CSIS, 2013). Many scholars reported that, the estimated social cost of carbon (SCC) was determined by FUND model at around \$6; by the DICE model at around \$28, and by the PAGE model around \$30 the average of the three models is about \$21 ("Climate Risks and Carbon Prices: Revising the Social Cost of Carbon — Economics E-Journal," 2012).

Frank Ackerman of the Stockholm Environment Institute and Elizabeth Stanton of U.S. Center Somerville who wrote an article about this issue, they defined the social cost of carbon as "marginal damage caused by an additional ton of carbon dioxide emissions". According to the article, the social cost of carbon in United States was estimated by a U.S. government working group to be \$21 (CO_2) /ton in 2010 (E-Journal, 2012).

Nordhaus (1994a), Nordhaus (1994b) Fankhauser (1995), Tol (1995), Nordhaus and Yang (1996), Plambeck and Hope (1996), Mendelsohn et al. (2000), Nordhaus and Boyer (2000), Tol (2002), Maddison (2003), Rehdanz and Maddison (2005), Hope (2006), Nordhaus (2006), Nordhaus (2008). All these major studies used different estimations of social cost of carbon that were based on different temperature scenarios to yield with different results concerning the climate impact on the GDP growth. These results ranging from -4.8% of GDP Nordhaus, (1994a); to 2.3% of GDP (Tol (2002)

We cannot talk about the climate change without mentioning the Stern Review on the economic impact of climate change. The Stern Review is a 700-page report released for the British government on October of 2006 by economist Nicholas Stern; chair of the Grantham Research Institute on climate change and the Environment at the London School of Economics (LSE) and also chair of the Centre for Climate. The Stern Report is considered one of the most important climate change documents in the literature. It is executive summary states that,

"Models of the global effects –Climate change will have serious impacts on world output, on human life and on the environment–. All countries will be affected, the most vulnerable – the poorest countries– and populations will suffer earliest and most, even though they have contributed least to the causes of climate change" (Stern, 2006),

The Stern Report suggests keeping greenhouse gas levels between 450 ppm and 550ppm (CO_2) equivalent to avoid the worst impact of climate change; global action must begin immediately to reach the goal. The report estimated that the current level is 430ppm (CO_2) and estimates and more than 2ppm annually (Stern, 2006). To reach the proposed reduction target, Stern Review proposes that at least 25% below or much more the current levels must be maintained by 2050 (Stern, 2006). The report calculated the annual costs of achieving stabilization to be between 500 and 550ppm (CO_2) this cost turns out to be around 1% of the global GDP per year, if strong action is taken now (Stern, 2006). Stern believes the burden of emission reduction should be by rich and developing countries; Thought the rich world must take a larger share of emissions cuts around 60-80% of their current level by 2050 developing countries must take significant action too (Stern, 2006).

In the next fifty Stern believes that such increases in global average temperature will have serious impact on economic growth as well as on human health and wealth. The Stern Review further calculates that about five percent of the global gross domestic product (GDP) yearly will be lost due to climate change (Stern, 2006).

William Nordhaus (1991); is an economist and Sterling Professor of Economics at Yale University. He is best known for his work in economic modeling and climate change. He conducted a comprehensive study of the climate-change impact on the U.S. economy and has a different view than Stern; He suggested that a temperature rise of 30°C will reduce GDP growth only 0.25percent. Moreover, Nordhaus's study concludes that the damage may only increase to 1-2 percent of the gross domestic product even if some other indirect factors included (Nordhaus, 1991).

The debate between Nicolas Stern and William Nordhaus is a serious one and has a considerable weight in the current literature on climate-change impact. Stern's idea mainly concerns taking a more immediately aggressive approach to handle climate change before it is too late To Stern, any delay will make matters much worse and more costly (Stern, 2006);whereas prof William Nordhaus, on the other is leaning towards a more moderate approach. Nordhaus; main idea is that, Stern's review utterly overestimates the cost of the future damage of climate change and underestimates the opportunity cost of taking action now to handle the damage of the climate change, Nordhaus thinks that most of Stern's calculations are based on a wrongly determined discount rate (Nordhaus, 1991).

The disagreement between Stern and Nordhaus is mainly based on economic theory and on the basic set of assumptions provided by each modeling techniques. Pindyck (2000) wrote an excellent article about this debate between Stern and Nordhaus over whether to act now or to act later. Pindyck thinks the uncertainty in all issues of climate change is behind the questions of whether to act now as proposed by (Stern) or later as proposed by (Nordhaus). Pindyck refers to economic theory which suggests a socially optimum point requiring that the society should mitigate (today) up to the level where the expected marginal costs equal the expected marginal benefits (MC=MB) (Pindyck, 2000).

According to Pindyck, this socially optimum decision is based on the assumption of absent fixed and sunk costs. Pindyck explained that climate change involves fixed costs and sunk costs on both the cost side, in terms of investments in clean technologies, and on the benefit side, in terms of accumulated emissions coming from cheap energy. Pindyck thinks the decision to act now or later to deal with climate change is based mainly on the fixed cost and sunk cost associated with each decision (Pindyck 2000).

It has been suggested in the literature that the use of a low pure-time discount rate in the Stern Review is the main reason for the major differences in the policy recommendations between the economists (Nordhaus, 2007). Stern himself justifies the using of a low discount rate in this code;

"We ask can the framework support strong controls on emissions, if restrictive assumptions about growth, damage and climate risk are relaxed. These assumptions arguably lead to gross underestimation of the benefits of emissions reductions in DICE and other Integrated Assessment Models (IAMs)" (Stern, 2013), Nordhaus, on the other hand has articulated his position in these words;

"Yet despite the obvious ecological risks of unmitigated climate change, the question remained whether the benefits of avoiding these risks would outweigh the perhaps substantial cost of cutting emissions. This is the central question that 'To slow or not to slow' sought to tackle, by combining a simple model of social welfare and production with an externality from greenhouse gas emissions" (Nordhaus, 1991)

The Convexity of the cost function is another basic assumption used by The Stern Review. The report states that, "If marginal cost is rising very steeply, it is optimal to remain on a lower part of the curve" (Stern, 2013).The idea here is that, if the cost function curve is convex, as Stern suggests, then in the short run, one may face lower costs and behave rationally by reducing emissions immediately to avoid high abetment costs in the future. The non-linearity of the cost function is an area of serious debate between Stern and other economists who essentially disagree with his premise and has accordingly raised many concerns about the validity of his basic assumptions.

The proper discount rate to use in assessing the costs and benefits of climate change is another matter of disagreement. Discount rate is defined by Anthony Millner of Grantham Research Institute at London School of Economics as "the rate at which our concern for the welfare of future people declines with their distance from us in time" (Millner, 2014).

The importance of the discount rate to climate-change economic analysis comes from the long-run nature of the climate-change issue and from the basic idea behind the economic analysis of climate changes which starts by measuring costs and benefits, discounting future costs and benefits, and then calculating their present values to make optimal policy options at the present time. Stern advocates using a low discount rate under the assumption that discounting the future too much will make spending now hard to justify compared to some low benefits expected fifty or hundreds of years in the future (Stern, 2006). Nordhaus suggests using 1.5% per year. It is higher than the rate proposed by Stern, taking into consideration not to value so much the future benefits from emission reduction now. Stern recommends aggressive and immediate mitigation action, whereas Nordhaus's analysis argues for a much less intensive climate policy because there are fewer benefits to be realized now from acting immediately (Nordhaus, 1991).

This debate has also extended into a debate over the social cost of carbon (SCC), which is defined by U.S. (EPA) as "an estimate of the economic damages associated with a small increase in carbon dioxide (CO_2) emissions, conventionally one metric ton, in a given year" (Anthoff et al. 2009). This dollar figure also represents the value of damages avoided for a small emission reduction (i.e. the benefit of a (CO_2) reduction) (EPA, 2015). In fact, many analysts believe that the Stern Report's use of low discount rate has led to very high social cost of carbon Stern's estimate is more than 10 times Nordhaus's value. These differences obviously lead to widely different policy recommendations.

Finally, the shape of the damage function of climate change is another crucial area of disagreement among economists. Estimate of climate change-damage vary according to whether there is a tipping point at which damage accelerates or not.

2.3 The Empirical Literature

The Dell, Jones and Olken study of 2008 was a panel study that examined the effect of temperature, precipitation and windstorms on economic outcomes. This study reaches the following important findings: First, climate change can impact the economy through different channels such as the agricultural, industrial, energy and health sectors. The paper also mentions the climate-change impact on labor productivity, political stability and overall economic growth (Dell, 2008). Second, the magnitude of the effects of climate change on the economy can be huge; they are roughly estimated to involve a 1–2 percent loss of GDP per 1°C in poor countries. Third, the functional form of the relationship between climate and the economy is not a simple linear function; a nonlinear functional form may exist too.

Dell (2008) and Dell et al (2008), report that as expected, temperature tends to have a negative impact on growth. Also as expected, precipitation tends to have a positive impact on economic growth. However, both are found to be insignificant suggesting that climatic factors do not play a major role in Africa. These interesting findings contradict the findings of other major studies on climate-change on African economies. Barrios et al. (2010), for example, use a rainfall dataset from the IPPC that presents results contrary to Dell's. Barrios et al. (2010) in fact presented strong evidence to link declining trends in the rainfall and slow economic growth in the African continent (Barrios et al. 2010).

Fankhauser and Tol's (2005) major empirical work investigates climate-change impacts on the capital-accumulation-and-saving rate in a published study entitled, "On Climate Change and Economic Growth". Fankhauser and Tol (2005) study show that climate change can cause poor economic growth. The study compares the dynamic and direct or static effects of climate change.

Studies by Zhang and others (2007), Tol and Wagner (2010) and Butkiewicz and Yanikkaya, (2005) investigate the climate-change impact on political stability and conflicts.

Their main findings reveal that, climate change can lead to lower economic growth in the long run due to political instability and conflict over scarce resources.

Climate change can impact all sectors of the economy, but the agricultural sector is found to be affected the most. Many studies in the literature provide some empirical explanations of the impact of climate change on agricultural production. These studies include the following: Cooper (2000), Parry and others (2007), and Gregory, Ingram and Brklacich (2005). Most of these studies indicate that agricultural production increases in higher latitudes due to climate change partly because of an increase in arable land in these areas. In the tropical zone, the impact of climate-change on agriculture production tends to fall, because of the expected shortage in water supply (Cooper, 2000; Parry and others, 2007 Gregory, Ingram and Brklacich 2005).

Using a Ricardian approach and a dataset on India and Brazil, Mendelsohn and Dinar (1999) find a negative impact of rising temperature on grain yield in these economies and conclude that climate change can impact food security in significant ways. Climate change can affect the food systems in several ways: e.g., by having direct effects on crop production and yield. Mendelsohn and Dinar (1999) stress the role of adaptation, especially in Indian and Brazilian farms, in reducing the effects of climate change on agriculture. Their study reveals that individual farmers play a very crucial role in adaptation to climate change. Mendelsohn, Dinar and Sanghi (2001) and Mendelsohn and Williams (2004) investigate the non-linearity of the impact of climate change and report that the market-sector impacts of climate change have a hill-shaped (concave) relationship with temperature.

The same study provides further evidence that climate change will likely benefit cool areas, will have modest effects on temperate locations, and will negatively affect hot areas. A small numbers of studies have begun to highlight the importance of year-to-year variability or changes in climate on economic growth. Brown and Lall (2006) use statistics of rainfall and temperature variability in a cross-country analysis study. Their study finds that poor countries tend to have higher levels of precipitation variability.

Dell et al. (2009) evaluated the effects of annual variations in precipitation and rainfall over the previous 50 years as a way to estimate the potential economic impacts of climate change. E. Blanc conducted a major study in 2008 aimed to trace climate variability on crop yield by using an African data set. He found that temperature has a negative impact on some major crops yields in sub-Saharan Africa.

Panel VARs have been used for many years to address a variety of issues of interest to applied macroeconomists and policymakers. Within the business-cycle literature, Canova et al. (2007) have employed a panel VAR to study similarities and convergences among G7 countries business cycles. Canova and Ciccarelli (2012) employ them to examine the cross-sectional dynamics of Mediterranean business cycles. Panel-VARS are also used to construct leading indicators of economic activity (see Canova and Ciccarelli, 2009). Finally, Love and Zicchino (2006) used a PVAR model to measure the effect of shocks on financial factors of a cross-sectional model of U.S. firms.

Conclusions

This section is a literature review of the economic impact of climate change. Extensive literature is found on the economic impact of climate change. Some studies focus on the link between climate change and economic growth based on regional classification of the world. Others look more at the sectoral-level impact. Most of these writings have some limitations, but they provide good start for further research.

This section of the study introduced a thorough review of the literature on the economic impact of climate change. This review includes consideration of the historical development of the literature on climate change. Major works written by scholars in the field were presented. Published materials from reliable sources have been used, including books, papers of international conferences, peers-reviewed papers and articles from well-recognized journals.

This literature review has helped in formulating this study by determining what has been covered in the literature and what has not. It has thereby helped determine the exact gap in the literature that needs to be covered by future research. The literature review also helps to provide some knowledge about how different scholars have used different methodologies to address the issue in a scientific manner.

CHAPTER 3 THE THEORETICAL FRAMEWORK

From the literature review of this study, it is evident that the impact of climate change on developing countries in general and African economies in particular is quite devastating and requires an urgent and sizable reaction before it is too late (Nwafor 2007; Jagtap 2007).

The motivation of this study is basically to contribute to the body of literature on this topical issue. This study is intended to explain the complicated issues of climate change within an African context. Many previous studies have shown that climate change will touch all aspects of life in many parts of the world in serious and highly unpredictable ways. It is certain now that; developing countries will take most of the burden of the negative impact of climate change. For all of the above-mentioned reasons, I have a personal motivation to write about this critical issue on behalf of millions of poor African and other vulnerable people around the globe.

In general, there is consensus among economists about the best theory or theoretical framework within which to analyze the economic impact of climate change. The question is how to value the costs and benefits of certain actions in response to climate change; evaluation of these costs and benefits requires careful economic modeling.

Most previous studies in the literature on the economic effects of climate change have adopted one of three theoretical approaches. These approaches are the general-equilibrium approach, the production-function approach (crop model) and the Ricardian approach.

The crop model is also called the simulation model (Lobell & Burke, 2010). This model uses a laboratory-like setting to create certain environmental conditions and then traces expected crop yields and variations of output based on different climatic scenarios (Guiteras, 2009). The crop model starts by aggregating all available physiologic, agronomic, and climatic data to forecast how particular crops grow in particular environmental settings (Lobell & Burke, 2010).

As many sources have indicated, this model is referred to as "eco-physiological" because it statistically describes the physiological and environmental process used to observe plant growth and development (Adams, Fleming, Chang, McCarl, & Rosenzweig, 1995; Lobell & Burke, 2010; Rosenzweig & Parry, 1994).

Crop models have been developed and are used in many studies around the world. Some examples include CERES developed in Hawaii, CROPSYST in Washington, the Food and Agricultural Organization (FAO) developed CROPWAT, the CROP-yield forecasting model, the ASPIM model developed in Australia and the SBW model developed in Pretoria (South Africa) (Iglesias, Rosenzweig, & Pereira, 2000; Rosenzweig & Parry, 1994; Tubiello & Rosenzweig, 2008). Guiteras (2009) lists as the main advantages of crop-models their ability to carefully control and randomize conditions of the environment. But these models suffer from major drawbacks such as failing to consider the adaptation capacity of the farmers (Guiteras, 2009).

The Ricarddian approach (cross-sectional) pioneered by Mendelsohn et al. (1994) overcame the shortcomings of the production-function approach (crop model). The Ricarddian approach uses different climatic conditions to assess performance of farm productivity. This approach is also called the hedonic approach (Lobell & Burke, 2010).

The Ricarddian approach traces the reaction of farmers to different climatic scenarios to study the link between the net revenue and agro-climatic conditions (KabuboMariara & Karanja, 2007; Mendelsohn, Nordhaus, & Shaw, 1994). In other words, land value or rent is considered a function of climatic, demographic, economic and physical conditions.

The Ricarddian (cross-sectional) approach, starts by collecting farm-survey or country-level data, then uses this collected data to detect the relationship between agricultural capacity (measured by land value) and climate variables (usually temperature and precipitation). Farmers' responses to different climatic conditions are considered in this approach; in this regard, one of the main advantages of this approach is its ability to automatically incorporate the climate-change adaptations by farmers.

The major criticisms of the Ricarddian approach are that it does not account for price changes. The approach also does not fully consider other variables that affect farmers' incomes (Mendelsohn and Dinar 1999, Cline 1996).

The Ricarddian approach has been successfully used in many countries around the world. For instance, in the United States (R. Mendelsohn & Dinar, 2003; R. Mendelsohn et al., 1994), in the United States and Canada (R. Mendelsohn & Reinsborough, 2007), in England and Wales (Maddison, 2000; Seo, Mendelsohn, & Munasinghe, 2005), in Sri Lanka (Seo et al., 2005), in Kenya (Kabubo-Mariara & Karanja, 2007), in Taiwan (Chang, 2002), in South Africa (Gbetibouo & Hassan, 2005), and in India and Brazil (Sanghi & Mendelsohn, 2008).

The computable general-equilibrium model uses linear and non-linear equations to simulate equilibrium (Deressa & Hassan 2009). The model can be used to directly or indirectly evaluate the impact of climate change on the various sectors of the economy (Winters, Murgai, Sadoulet, De Janvry, & Frisvold, 1996).

The main advantage of this model is that it takes more than one variable or the whole economy into account with the assumption that all sectors of the economy are mutually interdependent and that changes in one sector affect all other sectors.

The limitations of this model include its difficulty with making model selections, functional forms, data parameterization and data calibration. The model lacks specific statistical tests for model specification (Partridge & Rickman, 1998).

The next section goes in detail to explain each of the above- mentioned approaches and to explain their advantages, disadvantages and the rationale behind why one approach has been selected as a theoretical framework for this study.

3.1 The General-equilibrium Approach

General-equilibrium models are usually simulated models. (Lofgren et al, 2002). These models, as described by Lofgren (2000), consist of mathematical equations, a database model and an economy-wide square matrix. Production in each economic sector is modeled by nested CES functions.

The database model consists of an input-output table or a social-accounting matrix (SAM). The model uses some data or parameters which represent behavioral response (e.g., import demand elasticities) (Lofgren et al., 2002). The climate-change CGE models also use aggregated information based on a geographic information system (GIS) and general circulation models (GCMs) (Mendelsohn & Dinar, 2009). CGE models can be comparative-static or dynamic. Comparative-static models show the difference in the economy between two alternative future states (e.g., B¨ohringer, 2000), whereas dynamic models explicitly model the transition between different economic steady states (Mendelsohn & Dinar, 2009).

It is well known in the literature that CGE models have many advantages over other models. CGE models are able to assess the impact of climate-change on the whole economy and to estimate the impact of climate change on different industries as well.

However, some analysts have criticized CGE models for being over simplified and for lacking econometric specification. These models suffer from a high level of aggregation within sectors and regions. Another major disadvantage of global models is their inaccuracy in measuring the sensitivity of each sector to climate change (Mendelsohn & Dinar, 2009).

The computable general-equilibrium model uses linear and non-linear equations to simulate equilibrium (Deressa & Hassan 2009), and it can be used to adequately assess the impact of climate change on various sectors of the economy directly or indirectly (Winters Murgai, Sadoulet, De Janvry, & Frisvold, 1996). Frank Ackerman, a famous economist, criticizes the CGE model as follows:

[S]standard tools for such assessment computable general equilibrium (CGE) models -- are inadequate on several grounds. Their underlying theory suffers from well-known logical difficulties; in general, their equilibria may be neither unique stable nor efficient Moreover, real-world phenomena such as increasing returns to scale, learning, and technological innovation are neglected in CGE models. (Ackerman, 1998)

According to Ackerman, these models make the resulting equilibria inefficient; in the real world, they can lock society into sub-optimal technologies. More precisely, the equilibrium generated from general-equilibrium models is neither unique nor stable; the underlying assumptions of the model are unrealistic, as stated by Ackerman (Ackerman, 1998).

3.2 The Ricardian Approach

David Ricardo's (1772–1823) original work about the connection between the value of land and its productivity has led to the emergence of the Ricardian method, which is basically a cross-sectional approach, intended to study agricultural production. According to this approach, farmland net revenues (V) reflect net land productivity. This can be explained in the following equation, as used by Pradeep Kurukulasuriya and Robert Mendelsohn (2008):

$$V = \Sigma\, P_i\, Q_i\, (X, C, W, S, E) - \Sigma\, P_x\, X \quad (1)$$

where Pi is the price of crop i, Qi is the quantity of crop i, X is a vector of production input inputs, C is a vector of climatic variables, W is water flow, S is a vector of soil variables, E is a vector of economic variables such as market access and Px is a vector of input prices (See Mendelsohn et al., 1994). According to this model for farmer to maximize net revenue, farmer must choose the optimal amount of X (input) provided the properties of the farm and market prices. The Quadratic formulation of climate variables is basic feature of the Ricardian Model

$$V = B_0 + B_1 F + B_2\ F^2 + +B_3 H + B_4 Z + + B_5 G + u \quad (2)$$

According to the model, the expected marginal impact of a single climate variable on farm net revenue evaluated at the mean is as follows

$$E[dV/df_i] = B_{1i} + 2 * B_{2,i} * E[f_i] \quad (3)$$

The net-revenue function is U-shaped when the quadratic term is positive and is hill-shaped when the quadratic term is negative, as Mendelsohn states, the quadratic term reflects the nonlinear shape of the net-revenue climate-response function (Equation 2). Mendelsohn expects, that based on agronomic research and previous cross-sectional analyses, that farm value exhibits a hill-shaped relationship with temperature. For each crop, there is optimum temperature at which that crop grows best across seasons (Mendelsohn et al., 1994). The change in annual welfare, ΔU, resulting from a climate change of C_0 , C_1 can be measured as follows:

$$\Delta U = V\,(C_1) - V\,(C_0) \quad (4)$$

According to Mendelsohn, if the change increases net income, it is beneficial; if it decreases net income, it is harmful to farmers, who will behave accordingly if they decided to adapt to climate change (Mendelsohn et al., 1994).

Mendelsohn lists the advantages of this approach as follows: The method includes the direct effect of climate on productivity and the adaptive response by farmers to local climate. The disadvantages of this approach are that it does not consider the transition cost of adaptation. The Ricardian model does not takes the costs of different alternatives taken by the farmer when adapting to climate change into account (Mendelsohn et al, 1994).

The Ricardian model basic assumption that price is constant. Cline (1996), argued against that constant price assumption lead to overestimating benefits and underestimating costs. Another criticism of the Ricardian analysis concerns about that the model does not explicitly include irrigation. Irrigation should be explicitly included in the analysis as argued by Cline (1996) and Darwin (1999). This problem is addressed in the literature by explicitly modeling irrigation (Mendelsohn & Nordhaus, 1999; Mendelsohn & Dinar, 2003; Schlenker et al., 2005).

A final concern about the Ricardian method is that it reflects only current agricultural policies. Subsidizing specific inputs or regulating crops, these policies will affect farmer choices, but are not included in the analysis. The Ricardian models cannot be linked to general equilibrium models.

3.3 Why the Production Function Approach

The production function has two main approaches: the primal (production) approach and the dual (profit) approach. Reinsborough explains the two approaches. In the dual (profit) approach, some functional relationship is established between net revenue and the profit of a farm, and specific climate conditions (e.g., the adaptations of farmers) are not explicitly included. The primal (production) approach, on the other hand, uses an output-input relationship and aims to estimate production parameters at different input levels. In the production-function approach, after the proper functional form is decided, the yields of different crops are examined under different climatic scenarios (Reinsborough, 2003).

Production-function approaches face two major challenges: the simultaneity problem and the functional-form problem. First, the simultaneity problem means that observed inputs are correlated with unobserved shocks. In other words, input variables are not strictly exogenous but are partly predetermined or endogenous (Griliches & Mairesse 1995). Input variables are determined based on some behavioral manner by the farmer (e.g., a farmer driven by profit-maximization, or cost minimization when deciding to farm). A farmer tends to be affected by productivity shocks as well (e.g., droughts, nutrient deficiencies, or pest outbreaks).

All of the above-mentioned factors affect a farmer's choice of variable inputs with some delay (Griliches & Mairesse, 1995). In this case, a simple ordinary-least-squares (OLS) method would be biased. Second, for the production technology to be more theoretically consistent and flexible, it must be represented by an appropriate functional form (Tchale et al., 2005).

Most studies use the Cobb-Douglas, Von-Liebig (VL), Mitscherlich-Baule (MB) or transcendental-logarithm (translog) functions. The Cobb-Douglas function is widely used and is the easiest to estimate, but it is based on simple neoclassical properties that assume a unitary elasticity of substitution (Tchale et al., 2005).

The main advantage of the production-function approach is that yield sensitivity to climate is estimated by assessing an empirical-production function that links water, soil, climate and economic input to yields for specific crops. The effect of climate change is assessed by considering yield variations by comparing two alternative scenarios. Future climate scenarios are usually simulated using a general circulation model (GCM) (Lobell 2006)

The major drawbacks of this approach are that it is crop specific (which means it focuses on one crop at a time) and that the social and economic dimensions of agriculture are considered to be of less importance. In this model, farmer-adaptation strategies are not explicitly considered (Lobell 2006). This is what is called the “dumb-farmer” hypothesis.

3.4 The Production Function Conceptual Framework

This section provides a simple conceptual framework. The mechanisms which show how temperature might affect the four components in a production function are total-factor productivity (TFP), labor and capital inputs, and output. The conceptual framework is motivated by Deryugina and Hsiang (2014).

Consider a simple Cobb Douglas production function for an industry j:

$$Y= A\ L^{a} K^{b} \tag{1}$$

Here, Y denotes output and L and K denote labor and capital, respectively. The total-factor productivity (TFP) is represented by A. Output elasticities of labor and capital are measured by α and β, respectively. Taking natural logs of the above equation leads to the following function:

$$y = a + \alpha l + \beta k \tag{2}$$

where, lowercase symbols represent natural logs of variables. Temperature, denoted as T, may affect both productivity and inputs, and thus leads to the following production function:

$$y\ (T) = a\ (T) + \alpha l(T) + \beta k(T). \tag{3}$$

It is worth noting that TFP is a weighted average of labor and capital productivities. To see this, consider a Cobb-Douglas production function that distinguishes labor and capital:

$$Y = (A_L L)^a \; (A_K K)^b \tag{4}$$

where A_L and A_K denote labor and capital productivity, respectively. Taking natural logs of the above equation results the following equation:

$$y = \alpha aL + \beta aK + \alpha l + \beta k. \tag{5}$$

Comparing above equation with Equation (3), we get,

$$a = \alpha aL + \beta aK, \tag{6}$$

which, suggests that TFP is a weighted average of labor and capital productivities in which the weights are output elasticities of labor and capital inputs. It is well documented in the literature of climate change that temperature could affect TFP by affecting labor productivity. High temperatures impact cognitive function and psychomotor ability. They can also physiologically affect the human body and cause discomfort and fatigue (Hancock et al., 2007; Zivin et al., 2015).

Several studies have estimated the impact of temperature on labor productivity by using lab experiments (e.g., Niemel¨a et al. 2002; Seppanen et al. 2003, 2006).Temperature is found to affect TFP by affecting capital productivity. A variety of evidence shows that high temperatures also dramatically affect machine performance. Dell, Jones and Olken (2008) incorporate climatic variables into the production functions of their model, which was used as a baseline for the present study.

The model provides the theoretical basis for incorporating climate change in to crop yield equations and the guidelines for decomposition of the impacts of changes in weather on agriculture output and crops productivities. The production-function approach we use in this study relies on experimental evidence showing the effect of temperature and precipitation on agricultural yields. Consider the following production function in general form:

$$y_i = e^{\beta T} A_{it} L_{it} K_{it}$$

where, Y is aggregate output, L measures population, A measures labor productivity, and T measures weather. The above equation captures the level effect of weather on production; for example, it captures the effect of current temperature on crop yields. This model provides for theoretical and empirical investigations of the link between climate change and economic growth by using a simple climate-economy regression model. Our production-function specification is like that of Lee et al. (2012). The main advantage of using the production-function framework to examine the effect of climatic change on agricultural production is that it explicitly controls for other inputs.

This model is intended to capture the impact of climate variability on overall agriculture production. The baseline specification of the model is based on the Bond, Leblebicioglu, and Schiantarelli production function (2010), and it is adopted by Dell and Jones. The model is based on the production function of this form:

$$y_i = e^{\beta T} A_{it} L_{it} K_{it}$$

To explain the impact of climate on agriculture output, we use the following conceptual model:

Y= F (K, L, climatic variables) for sub-Saharan Africa.

This model investigates the economic impact of climatic factors in sub-Saharan African agriculture. We add to the body of empirical evidence by focusing on both rainfall and temperature, but in different setups and by calculating the variabilities in both.

Conclusions

In summary, there is no consensus among economists about which theory or theoretical framework can best analyze the economic impact of climate change. The question is how to value the costs and benefits of certain actions in response to climate change. Evaluation of these costs and benefits require careful economic modeling.

Most previous studies in the literature on the economic effects of climate change have adopted one of three main theoretical approaches: the general equilibrium approach and computable general equilibrium (CGE), the production- function approach and the Ricardian approach. Each of these methods suffers from some theoretical and practical shortcomings, but the production-function approach is the simplest and is widely used to model the economic impact of climate change.

We decided to use the production-function approach as a framework for this study. The next chapter presents the research methodology; the research-methodology chapter explains in more detail how we use the production-function approach in formal way.

CHAPTER 4 RESEARCH METHODOLOGY

4.1 Introduction

This chapter includes the research methodology of the study. In this chapter, the research strategy, the research method, the research approach, the research process and the data analysis methods will be introduced in more details. The ethical guidelines and the research limitations of the study will presented at the end of the chapter.

4.2 Research Strategy

This work is based on both theoretical and empirical analysis of the economics of climate change. The issue of economic impact of climate change has been covered extensively in the literature on both empirical as well as theoretical grounds.

But, what make this study distinguished are the followings; first, there are few empirical studies about the impact of climate change on the main crop yield within an African continent context, this study aims to fill this gap, second, earlier studies on climate change have used average temperature and cumulative rainfall as the two main climate variables (Chen et al. 2004; Isik and Devadoss 2006; Kim and Pang 2009),this study is the first one that has used the Production Function approach to estimate the impact of climate variability crop yield within Sub-Saharan African agriculture context.

Climatic variables used for this study are designed to capture more precisely the impact of climate variability on yield functions, third, past studies using panel data evaluated the impact of climate change on a particular crop or a group of crops as a whole, in this study, the impact of climate will be assessed using two major crops in SSA, Maize and Millet in a comparative manner. A full description of climatic variables is presented in the data section of the study.

In the second part of this study, we consider not only using per-capita GDP but also agriculture production index and agriculture value added as the main dependent variables. Our main interest lies in assessing the long-run economic effects of the climate, we also estimating the short-run impact of changes in rainfall and temperature on overall agricultural production.

There is so much to learn from the previous works regarding the economic impact of climate change, most of the studies and articles about the climate change will be covered in more details in the literature review section such rich literature will be analyzed or even criticized in some cases for the purposes of the study.

4.3 Research Methodology

In order to satisfy the objectives of this study, a quantitative method will be used for the following reasons: First, the main objectives of this work are to quantify the impacts of climate change on the economic performance of some SSA countries and to provide quantitative rigorous analysis of the potential impact and economic cost of climate change. These prime objectives of the study dictate using more precise techniques such as the quantitative analysis to bring about accurate and measurable precise results. Second, the quantitative method is more efficient and able to test the research hypotheses more accurately. Third, recent developments in the computing power and speed in data analysis tools have helped in producing high quality results in a timely manner.

More precisely production function approach is used for conducting this study. Production Function for each crop will be presented; the same methodology will be adopted for each function. The first step is to determine the structure of the dataset for each model. The second step is conducting unit root tests based on the data structure of each data set, if there are unit root within the variables, then we use each variable in the first difference. Third step is to conduct the cointegration test. The results of the cointegration test determine if an error correction model will be used; otherwise the variables are analyzed in their first difference forms.

A number of diagnostic tests will be conducted to detect the presence of cross-sectional dependence, serial correlation and heteroskedasticity. The outcome of these tests determines the choice of the proper estimator to be used. All regressions and tests are implemented using Stata12 and Eviews 9.

4.4 Research Approach

This study is the correlational research attempts to determine the impact of climate change on economic performance using statistical data. Relationships between all relevant variables of the analysis are used and interpreted to recognize trends and patterns and to trace if there are significant relationships between variables of the study.

4.5 Data Collection Method and Tools

Major works by scholars in the field will be presented within this section. Most reliable data sources from published books, papers of international conferences of climate change, peers reviewed papers and articles from well recognized journals will be investigated.

The main tools to conduct the statistical analysis are the STATA version 12; for estimating model one, Eviews version 9 will be used for estimating model two.

4.6 Research Process

The overall structure for any quantitative design is based in the scientific method. The basic steps of this quantitative study are:

- We start with making observations about the current climate change debate specifically within the context of African economies and raise the following question; does an annual climate variation affect overall agriculture production in SSA?
- We then set the study hypothesis such as

  Hypothesis 1 the relationship of climate change and overall agriculture output in SSA

  Under this hypothesis we seek to test the following null and alternative hypothesis

  H0: Climate change has no significant effect on overall GDP agriculture output in some Sub-Saharan African Countries.

  Ha: Climate change has significant negative OR positive effect on overall GDP agriculture output in some Sub-Saharan African Countries.

  More precisely in symbols terms H0, $\beta 3=0$ and Ha, $\beta 3<0$ OR $\beta 3>0$
- Then we make the model predictions based on studied hypotheses
- Then formulate a plan to test our prediction.
- Then verify our findings.
- Then make our final conclusions.

4.7 The Data Analysis Methods (Model One)

This section is about the Data Analysis Methods (Model One) .The sub-section will follow this format. Sub-section 4.7.1 about econometric model specification of the first model in which the climate variability impact on main crops yield will be presented. In this section, the production function approach is introduced to estimate the effects of weather variables on the Maize and Millet yield in Sub-Saharan African (SSA) countries. Sub-section 4.7.2 is going to explain in more details the estimation procedures of production function which is used to estimate the yield function for model both crops. Subsection 4.7.3 Variables Definition 4.7.4 Fixed Effect versus Random Effect methods.

4.7 MODEL ONE: THE IMPACT OF CLIMATE CHANGE ON CROPS YIELD

Dell et al. (2008) in their global assessment framework investigated the effects of annual variations in temperature and rainfall over the last half century. The results of their study revealed that, higher temperatures had negative impact in poor countries, while there were no climate impacts in rich countries. Study indicted the impact of climate change can extend to industrial output, investment growth and political stability.

Several recent studies have investigated the effects of climate variability on economic growth in Sub-Saharan Africa (SSA), these countries particularly vulnerable due to low levels of income and low level of adaptive capacity as cited by many studies.

4.7.1 Econometric Model Specification

The production function approach is commonly used and proves to be most efficient in applied economics and econometrics analysis is used in this study to estimate the effects of weather variables on the Maize and Millet in SSA major crops yield. In this regard we use two different functional forms, Cobb Douglas and linear quadratic functions.

4.7.2 Estimating the Crop Yield Functions

For each crop model, the climate variables, temperature, precipitation, area harvested along with time trend are included as repressors in the yield mean equation. Regression equations estimated for the two major crops in Sub-Saharan (SSA) countries (Maize and Millet) use these two functional forms Cobb-Douglass and Quadratic form;

4.7.2.1 Cobb Douglass Functional Form

We use the following Cobb Douglas production function;

$$\text{LnY}_{it}=\beta_0+\alpha_{\text{i}}+\delta_{\text{t}}+\beta_1\text{Ln }P_{it}+\beta_2\text{Ln }T_{it}+\beta_3\text{Ln }max_{it}+\beta_4\text{ Ln }mnt_t+\beta_5\text{ Ln }ha_{it}+v_{it} \quad (1)$$

where, Y for crop yield, i refer to the country or region and t refers to the year; αi denotes country level fixed effects; δ_{t} denotes year fixed effects .P, for precipitation, T, for temperature, mint, for minimum temperature, maxt, for maxi temperure and ha, for harvested area, $\boldsymbol{U_{it}}$ for error term.

4.7.2.2 Quadratic Functional Form

We use the following linear quadratic production function;

$$\text{LnY}_{it}=\beta_0+\alpha_{\text{i}}+\delta_{\text{t}}+\beta_1\text{ Ln }P_{it}+\beta_2\text{ Ln }T_{it}+\beta_3\text{Ln}P_{it}^2+\beta_4 Ln\,T_{it}^2+\beta_5(T_{it}P_{it})$$

$$\beta_6\,(T_{it}^2P_{it})+\beta_7\,(P_{it}^2T_{it})+\beta_8\text{ Ln }maxt_{it}+\beta_9\text{ Ln }mint_{it}+\beta_{10}\text{ Ln }ha_{it}+v_{it} \quad (2)$$

where, Y for crop yield, i refer to the country or region and t refers to the year; αi denotes country level fixed effects; δ_{t} denotes year fixed effects .P, for precipitation, T, for temperature, mint, for minimum temperature, maxt, for maxt temperure and area for harvested area, U_{it} for error term. We add some quadratic and interaction terms here to capture the non-linarites such as, T_{it}^2, P_{it}^2 for quadratic temperature and precipitation respectively, and $R_{it} * P_{it}$ term to capture the interaction between temperature and precipitation.

4.7.2 Econometrics Estimation Steps

All variables were subject to pre-estimation testing such as testing for non-stationarity, testing for cointegration. For testing cross sectional dependency, Pesaran, Friedman and Frees tests were performed. Two regressions were run for each crop using the Cobb Douglass and Quadratic forms estimating the crop yields. Cobb Douglass function forms Crop yield depends on climate and non-climate inputs whereas the quadratic form depends on the transformed climate variables called anomalies (details of variables definition are in the Appendix)

4.7.3 Variables Definition and Data Sources

In the first part of this study, we estimate the climate change impact on major crop yields in some Sub-Saharan African countries (Model One); crops selected for the analysis of this model are Maize and Millet for their importance as a major food source for many people in these countries.

This model, consist of two different specifications; model A is, intended to estimate the Maize function and consist of model A1 and model A2. Model A1, is estimating the Maize yield function using the Cobb-Douglas functional form and model A2 is for estimating the Maize function using quadratic functional form. Model B, is intended to estimate the Millet function and consist of model B1 and model B2. Model B1 is estimating the Millet yield function using the Cobb-Douglas functional form and model B2 is for estimating the Millet function using quadratic functional form.

Empirical work for model one uses data from a sample of selected Sub-Saharan African countries, the criteria of selection based on data availability only. Crops data extracted from

Food and Agriculture Organization (FAOSTAT), which is a well cited source and has data cover many variables needed for the study within reasonable timespan. Climatic variables were taken from Climatic Research (CRU), University of East Angelia which is one of the most important sources for climate change research data and provides the longest time series data. (Check the appendix section) for more details about the data set.

4.7.4 Fixed Effect versus Random Effect

To decide between fixed or random affects we perform a Hausman test where the null hypothesis is that the preferred model is random affects vs. the alternative the fixed effects (see Green, 2008, chapter 9). It basically tests whether the unique errors (u) are correlated with the regressors; the null hypothesis is they are not. We run a fixed effects model and save the estimates, then run a random model and save the estimates, then perform the test. If the p-value is significant if the p-value is significant (for example p value is less than 0.05) then use the fixed effects, if not use random effects.

We estimate the production function using the Cobb Douglas functional form and assume fixed effect based on our model assumptions. By including fixed effects (group dummies), you are controlling for the average differences across countries or regions in any observable or unobservable predictors, such as differences in soil quality, land size, use of fertilizers and other economic factors and sophistication.

4.8 The Data Analysis Methods (Model Two)

Section 4.8.1 is introduction about the second model in which the climate change impact on overall agriculture production in SSA countries will be presented. In this section, the Panel Autoregressive Model (P-VAR) is introduced to estimate the model. In subsection 4.8.2, the Panel Autoregressive Model (P-VAR) which will be used to estimate model two will be introduced in more details. In subsection 4.2.3, we will explain in more details why we use pvar model. Su-section 4.2.4 is for data sources and variables definitions. The data properties and sources for model two will be presented. Section 4.2.5, is for the baseline model. Sub-section 4.2.6 is about pre-estimation tests.

4.8 MODEL TWO: THE CLIMATE CHANGE IMPACT ON OVERALL AGRICLTURE PRODUCTION

4.8.1 Introduction

Climate change is most likely to have some negative impact on the agriculture sector, and consequently affect lives of people directly and indirectly through food shortage, food insecurity, and finally this in turns will be reflected in the economic wellbeing of many people around the globe. The critical importance of agriculture to human welfare around the globe was clearly demonstrated in the (2007-2008) food price crisis that emerged due to competing demands for agricultural products from the energy sector (Trostle, 2008).

Model two of this study intended to identify the effect of climate change on overall agriculture production in Sub-Saharan Africa , the analysis control for typical agricultural inputs such as harvested area, Labour, machinery, fertilizer and livestock, a long-run equilibrium relationship is expected between agricultural production and their related agricultural inputs and climate factors.

In order to analyze the dynamics of economic impact of climate change for some selected Sub-Saharan African countries, we use panel autoregressive model (P-var). The second part of this study intended to estimate the impact of climate change on overall agriculture production. This model in its baseline form will be based on the Bond, Leblebicioglu, and Schiantarelli production function (2010) and adopted by Dell and Jones, the model based on the production function of this form;

$$y_i = e^{\beta T} \quad A_{it} \, L_{it} \, K_{it} \tag{1}$$

To explain impact of climate on agriculture output

Y= F (K, L, climatic variables) For Sub-Saharan African countries (SSA)

This model investigates the economic impact of climatic factors on overall agriculture output in SSA countries.

This second model will contribute to the body of climate change literature in many ways; firstly, panel autoregressive method used to estimate this model is uniquely applied for the analysis of the climate change in African context, secondly, climate variables, average temperature and cumulative precipitation will be used, but in different forms and will be calculating different climatic variations, thirdly, the livestock variable is included in this work which was absent in most studies before, we considering not only per-capita GDP but also production index as well as production quantality as alternative dependent variables, fourthly, though we also estimate the short-run impact of changes in rainfall and temperature, our main interest lies in assessing the long-run economic effects of the climate.

We start by applying a unit root test for all variables as a pre-estimation procedure. The baseline model used in this paper is specified in general form as;

$$y_{it} = {'\Upsilon}_o + Z_{it}{'\Upsilon}_{ki} + \mathrm{B}\, x_{it} + e_i \qquad (2)$$

Where y_{it} is the level of agricultural output (or net production index); Z_{it} is a vector of control variables that are important in agricultural growth which consist of land, capital, fertilizers, and livestock x_i is the vector of climatic variables consisting of temperature and precipitation, and e_i is the disturbance term. Using cross-country Panel Data to estimate equation (2) has many challenges that are well documented in the literature of economic growth. (See Levine and Relent 1992, Temple 2000) .Hsiao (1986) on the other hand has listed the advantages of panel data techniques as follows; in Panel Data unobservable individual heterogeneity can easily be controlled for. Common time series data problems such multicollinearity, aggregation bias, and non-stationary can easily be avoided when using Panel Data Models. Individual and time effects can be identified in Panel Data Models; such effects cannot be identified in pure cross-sectional or time series data. Add to the abovementioned advantages of the panel data, Panel data usually contain more degrees of freedom and more sample variability than cross-sectional data, and improving the efficiency of econometric estimation (e.g. Hsiao et al., 1986). The major limitations of the Panel Data as summarized and stated by Hsiao (1986) are; large parts of panel data are unbalanced, also panel data are often suffering from measurement errors.

The total agricultural output assumed to be affected by the climatic variables, such as temperature as well as by some other economic variables. Here is the model in its general form;

$$Y_{it} = \beta_0 K_i^{\beta 1} L_i^{\beta 2} R_i^{\beta 3} T_i^{\beta 4} e^{\mu i} \tag{3}$$

Where Y_{it} is the total agricultural output for ith country in the region, β_0 is the constant, K_i is the capital input for ith country or region, L_i is the labor input for ith country or region and R_i and T_i, as auxiliary climatic factors that may affect agricultural production, U_i is the error term for ith country or region and, the parameters β_1, β_2, β_3, β_4 are the slope coefficients to be estimated for capital, labor, precipitation and temperature respectively.

More specifically the baseline model for this study in its specific form is as follows: consider the following production function

$$Y_{it} = \beta_0 * V_{it}^{\beta_1} * A_{it}^{\beta_2} * L_{it}^{\beta_3} * M_{it}^{\beta_4} * F_{it}^{\beta_5} * e^{\varepsilon_{it}} * e^{\beta_6 P_{it} + \beta_7 P_{it}^2 \beta_8 T_{it} + \beta_9 T_{it}^2} \tag{4}$$

Taking the natural log of both sides yield

$$\text{Ln } Y_{it} = \beta_0 + \beta_1 \text{Ln } V_{it} + \beta_2 \text{ Ln } A_{it} + \beta_3 \text{ Ln } L_{it} + \beta_4 \text{ Ln } M_{it} + \beta_5 \text{ Ln } F_{it}$$

$$+ \beta_6 \text{ Ln } P_{it} + \beta_7 \text{ Ln } P_{it}^2 + \beta_8 \text{ Ln } F_{it} + \beta_9 \text{ Ln } T_{it}^2 + \mu_t + \alpha_i + \varepsilon_{it} \quad (5)$$

where, Y is agricultural output and the inputs are, Area (A), livestock (V), Fertilizer (F), and (M) Machinery (capital) and (L) land. More importantly we include Rainfall, (P), and Temperature, (T), as auxiliary climatic factors that may affect agricultural production.

4.8.2 Panel Autoregressive Model PVAR

Panel VARs have been used most frequently to build different types of models in applied economics. Here in this work we interested in knowing the dynamics of climate change impact on agricultural output in SSA countries and we want to know if this impact depends on geographical, institutional or cultural characteristics, or on some other factors. Alternatively, one may want to examine whether climatic shocks generated have short-term or longer term-effects. Finally, our models want to examine what channels of transmission of climate change impact on agricultural output for SSA countries.

To estimate the model, we uniquely use a panel vector-autoregression model. Panel VAR models are now well established in applied macroeconomics. According to many sources in the literature, in PVAR models, all variables are treated as endogenous and interdependent, both in a dynamic and in a static sense.

Panel VARs have been used to address a variety of issues of interest to applied macro economists and policymakers. Within the realm of the business cycle literature, Canova et al. (2007) have used a panel VAR to study the similarities and convergences among group of seven countries (G7) business cycles, while Canova and Ciccarelli (2012) employ P-var model to examine the cross-sectional dynamics of Mediterranean business cycles. Panel var models; be used to construct coincident or leading indicators of economic activity (see Canova and Ciccarelli, 2009). Finally, Love and Zicchinoz[3] (2006) which is the main source for our econometric analysis, measure the effect of shocks to financial factors a cross of U.S. firms.

Following Raddatz (2007; 2009), this paper employs a panel vector-autoregression (PVAR) approach to isolate the response of a country's output (agriculture output) to climate change, capital and land, fertilizers and livestock inputs variables. Panel VARs usually used to capture the dynamics between variables in a set of equations.

The empirical strategy for this work is to use PVAR model, because it is the most suited model for the analysis of the consequences of unexpected macroeconomic shocks. This study employ panel vector Autoregression (PVAR) which is an extension of the traditional vector autoregression (VAR) introduced by Sims (1980) with a panel-data approach. The analysis based on PVAR offers several advantages. As stated by (Rymaszewska 2012)

- It is a more flexible method that treats all the variables in the system as endogenous and independent, without worrying about causality direction.
- Each variable in the system is explained by its own lags, and by lagged values of the other variables. It is a system of equations rather than a one-equation model.
- Panel VAR allow for unobserved individual heterogeneity and improve asymptotic results.
- The results of a panel VAR analysis are insightful and go beyond just coefficients, revealing the adjustments to unexpected shocks, as well as the importance of different shocks.

[3] Thanks for Love and Zicchino for making Stata codes used to estimate the P-var available and easily accessible online.

- PVAR modeling does not require the imposition of strong structural relationships.
- When we use PVAR, only a minimal set of assumptions are necessary to interpret the impact of shocks on each variable of the PVAR system. (Rymaszewska 2012)

The general form of a PVAR analysis is explained fully by Canova and Ciccarelli (2004). In this work, I use the PVAR approach to estimate the effects of climate change variables such as temperature and precipitation on agriculture output for selected sub-Saharan African countries. The analysis will cover the period 1980-2008.

Why using pvar model

4.8.3 Why using P-var Model

Business cycles studies before the early 1980s; usually decompose time series data into a trend component and a cyclical component as a straightforward exercise. The prevailing view was that the two components would be driven by different types of shocks. Those that had permanent effects (like productivity shocks) would contribute towards the trend, whereas those with transitory effects (like monetary changes) would contribute towards the cycle. In this framework, the data could be easily detrended using for instance a smooth deterministic trend, prior to the analysis of business cycles. Using Pvar model is very useful tool to distinguish between these two types of shocks regarding the climate change impact.

As we may know the geographical characteristics and economic structure of SSA make these economies more sensitive to climate shocks. If so, we would expect to find a significant agriculture productivity response to changes in climatic conditions. The responses to an increase or decrease in the soil moisture, land fertility, for example, are consistent with this hypothesis.

This study examines the effects of temperature and rainfall shocks on agriculture production index, agriculture value added and agriculture GDP.First, we find that the effects are highly asymmetric. If rainfall falls one standard deviation below the mean, agricultural output falls on average. — Whereas an increase in temperature has significant effects. Second, the drop in agricultural output is very short-lived, but it will have major effect on persistent decline in farmer's income in rural Africa. This indicates that famines are mainly caused by a persistent disruption of the food supply.

One of the major problems when analyzing the effect of climate variation on the SSA agricultural sector is that variables of interest like agricultural output and input (fertilizers, machinery and labor) prices also affect each other leading to endogeneity. problem For this reason, according to Sims 1980, we use a panel-data VAR model which has the benefit of capturing the interdependencies between multiple variables without requiring the strict identification restrictions of structural models (Sims 1980).

This approach also captures the possible persistence of variables across years; and shows to what extent climate variation might have had a long-run effect on those variables. While most commonly all variables in a VAR model are treated as endogenous, it also allows for the introduction of identifying restrictions disentangling the impact of an exogenous shock - in our case the temperature and rainfall variation - onto the remaining variables (Abrigo & Love 2016). Holtz-Eakin et al (1988).

4.8.4 Data Sources and Variables Definition

To examine the relationship between climate change, agriculture output and economic growth in selected SSA countries, secondary sources of data such as data on, Y, agricultural output and the inputs are Land, livestock, fertilizer, and capital, respectively. More importantly we include rainfall, R, and temperature, T, as auxiliary climatic factors that may affect agricultural production.Table (5.1) provides detailed description and sources for of all variables used in the study.

Model two of this research is based on panel dataset collected from different data sources covering the period between 1980 and 2008. The criterion used in the selection of the candidate countries was based on the data availability particularly, on the proxies used for climate change. Furthermore, data on most variables are gathered from the 'World Development Indicators', FAOSTAT and African Development Indicators databases of the World Bank. Climatic data choices are driven by data availability for the regions considered. In the current study, weather data are extracted from the CRU TS 23.3 dataset (Mitchell and Jones, 2005). The data are compiled by the Climatic Research Unit (CRU) at the University of East Anglia.

The data used to estimate model two, is derived from two sources. Our main variables of interest, the measures of rainfall and temperature, are taken from the Climatic Research Unit of University of East Angelia (version23.3) (CRU) data set; see Mitchell et al (2002) for a complete description of the data set.

All agricultural data are taken from the FAO online database. For a measure of agricultural output, we use the FAO net production index, where net production quantities of each commodity are weighted by the 2004-2006 average international commodity prices and summed for each year, and the aggregate for a given year is divided by the average aggregate for the base period 2004-2006.. To proxy land input,(M) in the production function we use FAO's measure of agricultural area, which includes arable land and the area used for permanent crops and permanent pastures, while fertilizer, (F), is measured as the quantity, in metric tons, of plant nutrients consumed for domestic use in agriculture. As a crude proxy of capital stock, (K), we use the total number of agricultural tractors being used. Livestock is proxied by the total head count of cattle, sheep, and goats.

4.8.5 The Baseline Model

To identify the effect of climate change, the analysis controls for typical agricultural inputs such as area harvested, machinery, and fertilizer, where applicable. Intuitively, a long-run equilibrium relationship is expected between agricultural production, on one hand, and their related agricultural inputs, and climate factors on the other.

The data characteristics and source for each variable identified in the equations are presented in (appendix B).For the estimating the baseline model the following P-VAR (1) model is employed by considering agriculture production index yield and climate variables

$$\text{proindex}_t = \alpha_0 + \alpha_1\text{proindex}_{t-1} + \alpha_2\text{Ferti}_{t-1} + \alpha_3\text{Live}_{t-1} + \alpha_4\text{Machine}_{t-1} + \alpha_5\text{Land}_{t-1} + \alpha_6\text{Temp}_{t-1} + \alpha_7\text{Pre}_{t-1} + \varepsilon_{1t}$$

where, proindex_t is agriculture production index, $\alpha_1\text{proindex}_{t-1}$is first lag production index, Ferti_{t-1}, Live_{t-1}, Machine_{t-1}, Land_{t-1} + Temp_{t-1} and Pre_{t-1} are first lag of fertilizers, livestock, machinery, land and climatic variables respectively, α_1 through α_7 are the model coefficients to be estimated . $\varepsilon_{1t}$is the error term.

4.8.6 The Pre-estimation Tests

The cross-section dependence (CD) test proposed by Pesaran (2004) tests the null hypothesis of zero dependence across the panel members and is applicable to a variety of panel data models, with small T and large N (Pesaran, 2004). Table 5.6 Presents the results obtained for three different CD test statistics: CD (Pesaran, 2004), Frees and Friedman tests.

Diagnostic test for Multicollinearity, Normality, Homoscedasticity, and autocorrelation were taken as a very important post estimation step before choosing the most robust model. This study, uses three distinct panel unit root tests on the variables for the sample used and covering the period 1980-2008, these tests are, Levin-Lin-Chu's (LLC), Im-Pesaran-Shin's, and Fisher Augmented Dicker Fuller based test. For the Maize and Millet Models, all test specifications we include deterministic time trend. The Schwarz-Bayesian information criterion (BIC) is used to determine length for the ADF regressions. We use a residual-based panel cointegration tests include the contribution by Westerlund (2005) that is based on variance ratio statistics and does not require corrections for the residual serial correlations.

4.8.7 The Robustness Check

We will try different specification for model robustness check such as;

1. We can use different determinants of overall agricultural production such as production quantities, agricultural GDP and agricultural value added.
2. We can add some more African countries from out of the SSA and see the difference in the results
3. We can split the sample into two categories based on their economic and agricultural potential, Less Favorable Agriculture Condition (LFAC) and NON LFAC and see the difference in the results.

4. We can add more lags and more variables to the baseline specification.

4.9 Ethical Considerations

Howard University has well recognized ethical rules for conducting researches; the university is committed to the ethical conduct of research by its personnel and students. As a Howard graduate student, I am obligated to adhere to these rules in conducting this study. I'm fully responsible for the quality of all data collected for this study. Highest standards of ethics and professional integrity in the performance of and in the reporting of research activities are followed in conducting this research.

4.10 Research Limitations

The size of the sample was relatively small; some problem with missing data and using of proxies might reduce the accuracy of the analysis. Long term nature of climate change makes the prediction and forecasting extremely difficult.

Conclusions

This chapter is intended to provide the required explanation to the research methodology and data handling process of this study. This chapter includes the research methodology of the study. In this chapter, the research strategy, the research method, the research approach, the research process and the data analysis were introduced in more details. The ethical guidelines and the research limitations of the study presented at the end of the chapter.

The production approach is used and proved to be most efficient in applied economics and econometrics analysis, this function will used for estimating model one of this study to estimate the effects of weather variables on the yield of Maize and Millet in SSA yield. To estimate model two, we uniquely use a panel vector-autoregression model. Panel VAR models are now well established in applied macroeconomics.

According to many sources in the literature, in PVAR models, all variables are treated as endogenous and interdependent, both in a dynamic and in a static sense, although in some relevant cases, exogenous variables could be included.

CHAPTER 5 THE DATA ANALYSIS FINDINGS AND RESULTS

5.1 Model One: Crops Yield and Climate Change

In this chapter, a range of econometric techniques are used to study the nature of the relationship between climate change and economic activities in Sub-Saharan Africa (SSA) and to determine what could influence the end results of this relationship. The analysis in this chapter will present a brief picture of the descriptive statistics of variables used to analyze the relationship between climate change and crop yields and overall agricultural production in Sub-Saharan Africa (SSA).

This chapter will focus more on the existence, nature and forms of the relationship between climate change and crops yield in SSA using a sample of 28 countries and covering the period between 1961-2006 to estimate model one. A sample of 16 countries and covering the period between 1980- 2008 will be used to estimate model two (See appendix section for the list of countries).

This chapter is organized as follows: Section 5.1 and its subsections show the data as well as the descriptive statistics for the crop model. In this section, we will present the empirical evidence to show the nature of the relationship between climate change and crops yield in SSA using the production function technique. Section 5.2 and its subsections show the data as well as the descriptive statistics for the second model which is about the impact of climate change on overall agriculture production, using the Panel Autoregressive modeling (P-var). This section, presents the empirical evidence intended to explain the nature of the relationship between climate change and agriculture output in SSA. The chapter summary is in Section 5.3. The conclusion of the chapter is in Section 5.4.

The main goal of this study is to provide qualitative and quantitative rigorous analysis of the potential impact and economic cost of climate change, the risks of increased climate variability, the cost of inaction and the potential and validity of other choices and their associated costs. This research also aims to quantify the impact of climate change on economic performance of some SSA countries, especially agricultural sector the engine of growth in these economies and to identify the channels of transmission from climate change to economic growth.

The study aims to answer the following questions. Model One is intended to answer the following three questions;

1. Does climate change variables variation affect crop yield in SSA?
2. Does climate change variables variation affect crop yield in SSA in different ways linearly or non-linearly?

Model two intended to answer the following two questions

1. Does climate variables variation affect overall agricultural output in SSA?
2. Does climate change affect the growth rate or just the level of output in SSA OR both?

This chapter will provide the evidence to answer the research questions and achieve the study prescribed objectives. To answer the above listed questions of model one, the production function approach with two different functional forms will be used.

5.1.1 Variables Definition and Sources

We estimate the climate change impact on major crop yields in some Sub-Saharan African countries; crops selected for the analysis are Maize and Millet. In the first part of this study, we estimate the climate change impact on major crop yields in some sub-Saharan African countries (Model One); crops selected for the analysis of this model are Maize and Millet for their importance as a major source of food for many people in these countries.

5.1.2 The Descriptive Statistics

This section presents descriptive statistics for each crop used in the model, the first model will test the impact of climatic variables mainly temperature and precipitation on crop yield for some selected countries in SSA. Two major crops selected for the study namely Maize and Millet. These crops selected for their importance as a main source for food for human and animals in SSA. (see table 5.1), the table lists ten variables used in the analysis, two of these variables are crop related variables, namely harvested area (ha) and crop yield (yield). The other eight variables represent climate variations namely temperature and precipitation.

We constructed new two variables called (TA) temperature anomaly and (RA) precipitation or rain anomaly. These two variables represent the deviation of each one from the long-term of average; the idea here is to make sure we have variables to traces short term variations of the climatic variables. We use these two variables in the baseline specification model. The other four climate variables are well known and used before in similar studies; we use them here for robustness check for the basic model.

The statistics in table 5.1 shows that the mean yield for Maize is **10553.84** for the sampled countries over the period. The standard deviation of Maize is **4330.195** confirms that there so much variability in Maize yield these countries. On the climate side, temperature averaged **24.74 ºC** within the period across the sample. Also within the period, the minimum and maximum temperatures recorded were **18.73** and **30.76 ºC**, respectively. Indeed, the temperature values explain that many countries included in the sample are found in the tropics. The precipitation values recorded reflects the tropical nature of the sample, the mean precipitation recorded was **1135.19** millimeters over time and space. However, this variable indicates a significant variation in the sample as the maximum precipitation recorded was **3332.9** millimeters with the lowest being **66.5** millimeter annually.

Table 5.1.

Descriptive Statistics (Maize)

Variable	Obs	Mean	St. Dev.	Min	Max
Ha	1334	429489.90	656543.30	936.00	5500000.00
Yield	1334	10553.84	4330.20	1587.00	31359.00
Temp	1334	24.74	2.78	17.55	29.40
Pre	1334	1135.19	539.71	66.50	3332.90
Mint	1334	18.73	2.77	11.40	23.10
Maxt	1334	30.76	3.20	23.50	36.60
SRA	1334	1125.90	537.87	62.15	3328.58
STA	1334	-36.97	13.53	-63.15	-10.51
RA	1334	0.00	149.49	-897.92	1367.17
TA	1334	0.00	0.43	-1.36	1.70

Note. Source of Data FAOSTAT, 2005

5.1.3 The Trend Analysis

This section examines climate variability for each crop at regional and climatic zone levels. Tables 5.3, 5.4, and 5.5 set out the inter-region climate and yield variability for the Maize. It is evident from the table that values of descriptive statistics for different climate variables vary considerably across and/or between climatic zones or regions.

Table 5.2.shows the correlation matrix for all variables used in the Maize model, the correlation matrixes does not show unusual or strange behavior (noise) for the variables. Most variables in the model have the expected signs.

Table 5.2.

Correlation Matrix (Maize)

	logyield	temp	pre	maxt	mint	RA	TA
logyield	1						
temp	-0.0283	1					
pre	0.0508	-0.2864	1				
maxt	-0.0723	0.9394	-0.5139	1			
mint	0.0282	0.9187	0.0192	0.7280	1		
RA	-0.0120	-0.0261	0.2770	-0.0324	-0.0148	1	
TA	0.1240	0.1539	-0.0470	0.1345	0.1532	-0.1697	1

Note. Source of Data FAOSTAT, 2005

5.1.4 The Descriptive Statistics for Climate Variability at Regional level

In this part, climate variability is examined for each region and for each climatic zone. Table 5.3 sets out the inter-region climate variability. It is evident from the table that values of descriptive statistics for different climate variables vary considerably across and/or between the districts or regions. Table.5.3 shows the Maize area temperature, the Sodano and West regions, have experienced highest mean temperature in Maize area, whereas the relative variability (CV) is the highest for Estern Region. The West region experiencing the lowest temperature variability in the continent

Table 5.3.

Temperature Variations in Maize Area by Region in 1961-2014

REGIONS	Code	Mean	Std	MIN	MAX	CV
Central	1	24.82	0.42	23.8	26.1	0.01
Sudano	2	27.04	0.50	25.70	28.3	0.02
Estern	3	22.58	2.46	17.55	26.4	0.10
West	4	27.04	0.50	25.70	28.30	0.01
South	5	22.40	1.03	20.50	25.00	0.04

Note. Our own calculation based on FAOSTAT

Table.5.4. shows the precipitation in Maize area, Central region experienced the highest mean precipitation whereas the relative variability in precipitation (CV) is the highest in the Sudano, followed by West and Estern region. Central region experiencing the lowest precipitation variability

Table 5.4.

Precipitation Variations in Maize Area by Region in 1961-2014

REGIONS	Code	Mean	Std	Min	Max	CV
Central	1	1435.42	206.79	957.40	1850.3	0.14
Sudano	2	395.41	206.69	66.50	919.2	0.52
Estern	3	1326.22	289.19	945.40	2392.4	0.21
West	4	1561.67	674.19	738.30	3018.90	0.43
South	5	968.23	199.36	431.10	1443.70	0.20

Note. Our own calculation based on FAOSTAT

Table.5.5. shows the Maize yield, Estern region has the highest mean yield, whereas the relative variability in mean yield (CV) is the highest in the Southern region, followed by Sudano and Central region. Table.5.5. shows the Maize yield, Estern region has the highest mean yield, whereas the relative variability in mean yield (CV) is the highest in the Southern region, followed by Sudano and Central region.

Table 5.5.

The Yield Variations in Maize Area by Region in 1961-2014

REGIONS	Code	Mean	Std	Min	Max	CV
Central	1	10691.2	4703.862	25907	3277	0.439975
Sudano	2	10514.72	4665.349	33349	3041	0.443697
Estern	3	13651.04	4392.618	34210	7018	0.321779
West	4	120479	328134.7	1949897	4254	2.723585
South	5	8308.73	4665.349	33349	3041	0.5615

Note. Our own calculation based on FAOSTAT

The statistics in Table 5.6. indicate that the mean yield for Millet **7740.481** is for the sampled countries over the period. The standard deviation for Millet yield is **3475.44** confirms that there so much variability in Maize yield these countries. On the climate side, temperature averaged **24.84 ºC** within the period across the sample. Also within the period, the minimum and maximum temperatures recorded were **18.73** and **30.76 ºC,** respectively. Again, the precipitation values recorded reflects the tropical nature of the sample units as the mean precipitation recorded was **974.83** millimeters over time and space. However, this variable indicates a significant variation in the sample as the maximum precipitation recorded was **3018.9** millimeters with the lowest being **45.8** millimeter annually.

Table 5.6.

The Descriptive Statistics (Millet)

Variable	Obs	Mean	St. Dev.	Min	Max
Ha	1288.00	520355.50	1060545.00	940.00	6200000.00
Yield	1288.00	7440.48	3475.45	655.00	19507.00
Temp	1288.00	24.84	3.07	17.15	29.40
Pre	1288.00	974.83	530.71	45.80	3018.90
Mint	1288.00	18.73	2.77	11.40	23.10
Maxt	1288.00	30.76	3.20	23.50	36.60
SRA	1288.00	966.00	527.51	62.15	3004.93
STA	1288.00	-34.36	11.99	-63.15	-10.51
RA	1288.00	0.00	119.77	897.92	527.62
TA	1288.00	0.00	0.44	-1.36	1.70

Note. Our own calculation based on FAOSTAT, 2002

Table 5.7. shows the correlation matrix for all variables used in the model; the correlation matrixes do not show unusual or strange behavior for the variables. All variables in the model have the expected signs.

Table 5.7.

The Correlation Matrix (Millet)

	logyield	temp	pre	maxt	mint	SRA	STA
logyield	1						
temp	-0.1005	1					
pre	0.5146	0.1336	1				
maxt	-0.1903	0.9694	-0.30	1			
mint	0.0004	0.9643	0.070	0.8711	1		
SRA	0.5146	0.0307	0.230	-0.0384	-0.0212	1	
STA	-0.2956	0.1438	-0.10	0.1376	0.1404	-0.2132	1

Note. Our own calculation based on FAOSTAT

Table.5.8. shows the Millet area temperature, the Sodano and West regions, have experienced highest mean temperature in Maize area, whereas the relative variability (CV) is the highest for Estern Region, Central region experiencing the lowest temperature variability.

Table 5.8.

The Temperature Variations in Millet Area by Region in 1961-2014

Region	**Code**	**Mean**	**Std**	**Min**	**Max**	**CV**
Central	1	24.70	0.55	23.75	26.20	0.02
Sudano	2	27.88	0.77	24.40	29.80	0.03
Estern	3	21.85	2.43	17.55	25.90	0.11
West	4	26.79	0.62	25.25	28.35	0.03
South	5	21.73	1.65	17.15	25.00	0.07

Note. Our own calculation based on FAOSTAT

Table.5.9. shows the precipitation in Millet area, Central region experienced the highest mean precipitation whereas the relative variability in precipitation (CV) is the highest in the Sudano, followed by West and Southern region from the figure above the Central region experiencing the lowest precipitation variability in the continent.

Table 5.9.

The Precipitation Variations in Millet Area by Region in 1961-2014

Region	Code	Mean	Std	Min	Max	CV
Central	1	1480.78	135.96	1172.70	1817.7	0.09
Sudano	2	446.51	283.16	45.00	149.10	0.02
Estern	3	1019.35	252.16	443.10	1560.80	0.24
West	4	1505.96	475.12	812.50	3018.90	0.31
South	5	734.61	311.54	131.00	1326.90	0.07

Note. Source our own calculation based on FAOSTAT

Table.5.10. shows the Millet yield, Estern region has the highest mean yield, whereas the relative variability in mean yield (CV) is the highest in the Sudano region followed by Estern and Western regions, and Central region. Southern region is experiencing the lowest mean Millet yield variability.

Table 5.10.

The Millet Yield Variations in by Region in 1961-2014

Region	Code	Mean	Std	Min	Max	CV
Central	1.00	8368.975	2103.715	15000	3125	0.251371
Sudano	2.00	2094.754	2568.158	12696	655	1.225995
Estern	3.00	9794.67	3998.929	20165	1667	0.408276
West	4.00	8953.839	3594.912	19065	2633	0.401494
South	5.00	5075.63	2534.249	19507	400	0.499297

Note. Source: our own calculation based on FAOSTAT

Figure 5.1. shows observed increasing trends in African annual-average near-surface temperatures over the period (1961-2020). The figure reveals drastic increases, over this region; temperatures have been rising at more than twice the global rate of temperature increase.

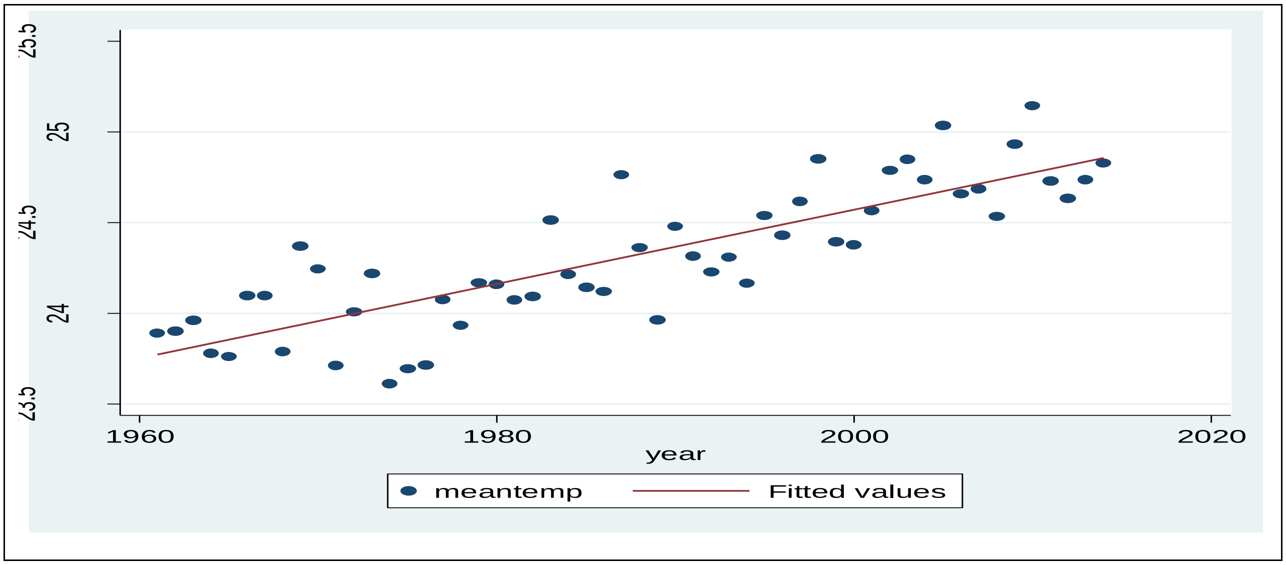

Figure 5.1.Maize Mean Temperature Trends 1960-2020 (Source of Data: CRU, 2003)

Figure 5.2. shows observed increasing trends in African annual-average precipitation over the period (1961-2020). The figure reveals drastic decrease, over this region

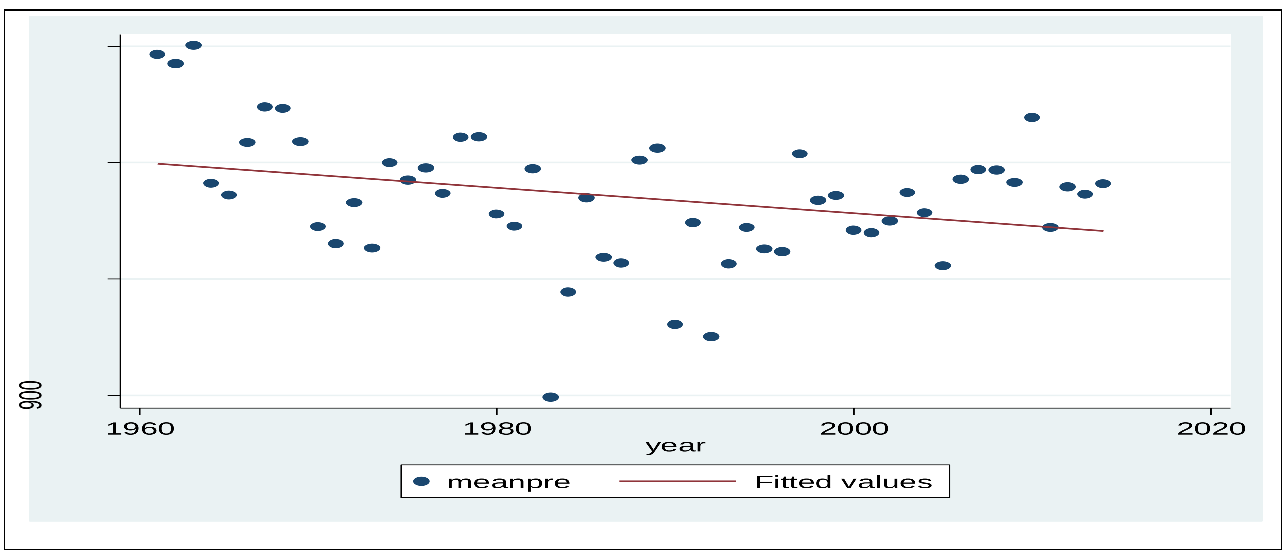

Figure 5.2.Maize Mean Precipitation Trends 1960-2020 (Source of Data: CRU, 2003)

5.1.5 Climate-Crop Yield Relationship

Correlation coefficient (CV) and multivariate regression analyses have been performed to determine the climate-crop yield relationship using STATA 12 software package. The Pearson's correlation coefficient was used to measure the strength of the association between crop yield and climatic variability. This produced a linear association. The range of correlation coefficients is ´1 to +1. (See correlation matrix tables). The complete dependency between two variables is expressed by either ´1 or +1, and 0 represents the complete independency of the variables.

To determine the relationship between climatic variability and major crop yields (kg/ha), a correlation analysis was performed. The results reveal that there was a negative relationship between the average temperature (temp) and maximum temperature (maxt) and rain anomaly (RA) variability and the yield of Maize, whereas precipitation (pre), minimum temperure (mint) and (TA) have positive relationship with Maize yield. Similar trend is observed, when we study the correlation matrix of the Millet yield and climate variables. Significant relationship was observed in the yield of Millet and temperature variables. There was a strong correlation between Millet yield and the seasonal maximum temperature (r = -0.19.The yield of Millet decreases with increasing maximum and minimum temperatures. There was a significant effect of precipitation on the yield of Millet (r = +0.51).

5.1.6 Changes in Yield Due to Climate Trends

Figure.5.3. and 5.4. trace the trends of both yield and climatic variations. In figure 5.3 the variations in temperature and variations in maize yield have shown similar trends (pattern). In figure 5.4 a similar trend is observed between Millet yield and precipitation in SSA. The question of this study is intended to answer empirically this question, is there any possible correlation between climate variations and crop yield in SSA countries?

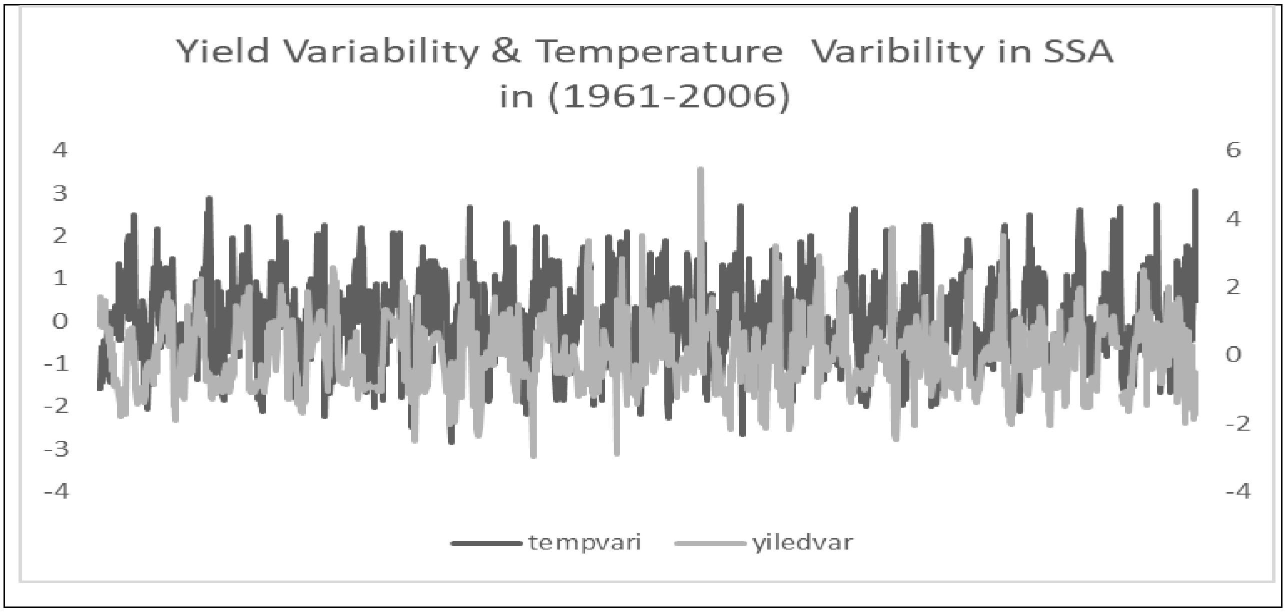

Figure 5.3.Maize Yields and Temperature

Source of Data: FAOSTAT, 20005

To empirically test whether there is a direct relationship between climatic variables and crop yields in SSA countries. The production function technique was used to analyze the relationship between anomalies of Maize and Millet yields, and climate variables precipitation and temperature anomalies during the period of (1961 to 2006). The anomalies in climate variables and crop yields can be used to estimate the quantitative relationships between climate change and crop yield.

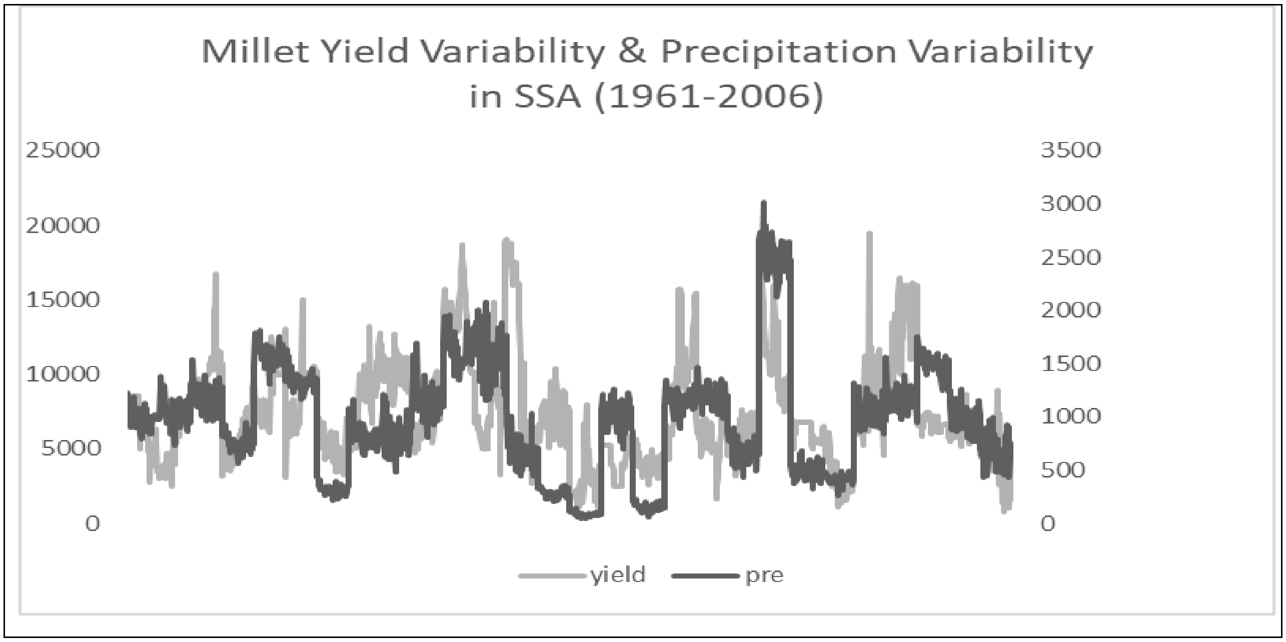

Figure 5.4.Millet Yield and Precipitation

Source of Data: FAOSTAT, 20005

5.1.7 Unit Root Test

This study, uses three distinct panel unit root tests on the variables for the sample used and covering the period 1961-2006, these tests are, Levin-Lin-Chu's (LLC), Im-Pesaran-Shin's, and Fisher Augmented Dicker Fuller based test. Among these tests, LLC tests are based on the common unit root process assumption that the autocorrelation coefficients of the tested variables across cross-sections are identical. However, the IPS and ADF-Fisher tests rely on the individual unit root process assumption that the autocorrelation coefficients vary across cross-sections.

The test results are presented in Table 5.11. and 5.12. for Maize and Millet Models. All variables used in the model except harvested area (ha), which turns stationary after first differenced. The LLC test provides strong evidence of stationarity in all the variables. The IPS and ADF-Fisher tests indicate that except for harvested area (ha), all variables are stationary at level. All variables become stationary, as can be seen from table 5.11, when we test for panel unit-root in first difference. Therefore, the variables in first difference are stationary or integrated of order zero (I (0)), which means their levels are integrated of order one (I (1)).

Table 5.11.

Unit Root Test (Millet)

Variable Name	LLC t*-stat H0: Unit root	IPS W-t-bar stat: H0: Unit root	ADF-Fisher H0: Unit root
lnyiled	-2.9017 *** [0.0000]	-13.1825*** [0.0000]	18.3180*** [0.0000]
Δlnyiled	-25.0109*** 0.0000]	-25.6056*** [0.0000]	113.016*** [0.0000]
lnha	2.7787 *** [0.9973]	-7.7376*** [0.3954]	7.3551*** [0.0000]
Δlnha	-18.0176*** [0.0000]	-23.3764*** [0.0000]	113.016*** [0.0000]
Ra	-12.9596*** [0.0000]	-18.2031*** [0.0000]	74.8537*** [0.0000]
ΔRa	-4.0631*** [0.0000]	-27.3163*** [0.0000]	178.636*** [0.0000]
temp	-6.0817*** [0.0000]	-18.4925*** [0.0000]	45.3974*** [0.0000]
Δtemp	-5.6231*** [0.0000]	-25.7237*** [0.0000]	154.698*** [0.0000]
pre	-13.1741*** [0.0000]	-26.7591 *** [0.0000]	86.00*** [0.0000]
Δpre	5.5041*** [0.0000]	-25.7633*** [0.0000]	178.636*** [0.0000]
TA	-6.0201*** [0.0000]	-18.4925*** [0.0000]	55.0245 [0.0000]
ΔTA	-38.33*** [0.0000]	-25.7237*** [0.0000]	151.889 [0.0000]
STA	-6.0201*** [0.0000]	-18.4925*** [0.0000]	55.0245*** [0.0000]
ΔSTA	-38.338*** [0.0000]	-25.7237*** [0.0000]	151.889*** [0.0000]
SRA	-13.1741*** [0.0000]	-18.2224*** [0.0000]	86.0062*** [0.0000]
ΔSRA	-30.4638*** [0.0000]	-26.7591*** [0.0000]	169.85*** [0.0000]

Notes. * and *** indicate significance at 10% and 1% levels respectively.

The test results are presented in Table 5.11 for Maize Model. The test results in general show evidence of stationarity in all the variables used in the model in level except harvested area (ha), which turns stationary after first differenced.

The test results are presented in Table 5.12 for Maize Model. The test results in general, show evidence of stationarity in level in all the variables used in the model except harvested area (ha), which turns stationary after first differenced.

Table 5.12.

Unit Root Test (Maize)

Variable Name	LLC t*-stat H0: Unit root	IPS W-t-bar stat: H0: Unit root	ADF-Fisher H0: Unit root
lnyiled	-4.5864*** [0.0000]	-11.2428*** [0.0000]	31.8710*** [0.0000]
Δlnyiled	-25.010*** [0.0000]	-23.6520*** [0.0000]	147.106*** [0.0000]
lnha	-0.8160*** [0.9973]	-7.3207*** [0.3954]	10.6187*** [0.0000]
Δlnha	-12.358*** [0.0000]	-23.6520*** [0.0000]	115.5490*** [0.0000]
Ra	-12.087*** [0.0000]	-20.9314*** [0.0000]	52.6969*** [0.0000]
ΔRa	-24.125*** [0.0000]	-28.0901*** [0.0000]	169.85*** [0.0000]
temp	-8.3706*** [0.0000]	-16.7734*** [0.0000]	55.0245*** [0.0000]
Δtemp	-24.78*** [0.0000]	-26.1627*** [0.0000]	151.889*** [0.0000]
pre	-12.0876*** [0.0000]	-21.7859*** [0.0000]	52.9223*** [0.0000]
Δpre	-24.125*** [0.0000]	-28.0901*** [0.0000]	169.8595*** [0.0000]
TA	-8.3706*** [0.0000]	-16.7734*** [0.0000]	45.3974 [0.0000]
ΔTA	-24.782*** [0.0000]	-26.1627*** [0.0000]	154.6987 [0.0000]
STA	-8.3706*** [0.0000]	-16.7734*** [0.0000]	55.0245*** [0.0000]
ΔSTA	-24.78*** [0.0000]	-26.1627*** [0.0000]	45.397*** [0.0000]
SRA	-12.087*** [0.0000]	52.9223*** [0.0000]	86.0062*** [0.0000]
ΔSRA	-24.1254*** [0.0000]	-28.0901*** [0.0000]	178.636*** [0.0000]

Notes. * and *** indicate significance at 10% and 1% levels respectively.

5.1.9 The Final Results Model One Climate Variability and Crop Yield (Maize)

To capture the yield response to climate, two regressions were run for each crop, using two different function forms Cobb Douglass and quadratic functions. For each of the climate variables, anomaly variables for both extremes have been included as repressors in the yield functions. Mean yield depends on climate and non-climate inputs. Two functional forms were used to estimate and analyze the mean yield functions. In model A1 the Cobb-Douglas functional form was used for the estimation, whereas, the quadratic functional form was used to estimate model A2.In the next section, we explain each functional form in more details.

5.1.9.1 The Cobb Douglass Functional Form Model (A1) Maize

In table 5.14. (Mean model summary) the results indicate that 0.16% of the variability in Maize yield is explained by the independent variables; all in all, both the F-statistic and the Probability test conformed to the fact that the model is reliable. Individual predictors are all significant at the 95% confidence interval although entire model is fit for the purpose of explaining the variation in Maize yield, but it can only explain 16% which mean more variables could also account for the change in the mean or the variation of Maize yield in SSA over the study period.

Table 5.13. displays the regression coefficients for Maize yield function. The results show that a 1% increase in crop area will significantly increase mean Maize yield (0.49988) Rainfall as expected has a positive and significant effect on Maize mean yield, a 1% increase in precipitation will significantly increases the mean Maize yield by (**0.0006%).** Temperature, on the other hand has a negative and insignificant impact on mean Maize yield, a 1% increase in temperature will decrease mean Maize yield by **(-0.0041**%). Both temperature anomaly TA and

Flood have negative impact on Maize yield, but TA impact is insignificant. Time trend has positive significant impact. Both temperature anomaly TA and Flood have negative impact on Maize yield, but TA impact is insignificant.

5.1.9.2 The Quadratic Functional Form Model (A2) Maize

In the quadratic model, the result shows that **a 1%** increase in harvested area will significantly increase mean Maize yield by (**0.48**%) The model shows a 1% increase in precipitation will significantly increases mean Maize yield by (**0.50%)** Temperature, on the other hand has a negative and insignificant impact on mean Maize yield, a **1%** increase in temperature will insignificantly decrease mean Maize yield by **(-0.158%).** The time trend is positive and significant. The quadratic terms used in this model to check the non-linearity of the relationship between mean crop yield and climatic variables. The Quadratic precipitation term is negative and significant with a coefficient of (**-01.27e-04).** The Interaction term of temperature and precipitation is negative and significant. The interaction of Quadratic temperature and precipitation is a positive and significant, and interaction term of quadratic precipitation and temperature is also positive and significant. Both temperature anomaly TA and Flood have significant negative impact on Maize yield.

When quadratic and interaction effects are both included in a specification, an interaction term incorporating the quadratic variable is also included to represent the nonlinear interaction effect. For instance, if P and P^2 are included to represent a nonlinear precipitation effect, and T x P is included to represent the effect of precipitation depending on temperature, Tx P^2 is included to represent the non-linear effect of precipitation depending on temperature. This nonlinear interaction terms can then represent the effect of excessive precipitation when temperature is high.

Table 5.13.

The Model A Results (Maize)

	CD Model		Quadratic Model	
Variables	Coefficients	P-value	Coefficients	P-value
Trend	0.01073	0.0000	0.00870	0.0000
HA	0.49988	0.0000	0.48325	0.0000
T	**-0.0041**	0.2550	**-0.00158**	0.9470
P	**0.0006**	0.0000	**.004503**	0.0000
P2			**-01.27e-06**	0.0000
TR			-0.000292	0.0000
T2R			5.12e-06	0.0000
R2T			4.50e-08	0.0010
TA	-0.07231	0.390	-.077190	0.0160
Flood	-.000112	0.027	.0003494	0.0000
Constant	-10.99428	0.0000	-11.67064	0.0000

Numbers in parenthesis are standard errors. *, **, and *** indicate that the parameter is significant at the 1%, 5% and 10% levels

Table 5.14. shows the model summary for mean Maize function. The Wald statistics have a P-value of **(0.000)** both for the Cobb Douglass and quadratic models. This implies that the repressors under both models are statistically significant. The values of the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were used to select the better functional form. The quadratic model is marginally better because it has a lower value.

Table 5.14.

Maize Model Summary

Model Summary	CD Model	Quadratic Model
Log Likelihood	-580.7443	-514.314
Wald chi -square	284.61	573.970
Prob >chi-square	0.0000	0.0000
AIC	174.3451	137.9101
BIC	200.2149	184.4757
Prob > F	0.0000	0.0000
R-squared	0.1599	0.2166

Note. Source: Own Calculations

5.1.10 The Results for Model 1 Climate Variability and Crop Yield in SSA (Millet)

For each crop and each region considered, the models detailed in Section 5.1.8 are estimated following procedures outlined in Section 5.1.1.To limit the number of output tables, only final specifications are tabulated. Prior to estimating production functions the unit root tests are performed on all variables in the panel. Detailed results for these tests are presented in 5.12 table. The null hypothesis of a unit root for all series is rejected in most cases, which implies that at least one of the series is stationary. Additional diagnostic tests of cross-sectional independence, first order serial non-correlation, and homoscedasticity are performed for each specification, but only test statistics for final regressions are detailed in the following subsections. Tests on joint significance of fixed effects and time dummies are also performed for each specification but only tests for final specifications are discussed.

5.1.10.1 The Cobb Douglass Functional Form (Model B1) Millet

Table 5.16 displays the regression coefficients for Millet yield model the results show that a **1%** increase in crop area will insignificantly increase Maize yield by (**0.05%).** Rainfall as expected has a positive and significant effect on Millet mean yield, a 1% increase in precipitation will significantly increase mean Maize yield by (**0.0005%).** Temperature, on the other hand has a positive, but insignificant impact on mean Maize yield, a **1%** increase in temperature will insignificantly increase mean Maize yield by (**-0.006**%). Both temperature anomaly TA and Flood have negative impact on Maize yield. Time trend is positive and significant.

5.1.10.2 The Linear Quadratic Form (Model B2) Millet

In the quadratic model, the result shows that **a 1%** increase in harvested area will insignificantly increase mean Maize yield by (**0.05**%) The model shows a 1% increase in precipitation will significantly increases mean Maize yield by (**0.4%)** Temperature, on the other hand has a negative and insignificant impact on mean Maize yield, a **1%** increase in temperature will significantly decrease mean Maize yield by (-06.00**%).** The time trend is positive and significant. The quadratic terms used in this model to check the non-linearity of the relationship between mean crop yield and climatic variables.

The Quadratic precipitation term is negative and significant with a coefficient of (-1.42e-04**).** The Interaction term of temperature and precipitation is positive and significant. The interaction of Quadratic temperature and precipitation is a **negative** and significant, and interaction term of quadratic precipitation and temperature is also negative and significant. Temperature anomaly TA has significant positive impact on Maize yield and Flood has significant negative impact on the yield.

Table 5.15.

The Millet Function Model Results

Variables	CD Model		Quadratic Model	
	Coefficients	P-value	Coefficients	P-value
Trend	0.00213	0.0082	0.0019	0.0180
HA	0.0541	0.4220	0.0503	0.4310
T	**-0.006**	0.1000	**-0.060**	0.0030
P	**0.0005**	0.0000	**0.0040**	0.0090
P2			**-1.42e-06**	0.0310
T2P			-2.47e-06	0.0590
P2T			-6.11e-08	0.0150
T R			0.000249	0.0000
TA	-0.00732	0.8600	0.044289	0.0200
Flood	-0.00044	0.0070	-0.00039	0.0020
Constant	4.245318	0.0804	5.818349	0.0020

Note. Numbers in parenthesis are standard errors. *, **, and *** indicate that the parameter is significant at the 1%, 5% and 10% levels

Table 5.16. shows Millet Yield function, dependent Variable: Millet Yield, significant level **P-value** < **0.05**** R-squared **(0.27)** for Cobb Douglas function and (**0.30**) for the quadratic function. **Prob (F-statistic) (0.0000)** shows the function to be well-behaved.

Table 5.16.

Model (B) Summary (Millet)

Model Summary	CD Model	Quadratic Model
Log Likelihood	-593.8366	-579.35
Wald chi -square	774.84	466.88
Prob >chi-square	0.0000	0.0000
AIC	451.99	440.11
BIC	477.68	468.36
Prob > F	0.0000	0.0000
R-squared	0.2707	0.3019

Note. Source Own Calculations

Table 5.17 shows model summary of both models diagnostic tests, this test reveals that, both models suffer from heteroskedasticity, serial correlation and Hausman test indicates that fixed effect is the right model. We did use robust standard errors in our final models.to reduce the heteroskedasticity.

Table 5.17.

All Models Diagnostic Tests

Applied Test	Maize Model	Millet Model
Breusch-Pagan test for heteroskedasticity	chi2(1) = 0.18 Prob > chi2=0.6688	chi2(1) =43.15 Prob > chi2 =0.0000
Woodbridge Test for Serial Correlation	F(1, 28) = 162.936 Prob > F = 0.0000	F(1, 27) = 9.783 Prob > F = 0.0042
Pesaran's Cross Section Dependency	-1.412, Pr = 0.1578	0.443, Pr = 0.6576
Hausman Test	chi2(4)= 44.18 Prob>chi2 = 0.0000	chi2(4)= 13.41 Prob>chi2 = 0.0095

Note. Source Own Calculations

5.1.11 Breusch-Pagan / Cook-Weisberg test for Heteroskedasticity

The ordinary least square (OLS) estimation constant variance with zero means and homoscedasticity in panel data is expected (Baltagi, 2005. When we use this test, the null hypothesis is that there is presence of homoscedasticity (constant variance). In our model we failed to accept the null hypothesis because estimated Chi2 values are found statistically significant at 1% significance level. In Both models, we can reject the null of constant variance (Homoscedasticity). So the model suffers from Heteroskedasticity. Remedy if assumption is violated, we did use robust standard errors in our final models.

5.1.12 Pesaran C-D Cross Sectional Dependency Test

In this test the null hypothesis is that residuals are not correlated across states. We failed to reject the null hypothesis because estimated values under Pesaran C-D tests are statistically significant that imply the presence of cross sectional dependency across states for mean yield. Both Cross sectional dependency tests, Pesaran and Friedman showing strong evidence of cross section dependency for Maize and Millet Models. We use this result to choose proper unit root test that take into consideration cross section dependency.

5.1.13 Wooldridge test for Autocorrelation

Wooldridge test for autocorrelation in panel data, we can reject Null of no first order autocorrelation for Maize and Millet Models which means that both Model suffers from serial correlation.

5.1.14 The Housman Test for Fixed Effect versus Random Effect

To decide between fixed or random affects you did run a Hausman test where the null hypothesis is that the preferred model is random affects vs. the alternative the fixed effects (see

Green, 2008, chapter 9). It basically tests whether the unique errors (ui) are correlated with the regressors, the null hypothesis is they are not. The results for the both models (Maize and Millet) show that the p-value is significant, so we decided to choose the fixed effect as the model tor this study.

5.1.15 MARGINAL IMPACT ANALYSIS

Every crop has an optimum climate levels. All levels of climate variables beyond these critical levels are suboptimal. The critical points for Mazie are shown in Figure 5.1.4. These points were calculated by changing only a specific season's temperature or rainfall in the estimated yield function while keeping all other factors constant at mean values. Temperature less than 25ºC decreases yield per hectare whereas temperature levels more than 25ºC were found to increase crop's yield .Due to the quadratic form of the relationship between yield and climate, temperature below 25ºC reduces yield. It is quite evident in the literature that, the decline in yield at temperatures lower than 25ºC could be associated with the increased activities of pests and insects due to favorable climate conditions.

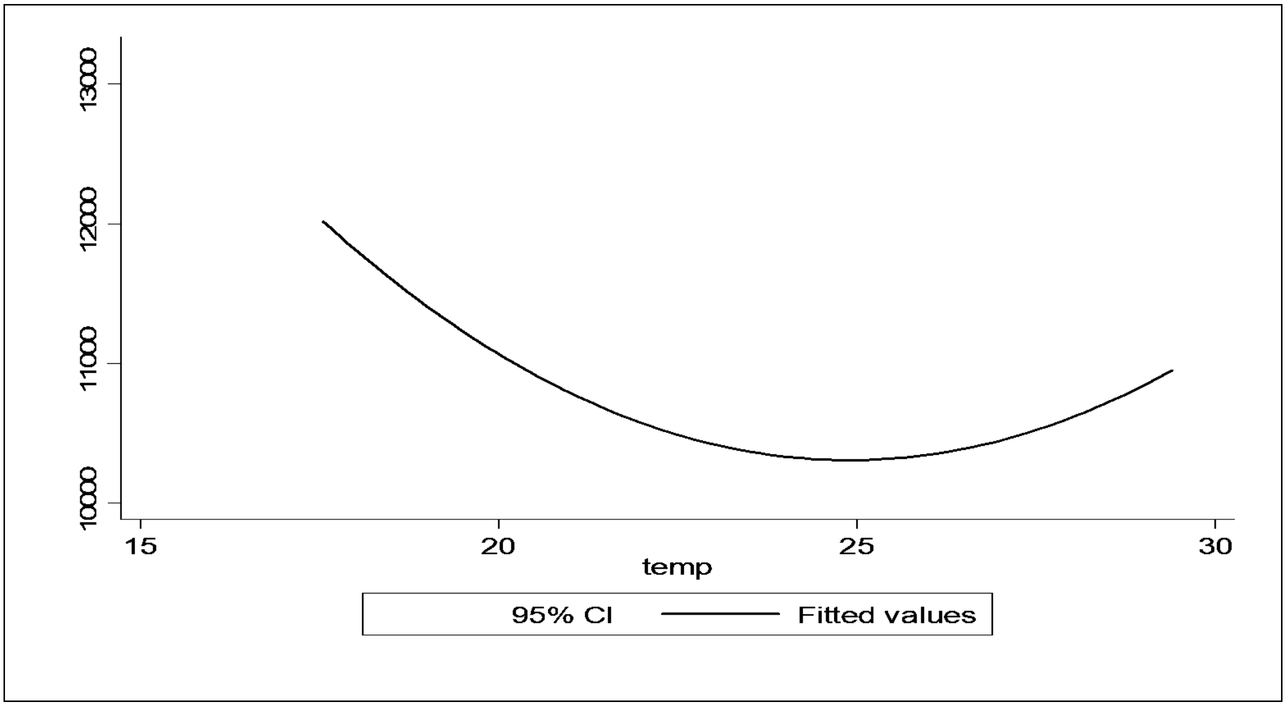

Figure 5.5.Maize Temp non-liner Relationship Optimum temp is 25 °C to 30 °C

According ARC-Grain Crops Institute in South Africa specialized in studies African crops, Maize is a warm weather crop and is not grown in areas where the mean daily temperature is less than 19 ºC or where the mean of the summer months is less than 23 ºC. The critical temperature detrimentally affecting yield is approximately 32 ºSchlenker and Roberts (2009) reported that Maize yield increased with temperature up to 29°C beyond that decline in yield is observed. However, Liu et al. (2008) found that 25°C is optimum for Maize growing. On the other hand Runge (1968) found high temperature beyond 35°C) along with 1 inch reduction in rainfall will cause 9 percent decline in Maize yield. Many studies find that the combination of heat stress and lack of moisture are responsible for reduction in maize yield.

Maize Rainfalls Impact

An annual rainfall of at least 500 mm is needed for Maize to grow and have good yield, the best expected yields usually in the 1200-1500 mm area; it is highly irrigated crop in many parts of the world as shown in many sources in the literature. Kitale experiments, for example, has shown that the first critical five growing weeks more rainfall are needed for maintaining higher yield. Figure 5.6. shows the Maize Yield and Precipitation Optimum Rain is between 1200-1500 mm.

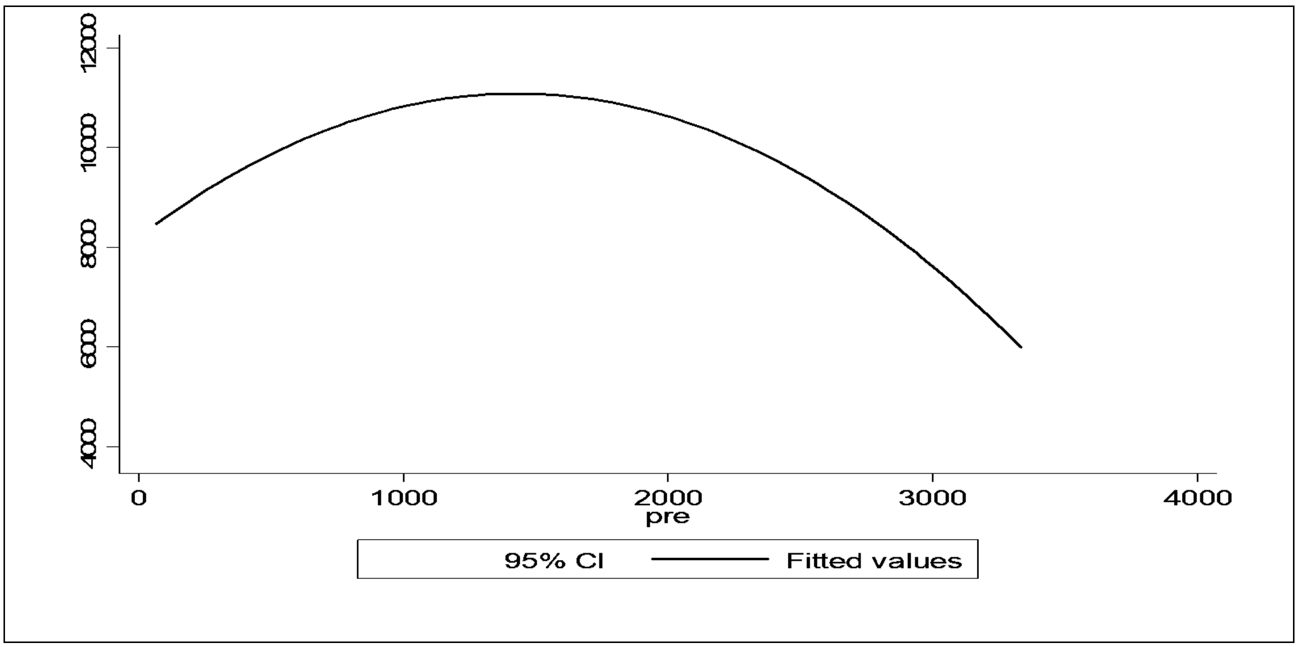

Figure 5.6.Maize Yield and Precipitation Optimum Rain is between 1200-1500 mm

Millet Climate Impact

Many different studies have shown different results of impacts of climate change on Millet yield. The reasons for these different results are; difference in model assumptions and scenarios, difference in time periods of the studies and differences in the areas of studies (Ringler et al. 2010). Nelson et al. (2009), for example projected that by 2050, millet tilled will decline by a 7–8% in SSA. Lobell (2010) expected more millet yield reduction of around 17% in SSA by 2050s. Knox et al. (2012), reported a 10% decline in Millet yield in Africa by the 2050s.

Millet Temperure Impact

Figure 5.7.shows that, Millet is generally sensitive to low temperatures at the seedling stage and at flowering. High daytime temperatures are needed for the grain to mature. The temperatures of 23 to 30 °C are needed for Millet to have best yield (Board on Science and Technology 1996). Figure 5.1.8 shows the Millet Temperature Non-liner Relationship Optimum Temp is 25 °C in SSA.

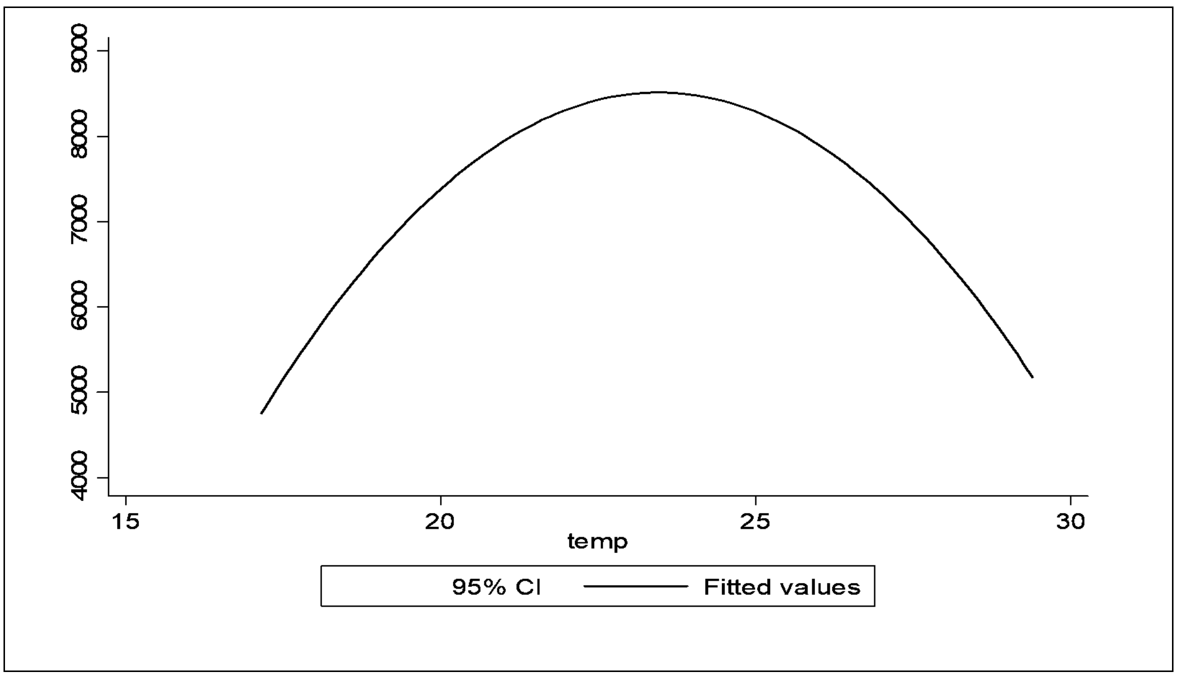

Figure 5.7.Millet Temp Non-liner Relationship Optimum Temp is 25 °C in SSA

Millet is cultivated mostly in the semiarid tropics and subtropics of Africa; however, it is also cultivated in other drought-prone sub-humid and medium-high altitude areas (Obilana 2003).

In SSA, the average temperature in Millet harvest areas in 1990 was 27.3°C, which was below the optimum Millet-growing temperature of 30°C (Liu et al. 2008). Climate change is expected to raise the temperature in Millet-growing areas closer to the optimum temperature, leading to a general increase in Millet yield

Millet Rainfalls Impact

Projected future changes in mean seasonal rainfall in Africa are less well defined. Under the low-warming scenario , few areas show trends that significantly exceed natural 30-year with a more rapid global warming scenario; large areas of Africa would experience changes in December-February or June-August rainfall that significantly exceed natural variability (IPPC, 2007). According to many scientific sources for African grains, Millet best grown in a moderate rainfall around (500-1,000 mm), well distributed rain during the growing season with no of prolonged droughts is important for Millet best yield. Dry weather is required for drying the grain at harvest time. Figure 5.8. shows the Millet Precipitation Non-liner Relationship.

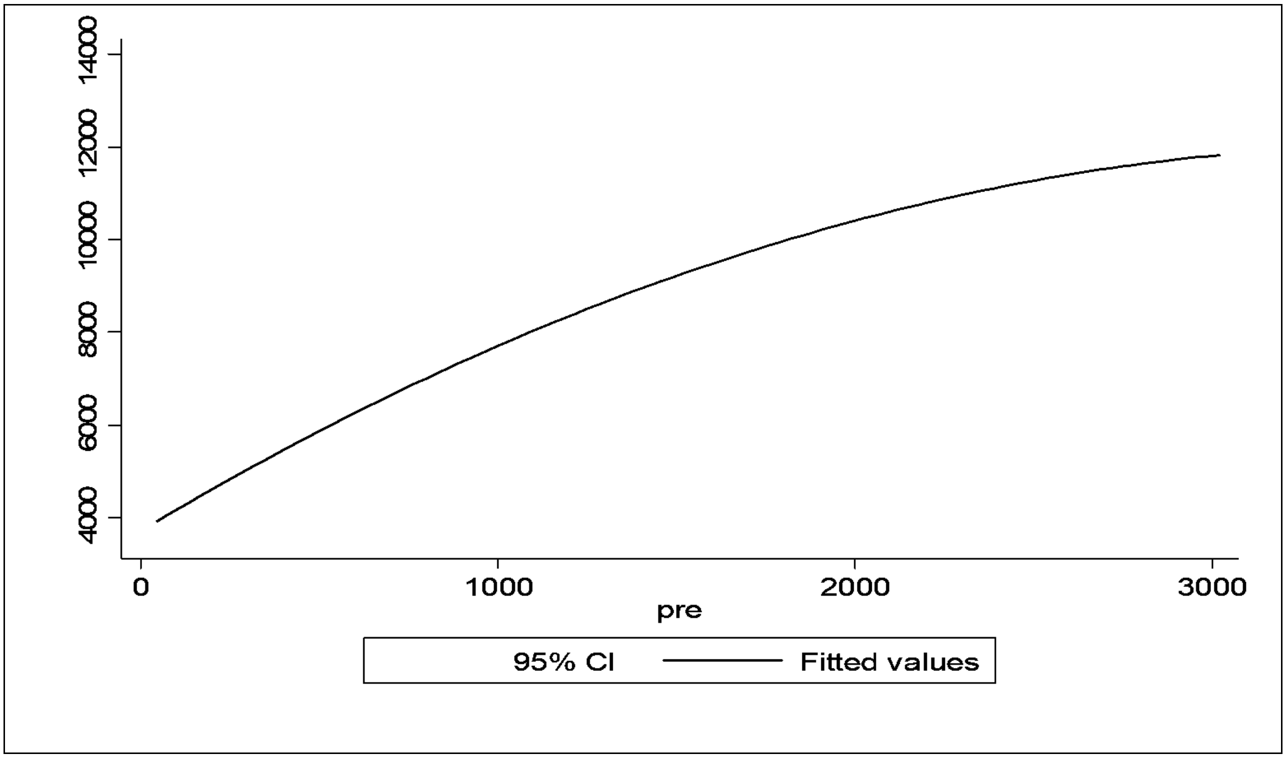

Figure 5.8.Millet Precipitation Non-liner Relationships

5.2 Model Two: Climate Change and Overall Agricultural Output in SSA

For analyzing, the dynamics of the relationship between climate change and agriculture output, we use a Panel-data Vector Autoregression (P-VAR) approach. To the best of our knowledge, this kind of investigation has not been done till date and we are the first to use PVAR approach for this type of study. Model two estimates the climate change impact on overall agriculture production measured by net production index, agriculture GDP, production quantity and agriculture value added, in 16 Sub-Saharan African countries, the study covers the period 1980-2008, major inputs such as land, capital, fertilizers and livestock along with temperature and precipitation as climatic variables, were used in this model to estimate the climate impact on agriculture output. The model estimation should be able to answer the following questions;

1. Does climate variables variation affect the overall agricultural output in SSA?
2. Does climate change affect the growth rate or just the level of output in SSA OR both?

This model, consist of three different specifications; model A is the baseline model, where we use net production index as dependent variable. In Model B, and Model C, we will use different dependent variables and change climatic variables to check the model robustness.

The model used in the study is the panel Vector Autoregression mode (P-var) that is proved to be good in estimating the dynamic relationships. In this study, PVAR model will be used to estimate the agriculture production (Output) and some climate variables for some Sub-Saharan African countries. VAR models were first developed by Sims (1980) as a better alternative to traditional dynamic simultaneous equation models to examine the dynamic interactions among the interrelated time series data.

5.2.1 Variables Definition and Sources

Empirical work in this chapter uses data from a sample of selected Sub-Saharan African countries, the criteria of selection based on data availability only. Major inputs such as land, capital, fertilizers and livestock data extracted from Food and Agriculture Organization (FAOSTAT), which is a well cited source and has data that covers many variables needed for this study within reasonable timespan.

Climatic variables were taken from Climatic Research (CRU), University of East Angelia, which is one of the most important sources for climate change research data and provides the longest time series data. Table 5.2.1 in Appendix A section 2 shows the sources of data for each variable as well as the time span in each case. The dataset on precipitation and temperature used in this paper is that developed by Dell et al. (2008) and also used by Jones and Olken (2010), which is built on data taken from the Terrestrial and Air Temperature and Precipitation: 1900-2006 Gridded Monthly Time Series, The gridded CRUTS (time-series) version 3.23 data are month-by-month variations in climate over the period 1901-2014, on high-resolution (0.5x0.5 degree) grids, produced by the Climatic Research Unit (CRU) at the University of East Anglia CRUTS 3.23.

For a measure of agricultural output, we use the FAO net production index. To proxy land input, (land), in the production function we use FAO's measure of agricultural area, which includes arable land and the area used for permanent crops and permanent pastures, while fertilizer, (ferti), is measured as the quantity in metric tons of plant nutrients consumed for domestic use in agriculture. As a crude proxy of capital stock, (machinery), we use the total number of agricultural tractors being used. Livestock (live) is proxied by the total head count of cattle, sheep, and goats.

It is worth noting that all variables except the climate variables are transformed to logarithmic form; thus, the coefficient estimates can be interpreted as the percentage change in the dependent variable for a 1% increase in the independent variable, all else constant. We estimate this model (model two) with strongly balanced dataset consisting of 16 Sub-Saharan African countries with annual data for 1980 to 2008. The overall sample size is N = 434. Variables definition presented in Appendix B, Descriptive statistics and the correlation matrix for all variables are presented in table 5.2.1 and 5.2.2 respectively.

5.2.2 The Descriptive Statistics

In this section, we will present descriptive statistics for variable used in the model, the first model will test the impact of climatic variables mainly temperature and precipitation on overall agriculture production for some selected countries in SSA. Four variables selected to be used as dependent variables interchangeably for the study namely production index (NetIndex), production quantity (prodq), production share of GDP (aggdp) and agriculture value added (agva). These variables were selected for their importance as main variables to determine the agriculture output. In the table below, we list twelve variables used in the analysis, four of these variables are climate related (independent variables) namely annual average temperature (temp) and annual average precipitation (pre). Other two variables were constructed using same raw data, deviation from long term mean temperature (dtemp) and deviation from mean precipitation (dpre). These two climate variables will be used in the baseline specification model. The other eight variables represent control variables (independent variables) represent major inputs of agriculture production namely, Land (land), machinery (machinery), Livestock (live) and fertilizer (ferti). We constructed new two variables called dtemp and dpre from deviation from their long-term of average temperature and precipitation, the idea here is to make sure we have variables to traces short term variations of the climatic variables.

Table 5.18 shows, the descriptive statistics indicate that the mean NetIndex is 73.03 for the sampled countries over the period and the standard deviation is 20.54 confirms that there so much variability in the agriculture production within these countries.

Table 5.18.

Model Two Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
dtemp	435.00	0.00	0.36	-0.94	1.13
temp	435.00	25.51	3.24	17.40	29.40
dpre	435.00	2.12	92.49	332.91	389.72
preci	435.00	799.78	418.41	66.50	1758.00
aggdp	435.00	0.25	0.13	0.02	0.62
agva	435.00	383096.30	522174.40	4.00	2173070.00
ferti	435.00	175030.80	1703297.00	0.09	33200000.00
machine	435.00	2133028.00	5273502.00	0.09	33200000.00
prodq	435.00	1559413.00	2555150.00	1.40	10500000.00
land	429.00	234.32	488.77	1.00	1946.00
proindex	410.00	73.03	20.54	26.69	122.77
live	386.00	73.63	21.59	25.53	129.25

Note. N = 434. All variables except climatic variables were converted to natural log form.

On the climate side, temperature averaged around **25.51** degree measured in Celsius (ºC), and standard deviation around **3.24** with minimum temperature of **17.4** and maximum of **29.4.** On the other hand, precipitation averaged around **799.76** millimeters (mm), with minimum precipitation of **66.5** and maximum of **1758** and standard deviation of **418.41**. Table 5.19 shows the model two correlation matrix.

Table 5.19.

Model two Correlation Matrix

	proindex	prodq	aggdp	agva	temp	dtemp	preci	dpre	ferti	machi	live
proindex	1.000										
prodq	0.074	1.000									
aggdp	-0.205	-0.177	1.000								
agva	0.120	-0.151	0.085	1.000							
temp	-0.293	-0.333	0.378	0.221	1.000						
dtemp	0.389	0.061	-0.040	0.112	0.124	1.000					
preci	0.121	-0.203	0.222	0.390	0.051	-0.019	1.000				
dpre	0.214	0.024	-0.015	0.032	0.036	-0.102	0.201	1.000			
ferti	0.222	0.270	0.023	0.085	0.061	0.240	0.115	0.070	1.000		
machine	0.163	-0.267	-0.029	0.071	0.128	0.064	0.263	0.059	0.083	1.000	
live	0.739	0.065	-0.061	0.091	0.304	0.326	0.145	0.175	0.159	0.007	1.000

Note. N = 434. All variables except climatic variables were converted to natural log form.

5.2.3 Unit Root Test

As the data set contains more than 20 years of observations, it requires testing of the unit roots for examining stationary of the series (Chen et al., 2004). Augmented Dickey Fuller (ADF) and IPS tests were used and the results are presented in Table 5.20 shows that all variables expect climate variables have unit root (non-stationary) at their level form in both tests Table 5.20 The optimal lag length selection was performed using the general-to-specific procedure suggested by Ng and Perron (1995).

All except the climate variables were transformed to natural logarithms. The ADF tests indicate that we are dealing with are a mix of I (1) and I (0) variables. Temperature (temp, dtemp) and precipitation (preci, dpre) climate variables appear to be stationary at level for the majority of countries, while the opposite for all other variable.

Table 5.20. shows the result of the unit root test for the model to estimate the climate change impact on overall agriculture production for a sample of Sub-Saharan African countries and covering the period of 1980-2008. We conducted two major unit root tests namely ADF-Fisher and IPS. The result showing that all variables except climate variables need to be first differenced to be stationary

Table 5.20.

Unit Root Test Model two

Variable	IPS	ADF-F	ADF-F	IPS
Level				First Difference
lnNetIndex	2.8061	2.4979	-23.3280***	-9.0158***
	[0.9975]	[0.9938]	[0.0000]	[0.0000]
lnaggdp	-1.3052	-1.3599	-17.4571***	10.3317***
	[0.0959]	[0.0869]	[0.0000]	[0.0000]
lnagva	0.8563	-4.2200	-22.8699***	13.1909***
	[0.8041]	[0.0000]	[0.3954]	[0.0000]
lnprodq	-1.6071	-2.4312	-19.7380***	11.9598***
	[0.0540]	[.0000]	[0.0000]	[0.0000]
lnmachine	-0.2135	-0.2678	-18.3677 ***	25.4875***
	[0.4155]	[0.3944]	[0.0000]	[0.0000]
lnlive	3.2353	2.3837	-19.6031***	42.9669***
	[0.9994]	[0.9914]	[0.0000]	[0.0000]
lnland	2.1829	1.9617	-16.2990***	10.2348***
	[0.9989]	[0.9751]	[0.0000]	[0.0000]
lnferti	-1.9808	-2.8051	-22.3726***	12.8902***
	[0.0238] *	[0.0025]	[0.0000]	[0.0000]
DTEMP	-7.4471	-9.7276***	-9.7276***	7.4471***
	(0.0000)	[0.0000]	[0.0000]	[0.0000]
DPRE	9.9426***	14.2420***	-14.2420***	9.9426***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
temp	7.4471***	-9.7276***	-9.7276***	-7.4471***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
preci	9.9426***	14.2420***	-14.2420***	-9.9426***
	[0.0000	[0.0000]	[0.0000]	[0.0000]

Note: * and *** indicate significance at 10% and 1% levels, respectively.

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5.2.4 Cointegration Test

A cointegration test is required to avoid the spurious regression problem. Tables 5.21 and 5.22 present two test results of panel cointegration in this study. The Westerlund and Kao tests use the Schwartz Bayesian information criterion (SIC) to automatically select the appropriate lag length. Table 5.21 reports the results of the cointegration tests, these are error correction based panel cointegration tests developed by Westerlund (2007.This result is further confirmed by Kao's test which fails to rejects the null hypothesis of no cointegration at 5 percent level of significance.

Table 5.21.

Westerlund Co-integration Test

Statistic	Value	Z-value	P-value
Gt	-4.080	-4.481	0.0000***
Gt	-14.268	2.097	0.9820
Pt	-15.908	-5.140	0.0000***
Pt	-14.551	0.485	0.6860

Notes: * and *** indicate significance at 10% and 1% levels, respectively

Table 5.22.

Kao Residual Cointegration test

Newey-West automatic bandwidth selection and Bartlett kernel

ADF	t-statistics	Prob
	-073635	0.4707
Residuals variance	0.145613	
HAC variance	0.022190	

Note. Null hypothesis No cointegration

Table 5.23.shows the lag length selection criteria. According to lag selection criteria test we choose BIC criteria with one lag following the rule of taking the lowest value which is (-221.2).

Table 5.23.

Lag Selection Criteria

Lag	CD	*J*	J Pvalue	MBIC	MAIC	MQIC
1	0.99156	52.7963	0.2940248	-221.2	-43.204	-114.57
2	9954496	26.6784	0.7328527	-156.27	-37.322	-84.902
3	9938153	11.6374	0.765388	-79.835	-20.363	-44.153

Note. Source Own Calculations

Table 5.24.shows the baseline model diagnostic tests that is to include Breusch-Pagan test for heteroskedasticity, Woodbridge Test for Serial Correlation and Pesaran's Cross Section Dependency.

Table 5.24.

Baseline Model Diagnostic Tests

Test Type	**Result**
Breusch-Pagan test for heteroskedasticity	chi2(1) = 3.17 Prob >chi2=0.070
Woodbridge Test for Serial Correlation	F (1, 14) =54.570 Prob > F =0.0007
Pesaran's Cross Section Dependency	5.298, Pr = 0.0000

Note. Source Own Calculations

5.2.5 Baseline Model Diagnostic Tests

Three basic tests will be conducted for this study. These tests are, Breusch-Pagan test for heteroskedasticity, Wooldridge test for autocorrelation in panel, and Pesaran's cross sectional dependency test.. Breusch-Pagan test for heteroskedasticity, the null is Ho: Constant variance (Homoscedasticity), according to the result of the model, we can reject the null meaning that the model suffers from heteroskedasticity. Wooldridge test for autocorrelation in panel data, the H0: no first order autocorrelation, we can reject the null meaning that the model has serial correlation.. Pesaran's Cross Sectional Dependency Test. In Pesaran's Cross Section

Dependency, the Null is no presence of cross sectional dependence; according to the result of this model we reject the null meaning that there is a presence of cross sectional dependency.

5.2.6. Model Two Results

Following the panel VAR literature [including Raddatz (2007; 2009)], we use impulse response functions (IRFs) to show ten-year forecasts of how agricultural production in SSA countries (Agriculture production index, Agriculture GDP and Agriculture value added) reacts to each climatic shock over time. These IRFs display the effect of 'orthogonalized' shocks; i.e. they display the response of one variable to a one standard deviation shock in another variable, while keeping all other shocks constant. Each IRF starts at 0, i.e. the year in which the shock occurs. Each IRF then shows the ten year- ahead forecast error of the response. We define the response in years 0 and 1 as immediate or short-term effects, in order to account for the fact that some shocks might happen very late in the year. Years 2-10 are the medium- and long-term effects. The reader can interpret significance in the shocks as follows: 5% and 95% confidence bands accompany each of the point estimates in the IRF. Years where both bands are above (or both below) the zero-line are years where the variable in question responds significantly (at the 10, 5, or 1 percent level) to an individual shock Impulse response functions provided by VAR models are used to know where the impact of change in one variable can be found through all the other variables.

As the data set contains more than 28 years of observations, it requires testing of the unit roots for examining stationary of the series (Chen et al., 2004). We conducted two major unit root tests namely ADF-Fisher and IPS. The result showing that all variables except climate variables need to be first differenced to be stationary). All results are presented in Table 5.23.

Table 5.23.gives the values of different information criterion for the various lag length of the VAR models. From the results, the optimal lag order is one, following the rule of choosing the values of minimum AIC, BIC and HQC.

For the estimating the baseline model the following P-VAR (1) model is employed by considering agriculture production index yield and climate variables

$$\text{proindex}_t = \alpha_0 + \alpha_1 \text{proindex}_{t-1} + \alpha_2 \text{Ferti}_{t-1} + \alpha_3 \text{Live}_{t-1} + \alpha_4 \text{Machine}_{t-1} + \alpha_5 \text{Land}_{t-1} + \alpha_6 \text{Temp}_{t-1} + \alpha_7 \text{Pre}_{t-1} + \varepsilon_{1t}$$

Where proindex_t is agriculture production index, $\alpha_1\text{proindex}_{t-1}$ is first lag production index, Ferti_{t-1}, Live_{t-1}, Machine_{t-1}, Land_{t-1} + Temp_{t-1} *and* Pre_{t-1} are first lag of fertilizers, livestock, machinery , land and climatic variables respectively, α_1 through α_7 are the model coefficients to be estimated . $\varepsilon_{1t}$is the error term.

This section presents the impulse response functions and the variance decomposition from the panel VAR. Before moving on to examine the responses in various sub-samples, it is important to check to see if the baseline results are robust to allowing for country specific effects. We employ the Pvar STATA program written by Inessa Love. For specific details of the procedure, we direct the reader to Love and Zicchino (2006).

5.2.6.1. GMM Estimation: The Model Results

In this section, the model results will be presented. Firstly, table 5.25. shows the main result of GMM estimation of panel var (PVAR) baseline model, where the production index is used as the dependent variables regressed against some inputs variables a long with climatic variables.

In Table 5.25.we have estimated first the panel of 16 Sub-Saharan African countries using five variables panel VAR model. For the baseline model, we have found significant positive effect from temperature and significant negative effect from precipitation to agriculture production index. The result show that the use of fertilizers and machinery both have negative significant impact on agriculture production index, whereas, Livestock has positive significant effect on agriculture production index for SSA countries

Table 5.25.

The GMM Estimation: The Model Results

Variable	**Coef.**	**Std.Err.**	**P>Z**
dlogproindex			
L1.	-0.2665	0.0538	0.0000***
dlogferti			
L1.	-.0043138	0.0022	0.0490**
dlogmachine			
L1.	-0.0032	0.0013	0.0110***
dloglive			
L1	-.0949535	0.055	0.089*
DTEMP			
L1.	.0331852	0.0166	0.046**
DPRE			
L1.	-0.0001	0.0000	0.0370**
No. of Obs	389		
No. of panels	15		

Note. Two variable PVAR model is estimated by GMM, country-time and fixed effects are removed prior to estimation. Reported numbers show the coefficients of regressing the row variables on lags of the column variables. Heteroskedasticity adjusted t-statistics are in parentheses. ***, ** and * indicates significance at 1%, 5% and 10% level, respectively

5.2.6.2 The Variance Decomposition Function (VDF)

Variance-decompositions function explains how much percent of variation in the row variable explained by column variable. Table 5.26., explains the Variance Decomposition Function (VDF) for baseline model. This function provides explanation to variation in one variable that caused by another variable and explain how much that affect in them. Hence, we find from the results of our models that all variables explain most of the variation in themselves and explanatory power of the variables had been affected by change in the ordering of the variables. Results from FEDV also indicate that temperature explains about **(2.00**) percent at the beginning of the period and reach about **(6.00)** percent in period two up to the end of period ten and precipitation explains about (**0.55)** percent at period one and reach about **(7.00**) up to the end of the period fraction of the agriculture production index.

It is evident in table 5.26.that lagged value DTEMP has positive and significant impact on Logprodindex, lagged value of DPRE has positive and significant impact on Logprodindex. Lagged value DTEMP become negative and significant impact on Logprodindex after third year, and lagged value of DPRE become negative and significant after second year.

Table 5.26.

Variance Decomposition Function (VDF)

Response			Impulse variable		
Variable	dlogproindex	dlogferti	dlogmachine	DTEMP	DPRE
dlogproindex					
0	1	0	0	0	0
1	.8929955	0070079	.0000677	.0285401	.055075
2	.8298507	.0085802	.0096933	.0570235	0716243
3	.8251752	.009866	.0083575	.0574774	.0729065
4	.8247836	.0101045	.0105353	.0575053	.0729153
5	.8247447	.010138	.0105327	.0575024	.0729157
6	.8247409	.0101417	.0105334	.0575023	.0729153
7	.8247404	.0101421	.0105335	.0575023	.0729153
8	.8247403	.0101422	.0105335	.0575022	.0729153
9	.8247403	.0101422	.0105335	.0575022	.0729153
10	.8247403	.0101422	.0105335	.0575022	.0729153

Note. Variance-decompositions function explains how much percent of variation in the row variable explained by column variable.

From the above table, we can see all other variables that contribute to agriculture production index variations with different degrees and have significant different signs and different magnituates.

5.2.6.3 Impulse Response Functions

Impulse Response Function for Baseline Model Response of logprodindex to Temperature

We employ forward mean-differencing (Arellano and Bover 1995) to eliminate the fixed effects. This procedure is also called a Helmert transformation, and keeps the orthogonality between variables and their lags, so we can use lags are as instruments. Another issue is that of the cross-section autocorrelation related to the common factors (Levin and Lin 2002. We need stationary data in order to proceed with panel VAR. Our data is necessarily stationary as it is in first differences; however, to test whether the main variables of interest are stationary by using three different panels unit root tests: the Levin and Lin (2002) test, the Breitung (2001) test and the Im, Pesaran and Shin (2003) test.

This section presents the results of the pvar model presented in the previous section. The main focus of this study is to trace the response of agriculture output to two climatic shocks (i.e., temperature and precipitation shocks). We first present results on baseline model where the agriculture production index will be used as a dependent variable, and other agriculture production inputs such as land, machinery, fertilizer and livestock will be used as independent variables along with some climatic variables (temperature and precipitation). Then we proceed to report on the economic impacts of agriculture production due to temperature and precipitation shocks using population-weighted climate variables such as average temperature and total annual precipitation. After this, for a comparison, we use different climatic variables such as DTEMP and DPRE which, in fact, these variables are representation the deviation of temperature and precipitation from their long term mean (anomaly). Lastly, for robustness check we use different type of agriculture output (agriculture GDP, agriculture value added and agriculture production quantity, to see which one is affected most by climate change, such as temperature-precipitation interactions with other determinants of agricultural production.

Impulse Response Functions

Model One Baseline Model

In the baseline model specification agriculture production index (dlogproindex) will be used in its log and first differenced form as a dependent variable to present the response of agriculture production to the shock of climatic variables. The model will be presented with one lag. For robustness check we will use different climate variables and different lag structures. Figure 5.9 shows the estimated response of log production index to the temperature variable at time zero, as indicated at the top of each figures, (solid lines) and its 90 percent confidence interval (broken lines). Time horizon is in years. The response starts negative significant and decreasing up to the third year begin to turn positive and increasing and dies out after ten years. To generate the above figure, we used STATA 12 and Eviews 9 software.

In the Figure 5.9.temperature shocks tend to show negative impacts on agriculture production index for the first year, the impact became positive and significant in the second year. The shocks tend to introduce similar response patterns and short-lasting impacts for agriculture production index.

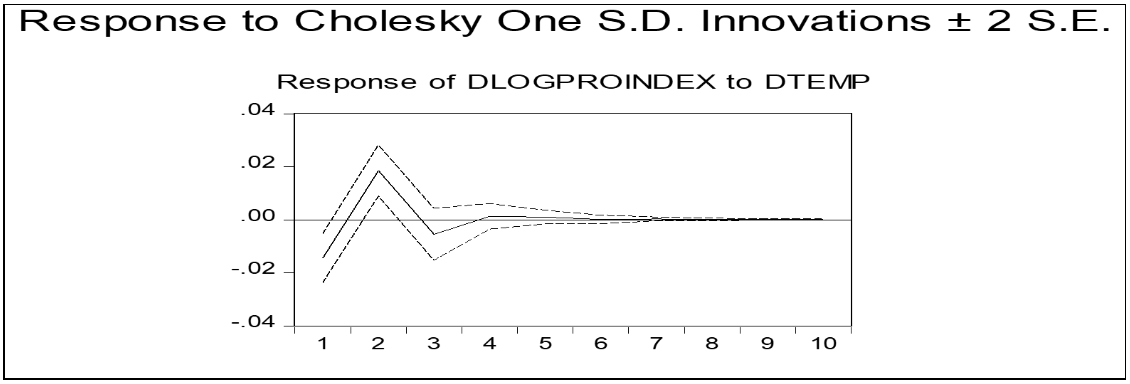

Figure 5.9.Response of Agriculture Production Index to Temperature Shock

The effect is significant in the first period of the shock but becomes insignificant only for agricultural production after that, which indicates the sensitivity of agriculture to temperature shocks. It becomes more significant in about one year after the event, showing the presence of delayed effects. The peaks of the impacts appear after third year from the beginning of the shock. The effect showing a negative impact followed by positive impact and keeps taking this pattern up to the sixth year. This pattern explains that the impact of temperature is just a level effect as oppose to growth effect which should last long because the climate change should affect the overall productive capacity (labor productivity, physical capital and land). What we see here is a level effect which means that the shock impact will last for short period after which the production will return to its normal level after climate shock clear, level effects are reversed when the climate shock is reversed. According to Dell “if last year’s temperature affects this year’s harvest (level effects are eventually reversed once the shock disappears). Therefore, to the extent temperature effects are level effects, the cumulated sum of the temperature effect and all its lags should be zero, in fact, the cumulated effect of temperature becomes stronger as more lags are added (this will be checked in model robustness section) (Dell, 2008).

In Figure 5.10 the cumulative effect showing stronger temperature negative impact up to the second year, the impact fade away after third year (level effect). In addition, there is a clear sign of recovery after shock.

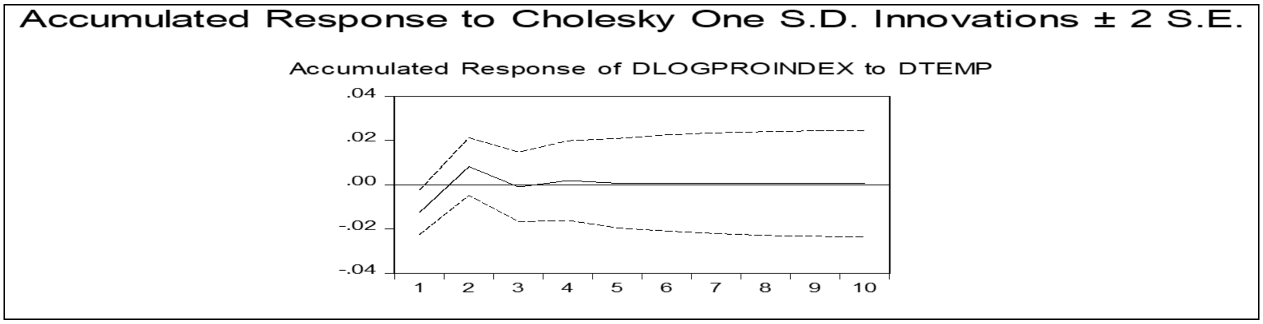

Figure 5.10.Cumulative Effects of Temperature on Production Index

Figure 5.11 depicts the impact of precipitation shocks to agriculture production index. The results are showing almost an opposite picture compared to that of temperature impact. Precipitation shocks tend to induce volatility of agricultural production in general but an overall positive effect agricultural growth. Specifically, the mean response of growth is positive in a declining trend and significant until the first year and half after the shock. The positive impacts only persist for about one year and half, afterword become negative up to the second year and then starts in positive direction for up to the fifth year.

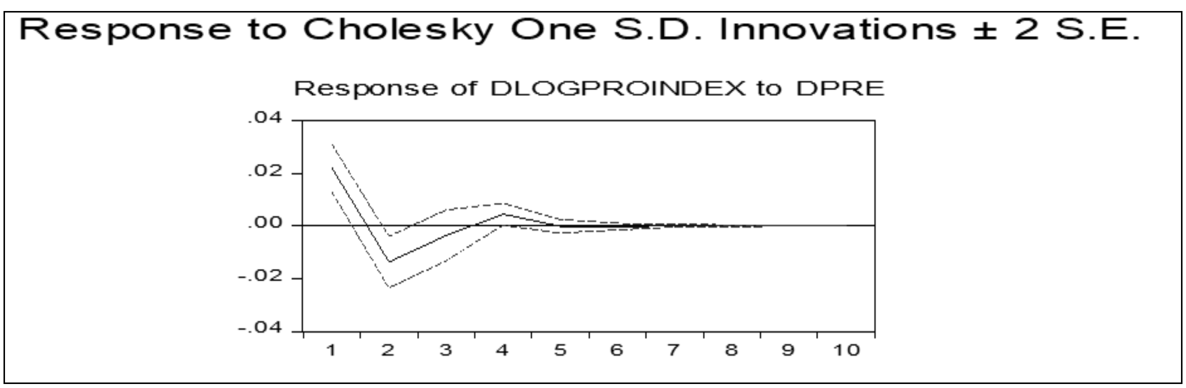

Figure 5.11.Response of Agriculture Production Index to Precipitation Shock

Figure 5.12 examining the cumulative effects, again, the agricultural sector tends to be more sensitive to precipitation shocks, with a larger cumulative effect the sensitivity of agriculture to precipitation shocks is also seen by the longer decay rate for agriculture shown in the graph. Given the climatic nature of aridity for Sub-Saharan Africa, we expected increased precipitation would introduce significantly positive impacts on agricultural growth (for instance, increased precipitation leads to more stream flow and more water available for irrigation).

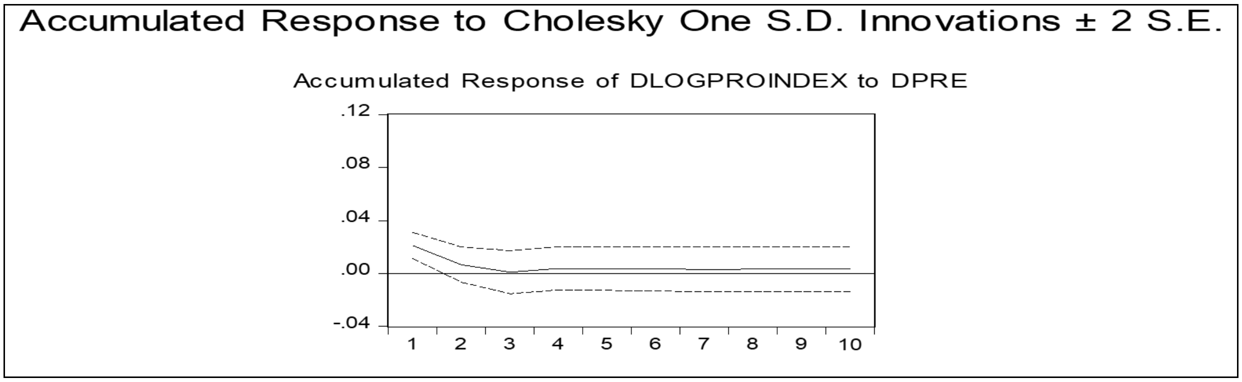

Figure 5.12.Cumulative Response of Production Index to Precipitation Shock

5.2.6.4 Robustness Check using Different Model Specifications

1. Model A: Using Agriculture Value Added as a Dependent Variable

Figure 5.13. presents the responses of the agriculture value added (Agriculture, value added (% of GDP). Agriculture corresponds to ISIC divisions 1-5 and includes forestry, hunting, and fishing, as well as cultivation of crops and livestock production. Value added is the net output of a sector after adding up all outputs and subtracting intermediate inputs (World Bank 2011).

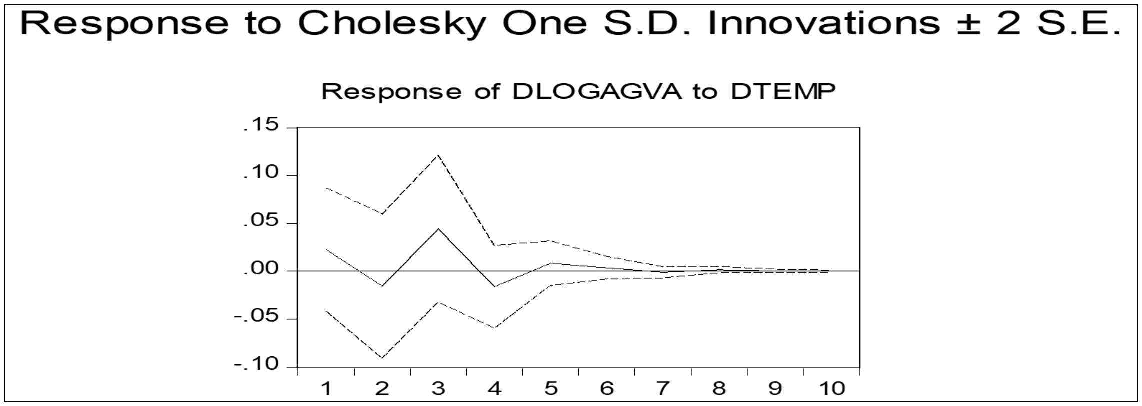

Figure 5.13.Response of Agriculture Value Added to Temperature Shock

Total GDP is defined as the sum of the value added from Total agriculture, industry and the services sectors. If the value added of these sectors is calculated at purchaser values, total value added is derived by subtracting net product taxes from GDP) to temperature shocks.

Temperature shocks tend to show negative impacts on agriculture value added for the first year, the impact became positive and significant in the second year. The shocks tend to introduce similar response patterns and short-lasting impacts to agriculture production index. The effect is significant in the first period of the shock but becomes insignificant only for agricultural production after that, which indicates the sensitivity of agriculture to temperature shocks. It becomes more significant in about one year after the event, showing the presence of delayed effects. The peaks of the impacts appear after third year from the beginning of the shock.

The effects showing a negative impact followed by positive impact and keep taking this pattern up to the eighth year. This pattern explains that the impact of temperature is just a level effect as oppose to growth effect which should last long because the climate change should affect the overall productive capacity (labor productivity, physical capital and land). What we see here is a level effect which means that the shock impact will last for short period after which the production will return to its normal level after climate shock clear. Level effects are reversed when the climate shock is reversed temperature persist in the medium run; i.e., they look more like growth effects than level effects (Dell, 2008).

Figure 5.14.depicts the impact of precipitation shocks to agriculture value added. The results are showing an almost an opposite picture compared to that of temperature impact. In Figure 4, we see a positive and declining Precipitation trends to agriculture value added. Specifically, the mean response of growth is positive in a declining trend and significant until the first year and half after the shock. The positive impacts only persist for about one year and half. Precipitation in general tends to induce volatility of agricultural production in general but it shows an overall positive effect agricultural growth for SSA.

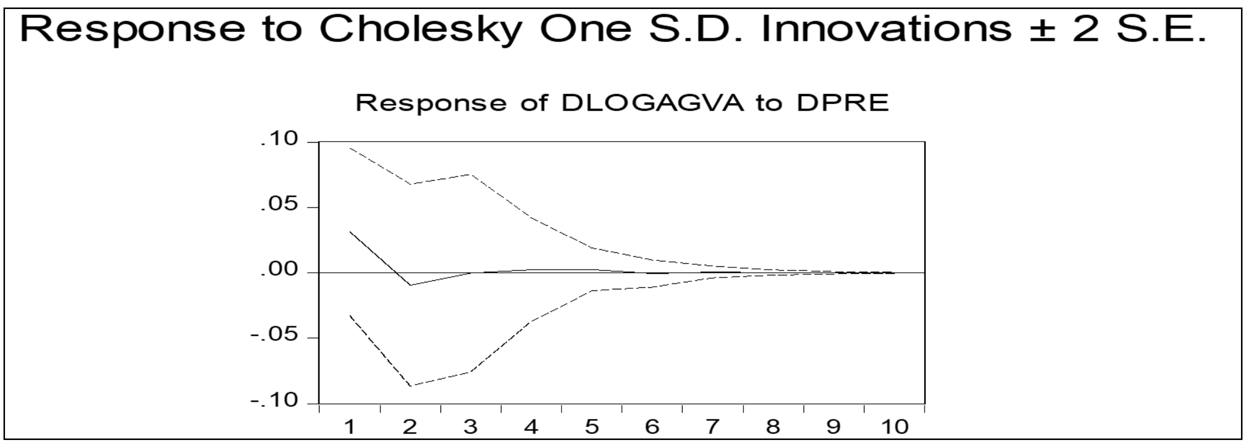

Figure 5.14.Response of Agriculture Value Added to Precipitation Shock

Model B: Using Agriculture GDP as a Dependent Variable

Figure 5.15 presents the responses of the agriculture GDP for SSA (Agricultural GDP is the Gross Domestic Product (GDP) coming from the agricultural sector) (World Bank, 2011).

In Figure 5.15 we see a negative and declining temperature impact trends to agriculture GDP. Specifically, the mean response of growth is negative in a declining trend and significant up to second period and starts to decay after the sixth year.

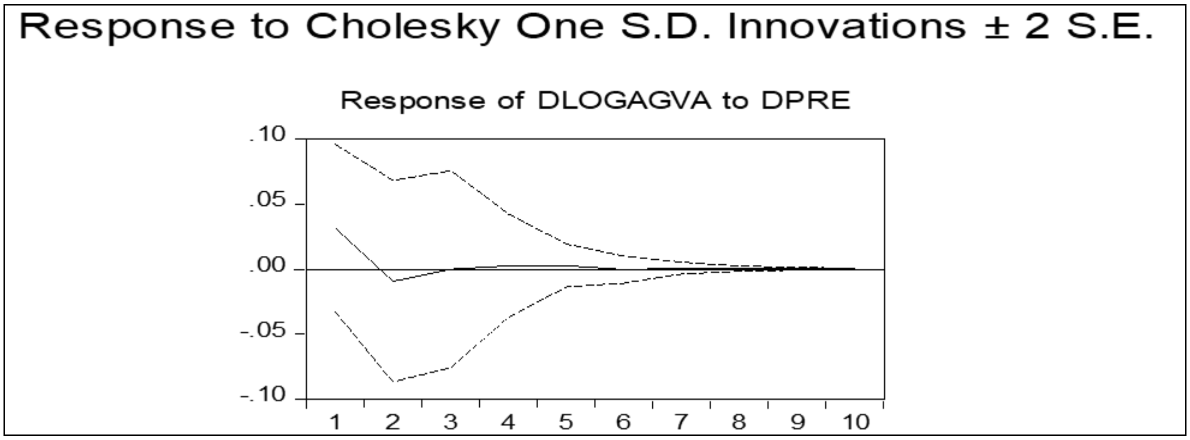

Figure 5.15.Response of Agriculture GDP to Temperature Shock

Figure 5.16.depicts the impact of precipitation shocks to agriculture GDP for SSA the results are showing an almost an opposite picture compared to that of temperature impact. The Figure shows the precipitation positive impact to agriculture GDP up to third period where it reaches its peak and starts to decline. Specifically, the mean response of growth is positive in an increasing trend. The marginal positive impacts persist for up to year ten. Precipitation in general tends to induce volatility of agricultural production in general but it shows an overall positive effect agricultural growth for SSA.

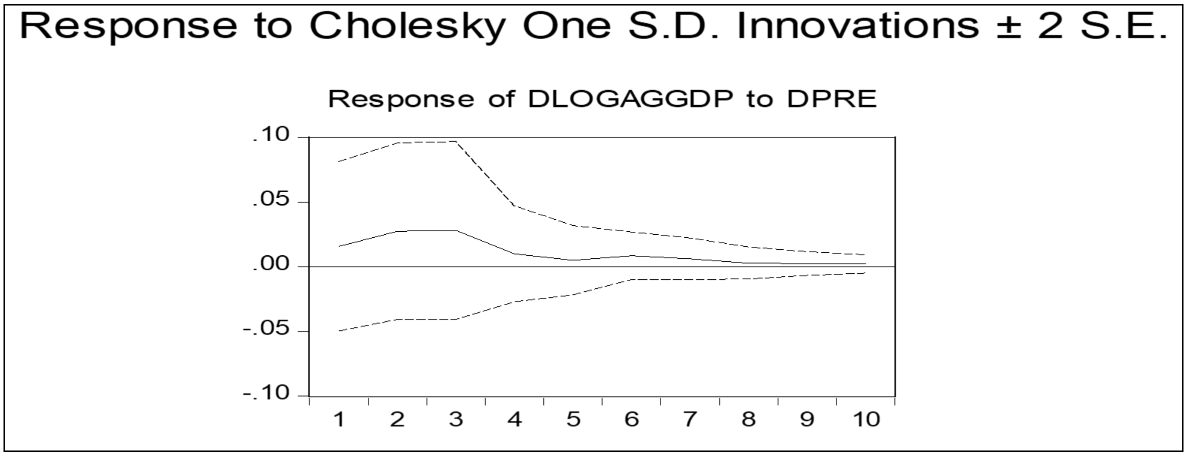

Figure 5.16. Response of Agriculture GDP to Precipitation Shock

THE ROBUSNESS CHECK (THREE VRIABLES MODEL)

TEMPERTURE SHOCKS

Figure 5.17.depicts the response of production index to temperature in the case of three variables model. Temperature shocks tend to show negative impacts on agriculture production index for the first year, the impact became positive and significant in the second year.

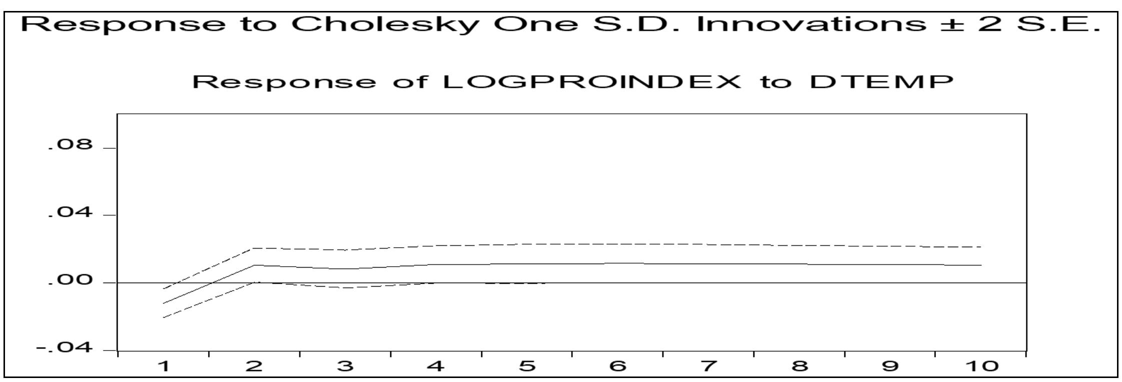

Figure 5.17.Response of Production Index to Temperature, Three Variables Model

Figure 5.18.depicts the response of production index to precipitation, in three variables model results are showing an almost an opposite picture compared to that of temperature impact. The Figure shows the precipitation has a positive and declining impact to agriculture index up to second period where it reaches its lowest point and starts to increase in positive and steady trend. Precipitation in general tends to induce volatility of agricultural production in general but it shows an overall positive effect agricultural growth for SSA.

PRECIPIATION SHOCKS

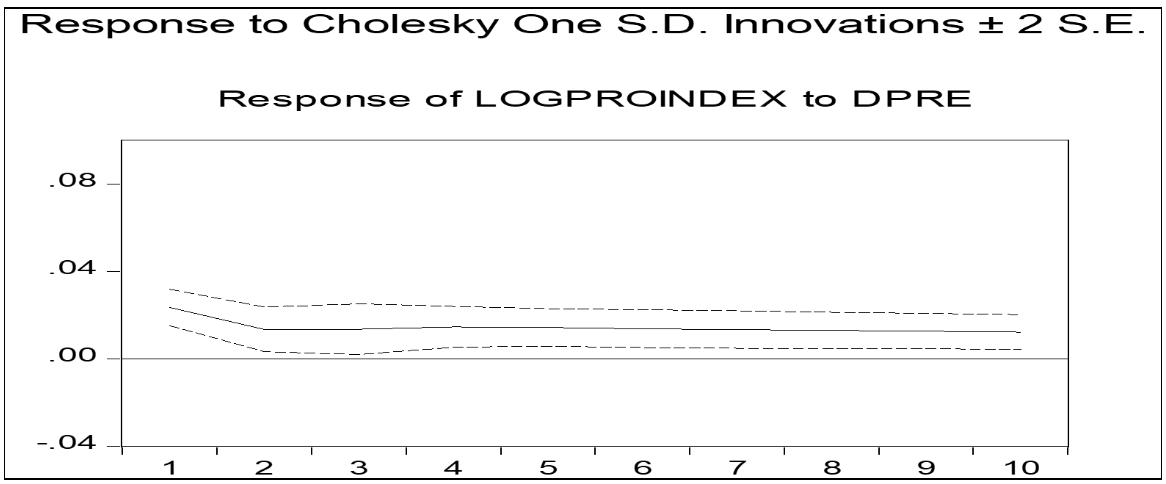

Figure 5.18.Response of Production Index to Precipitation, Three Variables Model

The effects showing a negative impact followed by positive impact and keep taking this pattern up to the eighth year. This pattern explains that the impact of temperature is just a level effect as oppose to growth effect which should last long because the climate change should affect the overall productive capacity (labor productivity, physical capital and land). What we see here is a level effect which means that the shock impact will last for short period after which the production will return to its normal level after climate shock clear. Level effects are reversed when the climate shock is reversed temperature persist in the medium run; i.e., they look more like growth effects than level effects (Dell, 2008). The effects showing a negative impact followed by positive impact and keep taking this pattern up to the eighth year. This pattern explains that the impact of temperature is just a level effect as oppose to growth effect which should last long because the climate change should affect the overall productive capacity (labor productivity, physical capital and land). What we see here is a level effect which means that the shock impact will last for short period after which the production will return to its normal level after climate shock clear. Level effects are reversed when the climate shock is reversed temperature persist in the medium run; i.e., they look more like growth effects than level effects (Dell, 2008).

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Figure 5.19.Shows, the effects showing a negative impact followed by positive impact and keep taking this pattern up to the eighth year. This pattern explains that the impact of temperature is just a level effect as oppose to growth effect which should last long because the climate change should affect the overall productive capacity (labor productivity, physical capital and land). What we see here is a level effect which means that the shock impact will last for short period after which the production will return to its normal level after climate shock clear. Level effects are reversed when the climate shock is reversed temperature persist in the medium run; i.e., they look more like growth effects than level effects (Dell, 2008).

The Growth Versus the Level effect

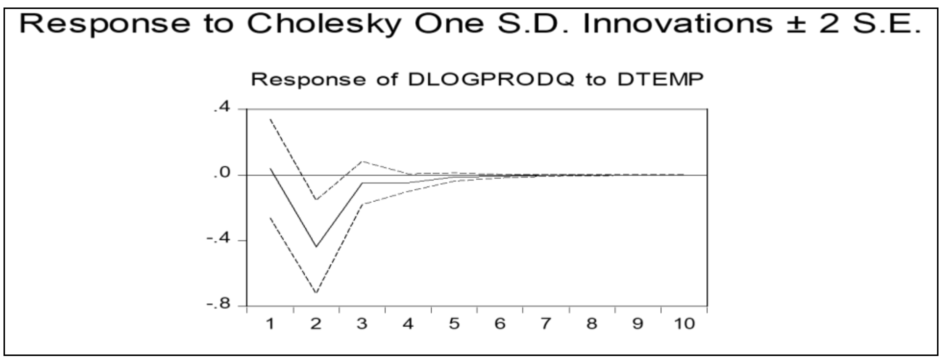

Figure 5.19.Growth vs. Level Effect: One Lag

Figure 5.20.Shows growth versus level effect in two lags model , the result indicates that regardless of lags, similar results explains the impact of temperature is just a level effect as oppose to growth effect which should last long because the climate change should affect the overall productive capacity (labor productivity, physical capital and land).

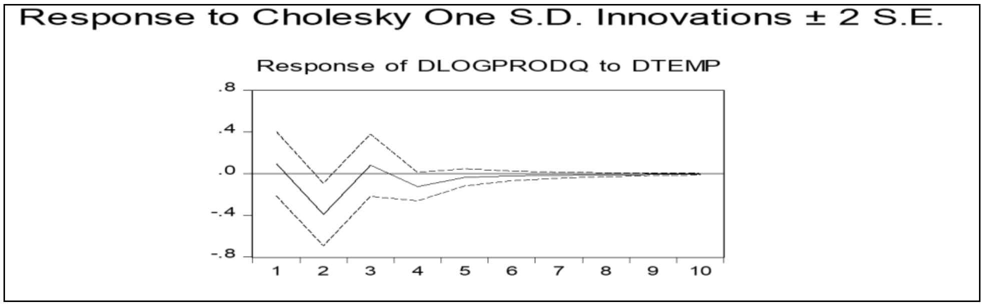

Figure 5.20.Growth vs. Level Effect: Two lags

Figure 5.21 shows the non-linear relationships between agriculture value added and temperure.(concave). Quadratic specification model, indicating that, there is an optimum level of temperure, beyond that level the agriculture production declines.

The Non-linearity Test and The Quadratic Specification Model

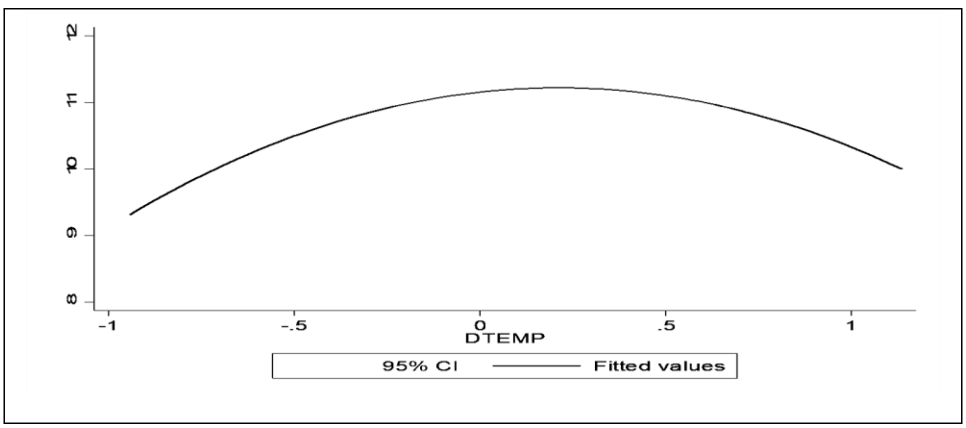

Figure 5.21.Agriculture Value Added and Temperature Non-linear Relationship

Figure 5.22.shows the non-linear relationships between agriculture value added and precipitation (convex). Quadratic specification model, indicating that, there is an optimum level of precipitation, beyond that level the agriculture production declines.

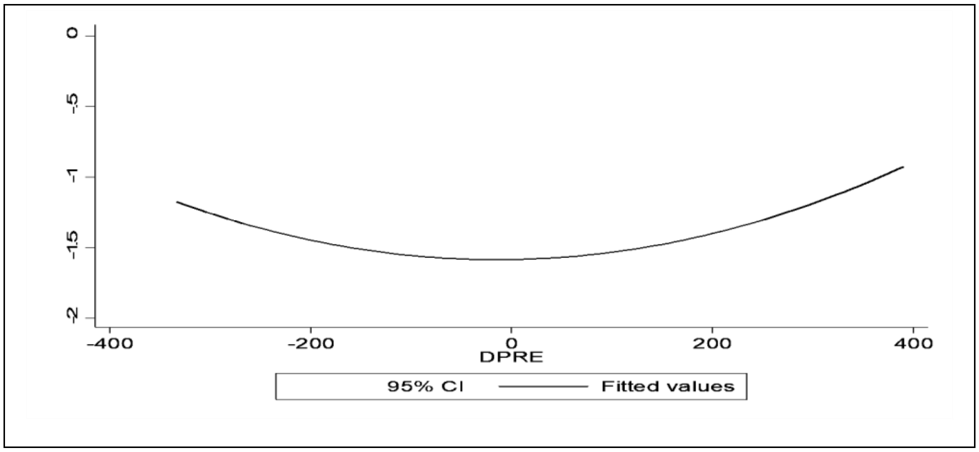

Figure 5.22.Agriculture Value Added and Precipitation Non-linear Relationship

5.2.6.5 The Granger Causality Wald Test

In theory, the idea behind the granger causality is as follows:

We can test for the absence of Granger causality by estimating the following VAR model:

$$Y_t = a_0 + a_1Y_{t\text{-}1} + ... + a_pY_{t\text{-}p} + b_1X_{t\text{-}1} + ... + b_pX_{t\text{-}p} + u_t \quad (1)$$

$$X_t = c_0 + c_1X_{t\text{-}1} + ... + c_pX_{t\text{-}p} + d_1Y_{t\text{-}1} + ... + d_pY_{t\text{-}p} + v_t \quad (2)$$

Then, testing H_0: $b_1 = b_2 = ... = b_p = 0$, against H_A: 'Not H_0', is a test that *X does not* Granger-cause *similarly*, testing H_0: $d_1 = d_2 = ... = d_p = 0$, against H_A: 'Not H_0', is a test that *Y does not* Granger-cause *X*. In each case, a *rejection* of the null implies there is Granger causality.

The VAR can be considered as a means of conducting causality tests, or more specifically Granger causality tests. Granger causality really implies a correlation between the current value of one variable and the past values of others; it does not mean changes in one variable cause changes in another. From Table 5.27, it is clear that the precipitation variable (DPRE) granger cause logprodindex, as shown the value is less than 5% significance level to be exact (0.029), we can strongly reject the null of no granger causality. On the other hand, the temperature variable (DTEMP) does not granger cause logprodindex, at 5% level, but it does at 10% level of significance, according to its significant value of (0.078).

Table 5.27.

The Granger Causality Wald Test

Equation\Excluded	chi2	df	Prob > chi2
dlogproindex			
dlogferti	3.872	1	0.049***
dlogmachine	6.453	1	0.011***
dloglive	2.900	1	0.089*
DTEMP	3.196	1	0.074**
DPRE	4.741 1	1	0.029***
All	15.864	4	0.003***

Notes: * and *** indicate significance at 10% and 1% levels, respectively

5.2.6.6 The Model Stability Test

Baseline Model Stability Diagnostic Test

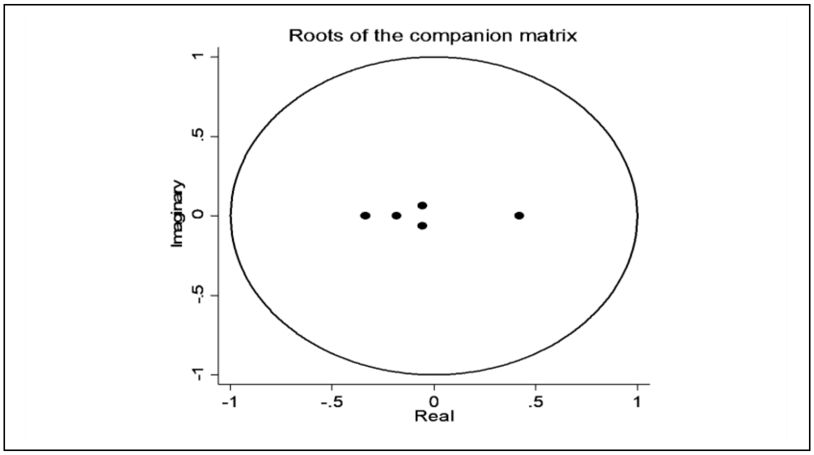

Figure 5.23.Model Stability

Table 5.28

Model Stability Eigen Value

Eigenvalue		
Real	Imaginary	Models
.4195876 0	0	.4195876
-.3370512	0	0 .337051
-.1826059	0	.1826059
-.0568725	-.0629759	.0848555
-.0568725	.0629759	.0848555

Note. Own calculation

The Robustness Check

pvar dlogproindex dlogferti dlogmachine dlogland DTEMP DPRE, lag(1)

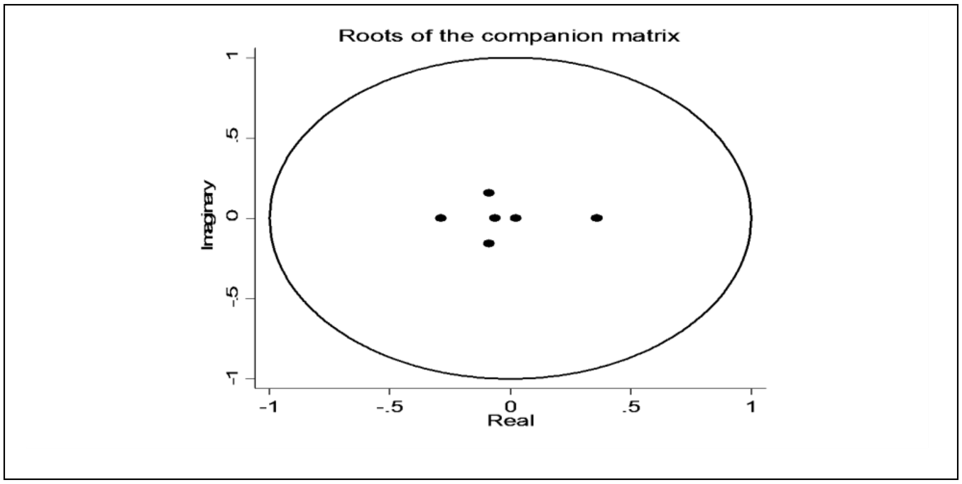

Figure 5.24.Alternative Specification Model Stability

Table 5.29.

Model Stability

Eigenvalue		
Real	Imaginary	Models
3590563	0.0000	.3590563
-.287249	0.0000	.2872498
-.089109	- .156000	1799072
-.089109	-.156000	1799072
-.062854	0.0000	.0628543
. 021968	0.0000	.0219680

Note. Own calculations

The Model passes all the stability tests by confirming that all eigenvalues lie inside the unit circle which means that the model has satisfied the stability condition for pVAR model. As mentioned earlier the main advantage of using PVAR is its ability to not to provoke serial correlation and preserve homoscedasticity of the variables intact

Conclusions

In Summary, this chapter intended to present clearly overall findings of the study. In the first part of the chapter, model one which is estimating the relationship between climatic variables and crop yield in some selected SSA is presented. In this presentation, we started with showing the of the pre-estimation testing results, such as variables definition and sources of information, descriptive statistics of the variables used in the study, and correlation matrix between variables used in this part of the study. Unit root and co-integration tests are presented in full details in this section.

In the second part of the chapter the results of baseline model specification are presented in more details (model A), followed by introduction of different specification to check the model robustness (Model B and C). At the end, the diagnostic tests to check the viability of the model in different set up are conducted and their all result presented. Model two which is intended to capture the relationship between climate change and overall agriculture output followed the same format of model one.

CHAPTER 6 RESULTS AND DISCUSSION

6.1 Model One: Impact of Climate Variability on Crop Yield in SSA

The main objective of model one of this study, was to evaluate the effects of climate changes on yield for two main crops of SSA countries using disaggregated data. Balanced panel data models were used to achieve the objective of the study.

This model intended to answer empirically the following three basic questions;

1. Does a climate variables variation affect crop yield variability in SSA?
2. Does climate variables variations affect crop yield in SSA linearly or non-linearly?

6.1.1 Maize Yield Function

The definition of variables for model one (Maize and Millet) is presented in List A.1 and A.2 (See the Appendix). Table 5.1. is descriptive static for Maize model, and table 5.6 is for descriptive for Millet model. Table 5.2. and 5.7. are the correlation matrices for the variables in Maize and Millet models respectively. The correlation matrixes do not show unusual or strange noise. The Unit root tests presented in Tables 5.11 and 5.12 for Maize and Millet model respectively. The test results in general show evidence of stationarity in all the variables used in the model except harvested area (ha), which turns stationary after first differenced.

6.1.1.1 The Maize and Millet Yield Function (Cobb Douglass)

The baseline specification model is consisting of model A1 which is intended to estimate the Maize mean yield using Cob Douglass framework. Model B following same manner and used to estimate Millet mean yield function. The results for baseline model (A and B) are presented in Tables 5.13, and 5.16 respectively.

In baseline models (A1 and B1) **Maize and Millet function** model are estimated using **Cobb Douglass** specification. In tables 5.14 and 5.17 (mean model summary) the results indicate that (**0.16**%) of the variability in Maize yield is explained by the independent variables, and (**0.27%**) of the variability in the Millet yield is explained by the independent variables.

Both models F-statistic and the probability test confirmed the fact that both models are reliable. Individual predictors are all significant at the 95% confidence interval although entire model is fit for the purpose of explaining the variation in Maize and Millet yield. Crop yield is a dependent variable, whereas, harvested area, temperature and precipitation are independent variables, assumed to impact crop mean yield function. Maize yield had a positive relationship with harvested area (Ha), the estimates of the coefficients of harvested area (Ha) in Maize and are positive and significant, they are **(0.496) (0.0000)** for Maize model and positive and in insignificant for the Millet Model **(0.05) (0.352)** .This result of Cobb Douglass functional form should be measured as elasticity, because the model functional form is log-log form.

The results imply that increase in harvested area has positive impact on mean yield. The results show that a 1% increase in crop area will significantly increases Maize yield by **(0.49%)** and Millet yield by (**0.05**). In the literature, many studies on impact of climate change in Africa came with different results indicate that Maize yields decrease as the area cropped increases due to decreasing marginal land productivity. In our case Increasing area under Maize and Millet production increases yields marginally, this is possibly since the marginal land used in production is inferior in quality. These results are similar to the findings of Boubacar (2010).

Rainfall as expected to have a positive and significant effect on Maize mean yield, a 1% increase in precipitation will significantly increase Maize yield by **(0.0006%)** and significantly increase Millet yield by **(0.00049%).** This result in line with the study by Omoyo and others on

Kenyan Agriculture climate impact have shown that the more reliable rainfalls the more yield for the Maize which implies that the less the rainfall fluctuations the less Maize yield variability thus stable rainfalls is good for Maize production (Omoyo et al 2015). The results appear to support the view of International Institute of Topical Agriculture (IITA) annual report for 2004.Ibadan, Nigeria: International Institute for Tropical Agriculture; 2004,this report shows that that higher variations in rainfall above the mean eventually leads to fluctuations in Maize yields and thus food insecurity. Another study on “The effects of drought on crop yields and yield arability in Sahel” which is more related to our study and focuses more on African Sahel, the study shows that the precipitation intensity variable has a negative coefficient and is statistically significant at 1 percent level. This result indicates that a poor temporal spread of rainfall is harmful to crop (Boubacar 2010) many other studies found that higher rainfall is found to be increasing Millet yield (Gupta 2016) and (Blank 2011).

Some other studies justify, the non-significant results stating that precipitation shocks could come in different frequency and duration (which offset some of the benefits from more precipitation). For example, heavy rainfall may result in floods. Floods could reduce seeded area; changing the time of seeding and harvesting for crops (Kulshreshtha 2011). Heavy precipitation could also damage infrastructure (e.g., the transportation sector, such as roads and railways). For example, the 2010 South Africa floods are estimated to have resulted in damages of $284 million including damage to farm infrastructure and lost crops (Government of South Africa2011).

Temperature, on the other hand has a negative and insignificant impact on mean Maize yield, a 1% increase in temperature will insignificantly decreases Maize yield by **(-0.004%)** and insignificantly decreases Millet yield by **(-0.006%).** These results in line with Schlenker and Roberts (2009) who reported that increased Maize yield with an increase in temperature up to

29°C followed by a sharp decline in yield with further temperature increases., Liu et al. (2008) indicated that the best Maize-growing temperature is 25°C. Lobell et al. 2011 found that any degree above 30°C can negatively affect Maize yield (Lobell et al. 2011). Other report suggests that a 1°C increase above norm reduces Maize yield by 10% (Brown 2009). Using worldwide temperature and yield trends, Lobell and Field (2007) reported a decrease of 8.3% in Maize yield per 1°C rise above normal. Many major studies confirm this result; higher temperature reduces crop yields, on an average. (Gupta 2016) According to Blanc, temperature has a negative and significant effect in the SSA regression and the impact of temperature is equal across countries (Blank 2011).

Time trend is positive and significant on Cobb Douglass both crops models. Both temperature anomaly (TA) and Flood have negative impact on Maize yield.

6.1.1.2 The Maize and Millet Yield Function (Linear quadratic)

The readings of results for the log-level model base on this formula, if we change x by 1 (unit), we expect our y variable to change by 100·β1 percent, we have to multiply every level variable by a 100.

In the quadratic model, the result shows that a 1% increase in crop area harvested will significantly increases mean Maize yield by **(0.48%.),** and increases Millet yield insignificantly by (**0.05%).** The model shows a 1% increase in precipitation significantly increases Maize yield by around **(0.50%)** and significantly increases Millet yield by **(0.40%).** This result confirms the Cobb Douglass specification in Maize model which came to the same conclusion that both harvested area and precipitation have positive and significant impact on both crop yields.

The time trend variable is a positive and statistically significant in the Cobb Douglass and the quadratic function in both crops as well. This implies that crop yields increase over time due to technological progress such as improved irrigation coverage, expansion of high yielding varieties (HYVs) and increased use of fertilizer. These latter results are in line with the findings of Anderson and Hazell (1987), Isik and Devadoss (2006) and Kim and Pang (2009).

In the quadratic model Temperature on the other hand as expected has a negative but insignificant impact on Maize yield, and has a negative and insignificant impact on Millet yield. This implies that a 1% increase in temperature will insignificantly decreases Maize yield by around **(-0.2%), a** 1% increase in temperature will significantly decreases Millet yield by around (-6.0%)**.**These results in line with Schlenker and Roberts (2009) who reported that increased Maize yield with an increase in temperature up to 29°C followed by a sharp decline in yield with further temperature increases.

These results in line with Muchow et al. (1990) studied the effect of temperature in Maize yield in the United States, where mean daily temperature between 18°C to 29°C, the study reported a 2°C rise in temperature lead to around 4–8% yield reduction and a 4°C rise in temperature lead to around 8–16% yield reduction with. Quantitative projections show both negative and positive impacts of climate change on Millet yield. The different results can be due to the difference in scenarios, difference in timeframe and different model assumptions (Ringler et al. 2010).

The quadratic terms used in this model to check the non-linearity of the relationship between mean crop yield and climatic variables. The quadratic term of the precipitation in Maize model is a negative and significant with coefficient of **(-1.27E-04).** This result implies that precipitation impact on Maize yield according to this study data sample and timeframe is non-linear, in fact it is a concave curve since the quadratic term is a negative and non-quadratic term of precipitation is a positive. For the Millet function, the quadratic term of the precipitation in is a negative and significant with coefficient of (**-1.42E-04).** This result implies that precipitation impact on Millet yield according to this study data sample and timeframe is non-linear, in fact it is a concave curve.

This result somewhat differs with Aye who did similar study on Nigerian grain yield and came to the following conclusion" Precipitation has a negative impact on the mean Maize yield, however, only the square of temperature is statistically significant. Whereas temperature is positively and significantly related to the mean Maize yield, its square is negatively and significantly related to mean Maize yield" (Aye 2012). Another interesting study by Thornton & Cramer, 2012 indicated that increasing mean growing season temperature does not seem to be the major problem for crop production. Instead, rising temperature becomes a problem to crop production after some critical level, indicating the commonly found bell-shaped relationship. The literature suggesting that, increments in the maximum and minimum growing season temperature may be more critical for development of Maize and rice crops (Thornton & Cramer, 2012).

Based on these studies, Millet is more resilient to climate change than Maize or wheat but less resilient than sorghum. It is expected that there will be about a 15% yield loss in East Africa by the middle of the century. Most recent major study conducted by MIT in 2017, across most of the continent, the researchers found most of the climate models agreed on the direction of change in Maize production due to climate change. Under the worst-case scenario, in which global temperatures will rise by 4 degrees Celsius, these models estimate the Sahel and southern Africa will experience widespread yield losses, with some grid cells showing losses of up to 50 percent.

The most pessimistic simulation runs predict a 30 percent reduction in Maize production in southern Africa by 2090, with losses in Zambia reaching 40 percent (Dale et al. 2017).

Our basic results tests for these variables confirm the assertion. Maize and Millet in SSA respond non-linearly to precipitation. Nonlinear relationship between temperature and yield is not detected implies that more heat is always harmful to crop yield. The generally negative coefficients of the squared precipitation or temperature variables indicate that the relationship between crop yield and climate is inverse U-shaped. Many major studies concluded that, extreme temperature that is higher than 32 degree Celsius (i.e., overheat degree days) during the growing season is found to be harmful for corn and other crops yield. This result is consistent across all the yield model specifications. The relationship between precipitation and Maize or Millet yield seems likely to be concave. This relationship implies that there is an optimal level of minimum required level of precipitation, any increase or decrees from that level would reduce yield per hectare.

The interaction term between the precipitation and the temperature in the quadratic mean yield function for Maize is negative and statistically significant. This implies that temperature and precipitation are not independent, this result agree with Aye 2012 study on Nigerian grains (Aye 2012).Interaction between precipitation and quadratic temperature on Maize is a positive meaning that excessive temperature up to certain level will have positive impact on Maize yield. But the Interaction between precipitation and quadratic temperature on Millet is a negative meaning that excessive temperature up to certain level will have negative impact on Millet when interacting with precipitation.

The temperature and quadratic (excessive) precipitation in Maize function is a positive and significant implies that the positive impact of excessive rain can reduce the negative impact of high temperature. The interaction between quadratic temperature (excessive) and precipitation is insignificantly positive, implies that more rain can reduce the negative impact of heat on Maize yield. In Millet model interaction term between rain and temperature is positive and significant. The interaction between the temperature and quadratic (excessive) precipitation and precipitation and (excessive) temperature in Millet function are significantly negatives implies that there is a negative reaction of one variable to any excessive amount of the other.

Both quadratic interaction terms are negative and significant. Both mean yield function for Maize and Millet are concave and statistically significant. This implies that temperature and precipitation are not independent. There is optimal level of both temperature and precipitation when they react with each other for the yield to reach its maximum, beyond that level the yield starts to decline. Temperature anomaly TA has significant negative impact on Maize yield and Flood has significant positive impact on the yield. Temperature anomaly TA has significant positive impact on Millet yield and Flood has significant negative impact on the yield.

6.1.2 The Research Findings for Model One

The findings of this study should empirically provide insightful answers to the research questions. Firstly, the study raised the question, "Does climate change variables variations affect crop yield variability in Sub-Saharan African countries (SSA)?" This study has shown beyond any reasonable doubt that the variability of climatic variables has significant impact on Maize and Millet yield functions. Using Cobb Douglass functional form, Rainfall as expected has a positive and significant effect on Maize yield, a 1% increase in precipitation will significantly increase Maize yield by (0.0006%) and significantly increase Millet yield by (0.0005%).

For the quadratic model, Rainfall as expected has a positive and significant effect on Maize yield, a 1% increase in precipitation will significantly increase Maize yield by (0.005%) and significantly increase Millet yield by (0.004%). Generally temperature is found to be negatively insignificant in both model Maize and Millet functions. Secondly, the study asked this question “Does climate change variables variations affect crop yield in SSA, linearly or non-linearly?” .From the literature review we have shown that, the effects of weather conditions on crop yields are not simple linear relationships (Deschene and Greenstone, 2007; Schlenker and Roberts, 2009).

Most recent studies have adopted a non-linear specification for each climate variable where linear and quadratic terms are used as repressors, reflecting the effect of a physiological optimum for crop yield (Yingjie, 2008; Chang, 2002; Schlenker et al., 2009). This approach also allows a non-monotonic relationship between climate and yield; warming might increase crop yields in cooler areas but decrease yields in warmer regions (Segerson and Dixon, 1999).

Crop yields are expected to increase over time because of technological innovations such as the adoption of new varieties, improved application of fertilizers and irrigation, and expansion or contraction of crop acreage. Technological innovation is usually represented by a linear or quadratic time trend in empirical studies (Choi and Helmberger, 1993; Kaufmann and Schnell, 1997; Mc Carl et al., 2008).

Our basic results tests for these variables confirm the assertion. Maize and Millet in SSA respond non-linearly to precipitation. Nonlinear relationship between temperature and yield is not detected implies that more heat is always harmful to crop yield. The generally negative coefficients of the squared precipitation or temperature variables indicate that the relationship between crop yield and climate is inverse U-shaped.

Many major studies concluded that, extreme temperature that is higher than 32 degree Celsius (i.e., overheat degree days) during the growing season is found to be harmful for corn and other crops yield. This result is consistent across all the yield model specifications.

The relationship between precipitation and Maize or Millet yield seems likely to be concave. This relationship implies that there is an optimal level of minimum required level of precipitation, any increase or decrees from that level would reduce yield per hectare. The sole purpose of using quadratic terms in this study is to check the non-linearity assumption of the relationship between mean crop yield and climatic variables. See table 6.1 for summary of the non-linear relationship.

Table 6.1.The Non-lineal Relationship Between crop Yield and Climatic Variables

Maize	Non-Quadratic-term	Quadratic term	Functional Form
Precipitation	0.005	-01.27e-06	Concave
Millet			
Precipitation	0.004	-1.42e-06	Concave

Source: Own Calculations

6.2 Model Two: The Impact of Climate Change on Overall agriculture Production

Model two intended to estimate the climate change impact on overall agriculture production measured by net production index, agriculture GDP, production quantity and agriculture value added, in 15 Sub-Saharan African countries, the study covers the period 1980-2008, major inputs such as land, capital, fertilizers and livestock along with temperature and precipitation variables were used in this model to estimate the climate impact on agriculture output. The model estimation should be able to answer the following questions;

1. Does climate variables variation affect overall agricultural output in SSA?
2. Does climate change affect the growth rate or just the level of output in SSA OR both?

This model, consist of three different specifications; model A is the baseline model, where we use net production index as dependent variable. In Model B, and C, we use different dependent variables and change climatic variables to check for robustness of the model.

The model used in the study is the panel Vector Autoregression mode (P-var) that is proved to be more efficient in estimating the dynamic relationships. In this study, PVAR model will be used to estimate the agriculture production (output) and some climate variables for some Sub-Saharan African countries. The definition of variables for model two is presented in List A1 (See the Appendix). Table 5.18 is descriptive statistics for the model and 5.19 is the correlation Matrix. The correlation matrixes do not show unusual or strange noise. Unit root tests presented in Tables 5.18, the unit root test results show that, all variables except climate variables need to be first differenced to be stationary. The co-integration test results provided in tables 5.21 and 5.22

6.2.1 The Baseline Model Production Index as a Dependent Variable

In this section, the model results of the baseline model will be presented. Firstly, table 5.25 shows the main result of GMM estimation of panel var (PVAR) baseline model, where the production index is used as the dependent variables regressed against some inputs variables a long with climatic variables. In Table 5.25 we have estimated first the panel of 15 Sub-Saharan African countries using five variables panel VAR model. For the baseline model, we have found significant positive effect from temperature and significant negative effect from precipitation to agriculture production index. The result show that the use of fertilizers and machinery both have negative significant impact on agriculture production index, whereas, Livestock has positive significant effect on agriculture production index for SSA countries. This result agrees with study of Fisher and Velthuizen (1996), who reported that the climate change impact on Kenya has shown that higher temperatures would have a positive impact in highland areas. On the other hand Downing (1992) shows that in western Kenya, an increase in temperature by 2.5° C will lead to an increase of 67 percent in high potential land. Indeed, this results also somewhat different from a study conducted by Odusola of UNDP and Abidoye of University of Pretoria using annual data for 34 countries from 1961 to 2009; this study did find a negative impact of climate change on economic growth in Africa. Their results show that a 1 degree Celsius increase in temperature reduces GDP growth by 0.27 percentage point for the region. A higher impact of 0.41 percentage point was however observed when the sample period was reduced to 1961 to 2000 indicating a reduction in the influence possibly given increase in efforts towards adapting to climate change. The two largest economies in the Sub-Saharan Africa (South Africa and Nigeria) played some significant role in ameliorating the negative economic impact of climate change in the region according to the above mentioned study. (Odusola and Abidoye 2015)

Table 5.26. explains the Variance Decomposition Function (VDF) for baseline model. This function provides explanation to variation in one variable that caused by another variable and explain the degree of such impact. Hence, we find from the results of our models that all variables explain most of the variation in themselves and explanatory power of the variables had been affected by change in the ordering of the variables. Results from FEDV also indicate that temperature explains about **(2.00)** percent at the beginning of the period and reach about **(6.00)** percent in period two up to the end of period ten and precipitation explains about **(0.55)** percent

at period one and reach about (**7.00**) up to the end of the period fraction of the agriculture production index.

Impulse Response Functions: **Model 1 Baseline Model**

In the baseline model specification agriculture production index (dlogproindex) will be used in its log and first differenced form as a dependent variable to present the response of agriculture production to the shock of climatic variables. The model will be presented with one lag. For robustness check we will use different climate variables and different lag structures later. Figure 6.1.presents the responses of the agriculture production index to temperature shocks.

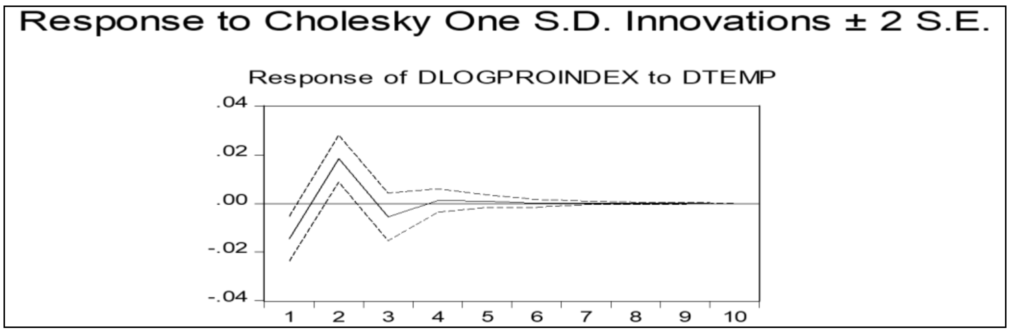

Figure.6.1. Response of agriculture production index to temperature shock

In the Figure, temperature shocks tend to show negative impacts on agriculture production index for the first year, the impact became positive and significant in the second year. The shocks tend to introduce similar response patterns and short-lasting impacts for agriculture production index. The effect is significant in the first period of the shock but becomes insignificant only for agricultural production after that, which indicates the sensitivity of agriculture to temperature shocks. It becomes more significant in about one year after the event, showing the presence of delayed effects. The peaks of the impacts appear after third year from the beginning of the shock. The effect showing a negative impact followed by positive impact and keeps taking this pattern up to the six years. Figure 6.2.depicts the impact of precipitation shocks to agriculture production index.

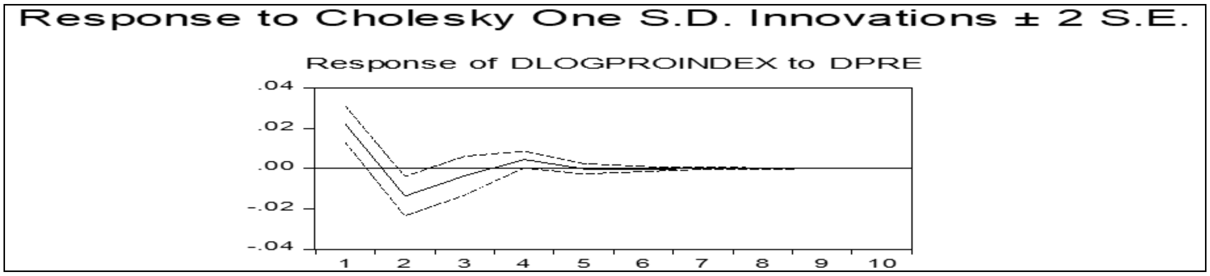

Figure 6.2.Response of agriculture production index to precipitation shock

. The results are showing almost an opposite picture compared to that of temperature impact. Precipitation shocks tend to induce volatility of agricultural production in general but an overall positive effect agricultural growth. Specifically, the mean response of growth is positive in a declining trend and significant until the first year and half after the shock. The positive impacts only persist for about one year and half, afterword become negative up to the second year and then starts in positive direction for up to fifth year. This result agrees with Belloumi study which clearly showed that the precipitation affects positively agricultural production in Eastern and Southern African countries. (Belloumi 2014)

6.2.2 Model B: The Agricultural Value Added as a Dependent Variable

As a robustness check we use agriculture value added as a dependent variable. Figure 6.3.presents the responses of the agriculture value added to change in temperature.

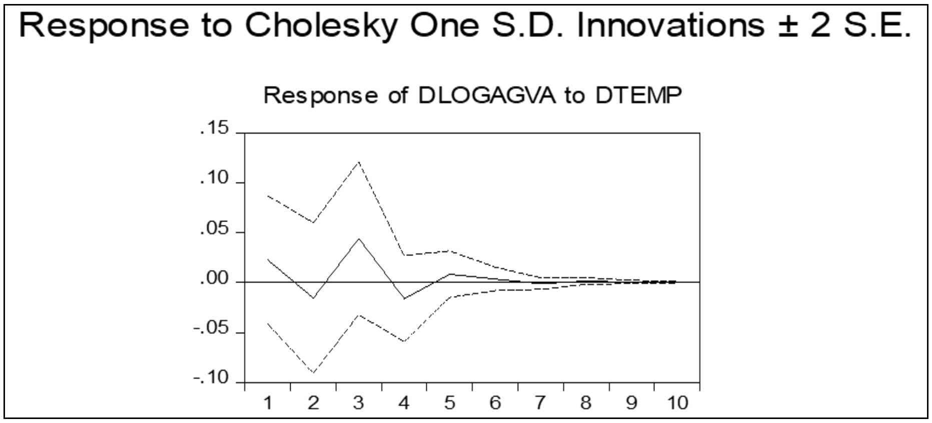

Figure.6.3. Response of agriculture value added to temperature shock

Temperature shocks tend to show negative impacts on agriculture value added for the first year, the impact became positive and significant in the second year. The shocks tend to introduce similar response patterns and short-lasting impacts to agriculture production index. Figure 6.4 depicts the impact of precipitation shocks to agriculture value added.

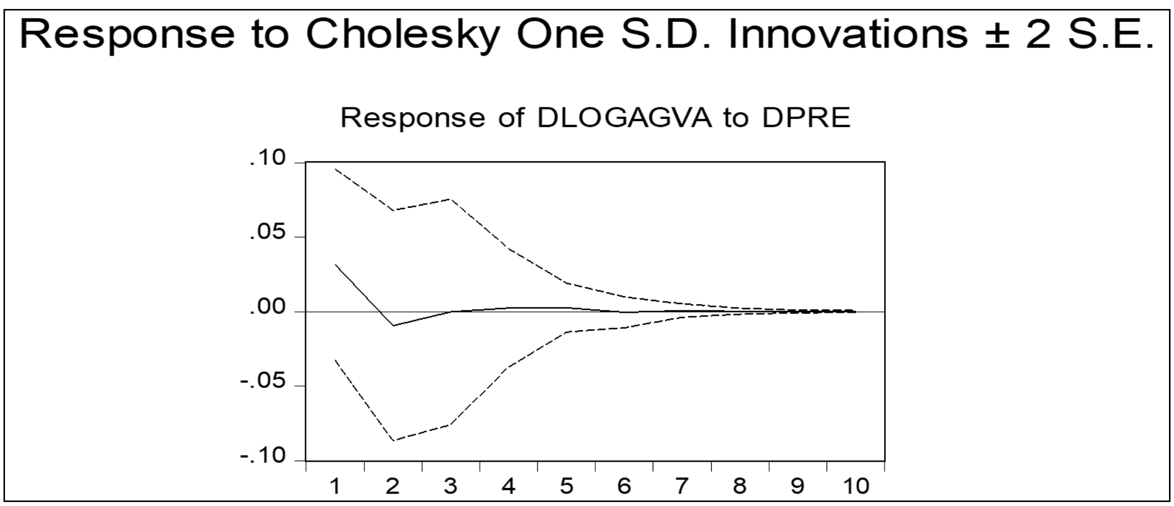

Figure 6.4.Response of agriculture value added to precipitation shock

The results are showing an almost an opposite picture compared to that of temperature impact. In Figure 6.4. we see a positive and declining Precipitation trends to agriculture value added. Specifically, the mean response of growth is positive in a declining trend and significant until the first year and half after the shock. The positive impacts only persist for about one year and half. Precipitation in general tends to induce volatility of agricultural production in general but it shows an overall positive effect agricultural growth for SSA.

6.2.3 Model C: The Agriculture GDP as a Dependent Variable

In Figure 6.5., we see a negative and declining temperature impact trends to agriculture GDP. Specifically, the mean response of growth is negative in a declining trend and significant up to second period and starts to decay after the sixth year.

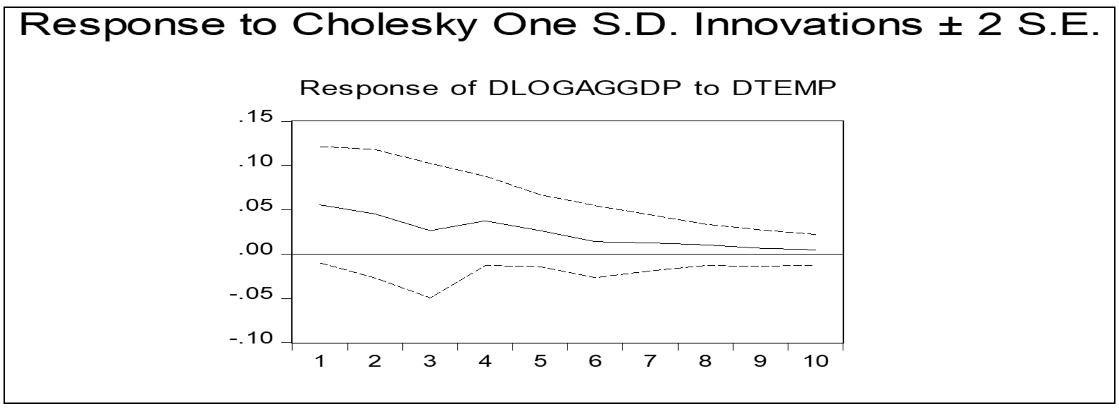

Figure 6.5.Response of agriculture GDP to temperature shock

Figure 6.6.depicts the impact of precipitation shocks to agriculture GDP for SSA the results are showing an almost an opposite picture compared to that of temperature impact.

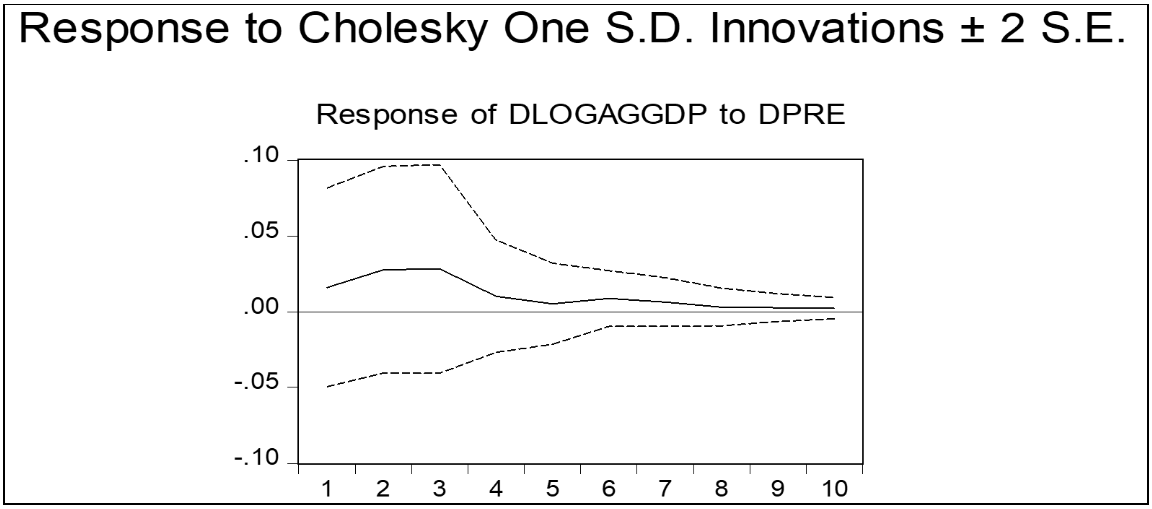

Figure 6.6.Response of agriculture GDP to precipitation shock

The Figure shows the precipitation positive impact to agriculture GDP up to third period where it reaches its peak and starts to decline. Specifically, the mean response of growth is positive in an increasing trend. The marginal positive impacts persist for up to year ten. Precipitation in general tends to induce volatility of agricultural production in general but it shows an overall positive effect agricultural growth for SSA.

6.2.4 The Research Findings for Model Two

The findings of this study should empirically provide insightful answers to the research questions. Firstly, model two should be able to answer these two questions;

1. Does climate variations affect overall agricultural output in SSA?
2. Does climate change affect the growth rate or just the level of output in SSA OR both?

This study clearly has shown that the variability of climatic variables has significant impact on overall agriculture output in SSA countries.

The Null Hypothesis of the first baseline model was

$$H0 = \beta_1=\beta_2=\beta_3=\beta_4=\beta_5=0$$

The model results indicated that the null hypothesis can be rejected at any significant level. The Alternative hypothesis HA = $\beta_1 \neq \beta_2$ (at least one of the independent variable is not equal to zero hence is significant) is accepted almost in all specifications. We have estimated the panel data model of 15 Sub-Saharan African countries using five variables panel VAR model. For the baseline model, we have found in the short run a significant positive effect from temperature and significant negative effect from precipitation to agriculture production index. The result has shown that the use of fertilizers and machinery both have negative significant impact on agriculture production index, whereas, Livestock has positive significant effect on agriculture production index for SSA countries. The research findings of this study should empirically be able to answer the following research question;

1. Does climate variables variation affect overall agricultural output in SSA?

The null hypnosis is clearly rejected in the model; both climate variables are rejected at 5 percent significance level. The Alternative hypothesis HA = $\beta_1 \neq \beta_2$ (at least one of the independent variable is not equal to zero hence is significant) is accepted almost in all specifications. There is enough evidence showing that there is climate variables temperature and precipitation effect on overall GDP in SSA countries. The robustness check provided further evidence to support this argument; we use different variables to define agriculture output as a dependent variable. Agriculture value added is used in model B and agriculture GDP is used in mode C. In both cases climate variability found to have significant impact on agriculture production in SSA countries.

The research findings should provide enough evidence to further answer the following question;

2. Does climate change affect the growth rate or just the level of output in SSA OR both?

Temperature shocks tend to show negative impacts on agriculture value added for the first year, the impact became positive and significant in the second year.

The shocks tend to introduce similar response patterns and short-lasting impacts to agriculture production index. The effect is significant in the first period of the shock but becomes insignificant only for agricultural production after that, which indicates the sensitivity of agriculture to temperature shocks. It becomes more significant in about one year after the event, showing the presence of delayed effects. The peaks of the impacts appear after third year from the beginning of the shock. The effect showing a negative impact followed by positive impact and keeps taking this pattern up to the eighth year.

This pattern explains that the impact of temperature is just a level effect as oppose to growth effect which should last long because the climate change should affect the overall productive capacity (labor productivity, physical capital and land). What we see here is a level effect which means that the shock impact will last for short period after which the production will return to its normal level after climate shock clears. Level effects are reversed when the climate shock is reversed, if temperature impact persists in the medium run; they look more like growth effects than level effects as explained by Dell (Dell, 2008).

The Policy Implication

Potential impacts of climate change on agricultural productivity and associated social and economic costs are at the core of the current debate at global level**.** The analysis presented in this study has important policy implications. Production of Millet and Maize have declined in many parts of SSA in the past few decades due to increasing water stress, arising partly from increasing temperatures and rainfalls volatility. In turn, this will increase vulnerability of poor rural farmers, especially in the arid and semiarid tropics in addition to implications for food security (Bates et al. 2008). Given that agriculture is a major source of livelihood for farmers in SSA, increasing yield variability will have serious consequences for SSA economies.

Hence, it is highly recommended to undertake sensible policies to mitigate and adapt to climate change impacts on agricultural sector to the possible extent. The literature review has shown that the degree of projected impacts of climate change on agriculture in SSA varies widely among different studies. The differences in models results due mainly to using different set of variables and different model assumptions, it is more productive to streamline a methodological framework to study climate change at least within an African context.

The current and projected trends in climate variations and volatility eventually will lead to a serious food shortages and food insecurity within African region. Therefore African policy makers in Africa need to act in a timely manner and take the necessary actions needed to reduce the consequences of the climate change on poor population in the region.

This study observed some variations in crops yield due to the climate variations, such results should be used as a basis for further comprehensive studies and policy actions that aim to reduce such variabilities. Different aspects of climate variability—temperature, precipitation, and the interaction of the two—may affect crop growth and productivity in different manners.

African policy makers should seek international help in forms of financial and technical assistance to deal with extreme variations in climate. African policy makers should enforce environmental laws and regulations that will encourage people to plant tree which helps to regulate the local climate change through absorbing the excess amount of carbon dioxide in the atmosphere. It is also recommended that efforts should be made to increase the cultivation of crops on which the impacts of climate on their yield is minimum. Research should be conducted on the reproduction of more improved seeds that that will tolerate heat waves in the study area which is likely to occur in the near future.

Limitations of this study are that the country level data might not reflect true picture of the impact of climate change on different agro ecological zones. Therefore, to show the regional differences, studies at regional level should be conducted.

Conclusions

This study investigated rainfall and temperature trend impact in Sub-Saharan Africa, covering the period of (1961-2006). The study has aimed to assess climate variability at the regional and climatic zone levels within Sub-Saharan African countries. Descriptive statistics reveal that there are significant variations in climate variables across regions and climate zones during the study period. However, the changes are clearer when regional level data are aggregated to climate zone. The First part of this study has developed a quantitative estimation of the impacts of climate variables on the mean and variance functions of yield of two most important crops in the region namely Maize and Millet. The production function and panel data are used to answer the research questions.

The major outcome of this study is that climate change will impact crop yield variability of major crop in Sub-Saharan African countries. The detailed results show that in general the average Maize yield is negatively related to temperature and positively associated with precipitation. Temperature has a negative but insignificant impact on Maize and Millet yield. Rainfall will significantly increase Millet and Mazie yield. These results agree with the findings of Chen et al. (2004) and many others. The study has confirmed that SSA countries food production is more vulnerable to the impact of weather and climate variability. This result suggests national or state level adaptation policies which may be more effective if it is well funded and well implemented.

From the study, it can be concluded that temperature shows negative but insignificant impact on both crops in both functional form Cobb bb Douglass and linear -quadratic model as well. Precipitation on the other hand has a positive and significant impact across crops and across models. The negative quadric precipitation coefficients and negative flood coefficients in our models along with the increasing future trends of rainfall volatility suggesting that more risk of more damaging impact of climate change if proper adaptation protection practices are not implemented.

Future climate projections for SSA have shown that temperature will increase but the precipitation may be more unpredictable and volatile. Although rain is expected to have beneficial impact for crop yield, it also leads soil erosion to poor soils outcomes. This fact is supported by many scholars in the literature and may justify our model findings that excessive rainfall has a negative impact on both crops. Overall, precipitation variability is more important in sub-Saharan Africa, pointing to the predominantly rainfed agriculture system.

Adaptation to negative impact of climate change is essential to ensure food security o protect the subsistence of rural households. Findings of this study can be used to help in designing an effective adaptation of agriculture to climate change.

Analyses of the four most commonly harvested crops in SSA reveal, in general, a significant impact of weather on yields. Regression analyses using temperature and precipitation provided significant and sensible estimates. Among other things, the introduction of clean and resource-efficient technologies and focusing on global solutions to economic, social and environmental sustainability. When drawing conclusions from the results, it should be noted that predictions of the impact of climate change are beset by uncertainty.

This study therefore is good start to identify the link between climate variability and crop yield variability within SSA. The new information provided by this study should help to direct further research and more effective policy to SSA region, where climate variability represents serious risks to rural population.

The Vector Autoregression (VAR) model is used to estimate model two to check the impact of climate change on overall agriculture production in Sub-Saharan African countries. The study used data covering the period 1980-2008. The results of historical data estimation reveal that, there is a significant impact of climate change on overall agriculture production in SSA. However, future crops production will significantly depend on the area under crop cultivation and the climate change variables. For the baseline model, we have found significant positive effect from temperature and significant negative effect from precipitation to agriculture production index at least in the short-run. The result has shown that the use of fertilizers and machinery both have negative significant impact on agriculture production index, whereas, Livestock has positive significant effect on agriculture production index for SSA countries

The Variance-decompositions function explains how much percent of variation in the row variable explained by the column variable. We have found from the results of our models that all variables explain most of the variation in themselves and explanatory power of the variables had been affected by change in the ordering of the variables.

Finally the major outcome from this work is that, there is a serious connection between climate variations and crop yield variations within Sub-Saharan African countries. This Study also has shown empirically that there is a connection between climatic variables and overall agriculture production in SSA. Both models have come to this conclusion which is supported by much theoretical and empirical evidence from the literature of climate change.

APPENDICES

Table A.1.

Variable Definitions and Data Source

Variable Name	Definition	Period	Source
Crop Yield	Crop yield in tn/ha	1961-06	FAOSTAT
Area Harvested	Harvested Area in Hector	1961-06	FAOSTAT
Production (prod)	Production Quantity in tonnes	1961-06	FAOSTAT
Average Temp(temp)	Average annual temperature in Celsius	1961-06	CRU
Precipitation (pre)	Annual total precipitation in (mm)	1961-06	CRU
RA	Rainfall anomaly is annual rainfall deviation from long run mean	1961-06	CRU
TA	Temperature Anomaly is annual mean temperature deviation from long run mean (mm)	1961-06	CRU
STA	TA standardized by diving by standard long run deviation	1961-06	CRU
SRA	SA standardized by diving by standard long run deviation	1961-06	CRU
Flood	Anomalies capturing Hight rainfall extremes	1961-06	CRU
Drought	Anomalies capturing Low rainfall extremes	1961-06	CRU
LotempAnom	Deviations of annual average temperature from the Long Period Average (Low)	1961-06	CRU
Hiempanom	Deviations of annual average temperature from the Long Period Average(Hight)	1961-06	CRU

Source: Own Calculations

Table A.2.

List of Countries Model One (Millet Model)

Country Name	Country Name	Country Name	Country Name
1.Angola	8. Ethiopia	15. Mauritania	22. South Africa
2.Benin	9. Gambia	16. Mozambique	23. Sudan
3.Burundi	10. Ghana	17. Niger	24. Tanzania
4.Burkina Faso	11. Guinea	18. Nigeria	25. Uganda
5.Cameroon	12. Guinea-Bissau	19. Rwanda	26. Zaire
6.Central_African_Rep	13. Kenya	20. Senegal	27. Zambia
7.Chad	14. Mali	21. Sierra Leone	28. Zimbabwe

Source: FAOSTA, 2005.

Table A.3.

List of Countries Model One (Maize Model)

Country Name	Country Name	Country Name	Country Name	Country Name
1.Angola	8. Ethiopia	15. Madagascar	22. Mozambique	29. Mauritius
2.Benin	9. Gambia	17. Malawi	23. Sudan	
3.Burundi	10. Ghana	17. Niger	24. Tanzania	
4.Burkina Faso	11.Comoros	18. Nigeria	25. Uganda	
5.Cameroon	12.Congo	19. Rwanda	26. Zaire	
6.Central_African_Rep	13.Gabon	20. Senegal	27. Zambia	
7.Chad	14. Gambia	21. Sierra Leone	28. Zimbabwe	

Source: FAOSTA, 2005.

Table A.4.

Countries Hit Most by Climate Change

Country Name	**Temperature**	**Precipitation**
Cameroon	(-0.6445) (0.0000)	(-0.0080) (0.6700)
Burkina Faso	(-0.1652) (0.0110)	(0.0643) (0.0020)
Zambia	(-0.0886) (0.3800)	(0.0634) (0.0760)
Malawi	(-0.1622) (0.0950)	(0.0230) (0.0330)
Nigeria	(-0.1000) (0.0921)	(0.0591) (0.0050)
Togo	(-0.4033) (0.0000)	(0.4033) (0.0000)
Mozambique	(-0.1403) (0.3350)	(0.0537) (0.1120)
Zimbabwe	(-0.4033) (0.0000)	(0.1155) (0.0000)

Source: Own Calculations

Table A.5.
Populations and Annual Population Growth (%)

Country	1961	1970	1980	1985	1990	1995	2000	2005	2015
Sub-Saharan Africa	02.40	02.59	02.86	02.89	02.83	02.75	02.72	02.71	02.73
Nigeria	02.04	02.29	02.86	02.56	02.58	02.49	02.51	02.59	02.62
South Africa	03.13	02.17	02.33	02.59	02.03	02.16	02.47	01.33	01.64
Burkina Faso	01.34	01.72	02.24	02.57	02.65	02.74	02.83	02.97	02.89
Cote d'Ivoire	03.59	04.50	04.36	03.90	03.52	03.17	02.32	01.83	02.42
Ethiopia	02.39	02.71	01.92	03.19	03.43	03.32	02.89	02.781	02.47
Angola	01.81	01.97	03.20	03.12	02.65	02.74	02.83	02.97	02.89
Burundi	01.90	01.87	02.64	03.18	02.86	01.69	02.14	03.49	03.29

Source: World Bank

Table A.6.

Employment Share of Agriculture (% of Total Employment)

Country	1991	2000	2010
Sub-Saharan Africa	74.80	70.06	64.27
Ethiopia	90.49	90.08	82.02
Kenya	97.47	99.76	94.19
Malawi	92.06	87.72	79.18
Tanzania	97.30	93.85	86.29
Zambia	80.28	68.92	69.32
Uganda	90.79	86.3	85.67
South Africa	19.81	13.25	08.69

Source: FAOSTA, 2005.

Table A.7.
Agriculture Share of GDP (%) for Some SSA Countries

Country	1961	1970	1980	1985	1990	1995	2000	2005	2015
Sub-Saharan Africa	-	-	23.99	24.58	23.74	22.90	19.86	20.93	17.50
S. Africa	11.53	07.16	06.19	05.19	04.63	03.86	03.28	02.66	02.36
Kenya	36.81	33.29	32.59	32.59	29.51	31.13	32.36	27.19	32.93
Nigeria	-	-	28.51	39.20	31.52	32.06	26.03	32.75	20.85
Sudan	55.98	43.62	32.85	33.54	40.57	38.67	42.17	31.52	39.32
Ethiopia	-	-	58.08	55.37	52.04	55.03	47.75	44.70	40.97
Ghana	39.68	53.89	60.05	48.43	45.06	42.70	39.41	40.93	20.98
Malawi	50.29	43.97	43.73	42.89	45.00	30.39	39.53	37.10	29.49

Source:FAOSTA,2005

Table A.8.
Annual Growth of Agriculture GDP (%)

Country	1970	1980	1985	1990	1995	2000	2005	2015
Sub-Saharan Africa	-	02.18	05.76	-0.60	03.34	00.78	05.48	03.25
Benin	-3.65	03.09	09.32	02.52	05.76	05.44	-0.22	-7.24
Congo Republic	08.74	07.59	00.73	01.58	6.47	04.36	04.41	05.24
Gambia	06.26	-3.95	-8.73	-2.17	-2.63	07.49	-2.26	07.02
Sierra Leone	02.04	0.87	-5.33	49.82	-9.85	07.79	06.82	03.12
Cameroon	04.89	0.24	8.63	-1.00	-1.63	03.99	02.68	05.30
Sudan	17.87	-5.50	-12.2	-20.2	05.99	-3.45	02.23	02.78
Burkina Faso	01.15	02.47	07.20	-6.52	06.36	02.48	10.45	-1.22

Source of Data: FAOSTAT, 2000

Table A.9.
Harvested Area for Major Crop by Region (in ha)

Region	Cassava	Maize	Sorghum	Millet
Africa	17307152	37058619	29355124	19727439
West	09911082	11160802	12865857	13240317
East	04015919	17266889	05679263	01689517
Central	03380151	04366775	02104656	01463004
South	-	03039759	00172008	00176081

Source of Data: FAOSTAT, 2005

Table A.10.
Production Area for Major Crop by Region (in tonnes)

Region	Cassava	Maize	Sorghum	Millet
Africa	145770528	78005212	29192947	12409333
West	087256084	19573735	12126555	08409531
East	028752310	30679856	07508353	01794209
Central	029762134	05022154	02175576	00902224
South	-	14518245	00290947	00046737

Source of Data: FAOSTAT, 2005

Table A.11.
Yield of Major Crop by Region (in ha/ha)

Region	Cassava	Maize	Sorghum	Millet
Africa	84226	21049	09945	06290
West	88039	17538	09425	06351
East	71596	17768	13221	10620
Central	88050	11501	10337	06167
South	-	47761	16915	02654

Source of Data: FAOSTAT, 2005

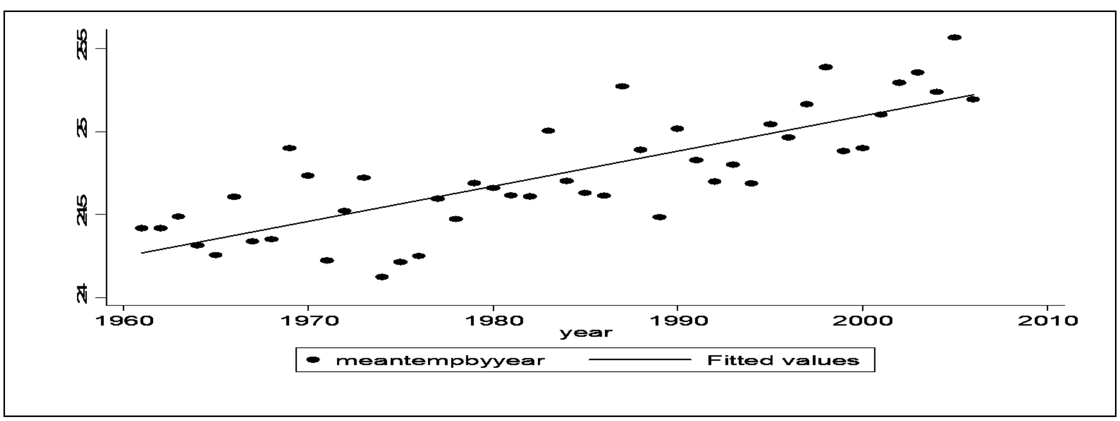

Figure A.1. Maize Mean Temperature Trends (Source of Data: CRU, 2003)

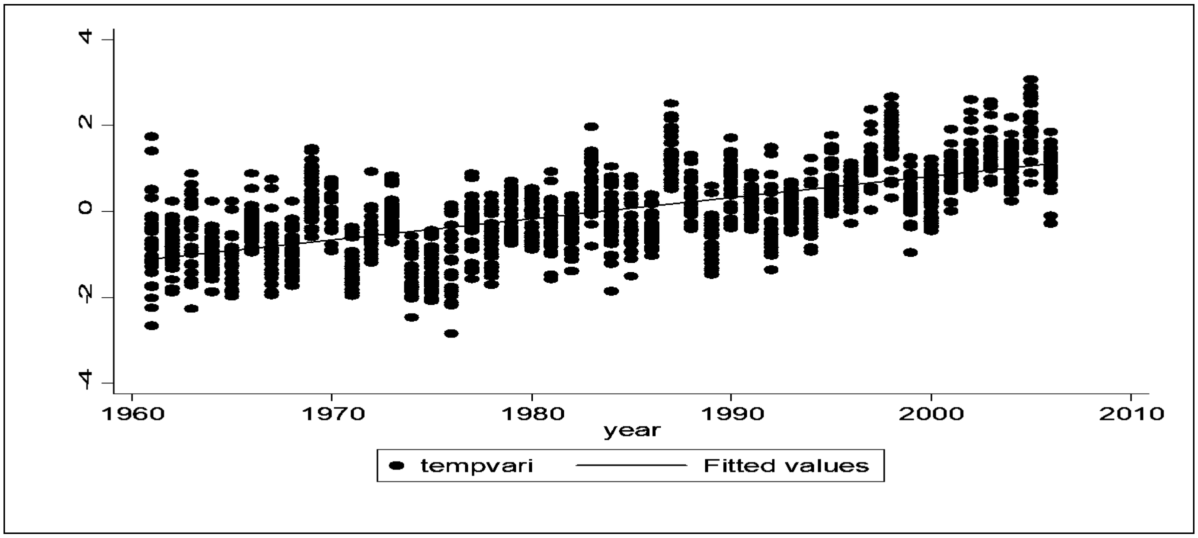

Figure A.2. Temperature Variability in SSA (1961-2006)
(**Source of Data: CRU, 2003)**

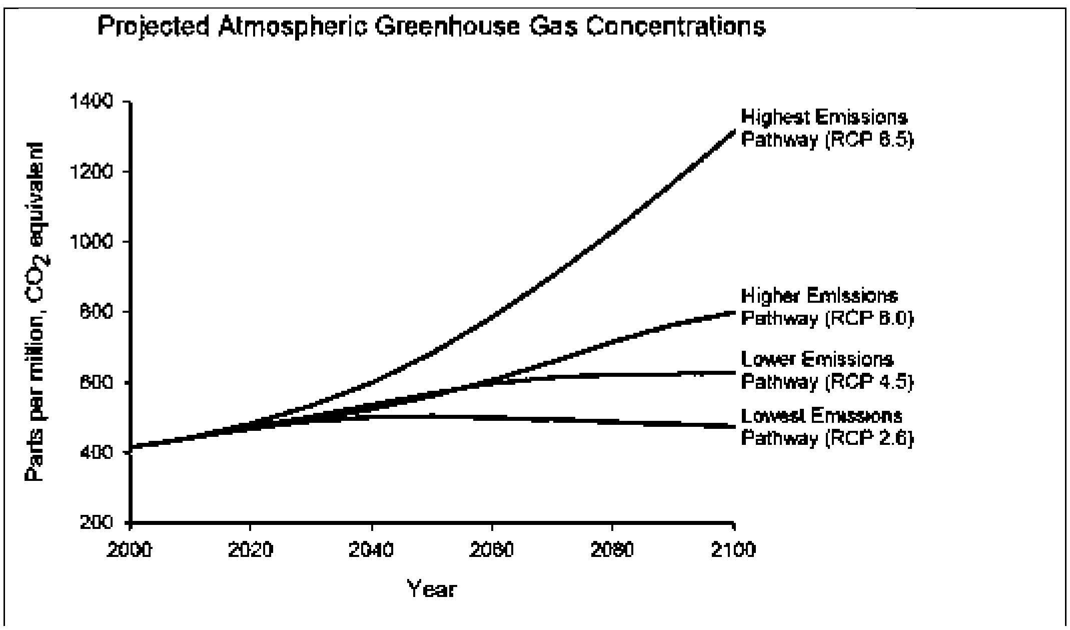

Figure A.3. This figure shows projected greenhouse gas concentrations for four different emissions pathways. http://www.iiasa.ac.at/web-apps/tnt/RcpDb

Table A.12.

Variable Definition and Data Source (Model Two)

Variable	Definition	Source	Period
lnNetIndex	Net production quantities of each commodity are weighted by the 2004-2006 average international price	FAOSTAT	1980-2006
lnagva	Agriculture, value added (% of GDP), Agriculture corresponds to and includes forestry, hunting, and fishing, as well as cultivation of crops and livestock production.	WDI	1980-2006 1980-2006
lnaggdp		WDI	1980-2006
lnprodq	Net production quantities of each commodity	FAOSTAT	1980-2006
lnmachine	As a crude proxy of capital stock, K, we use the total number of agricultural tractors being used	FAOSTAT	1980-2006
lnlive	Livestock is proxied by the total head count of cattle, sheep, and goats.	FAOSTAT	
lnland	measure of agricultural area, which includes arable land and the area used for permanent crops and permanent pastures	FAOSTAT	1980-2006
lnferti	while fertilizer, F, is measured as the quantity, in metric tons, of plant nutrients consumed for domestic use in agriculture	FAOSTAT	1980-2006
DTEMP	Average temperature measured by deviation from long-term mean of period 1980-2006	CRU	1980-2006
DPRE	Average precipitation measured by deviation from long-term mean of period 1980-2006	CRU	1980-2006
temp	Measures the annual average surface temperature for the region of the study measured in Celsius	CRU	1980-2006
preci	Measures the annual average surface precipitation for the region of the study measured in millimeters	CRU	

Source: Own Calculations

Model D: Adding More lags (Robustness Check for Model Two)

Temperature Shocks

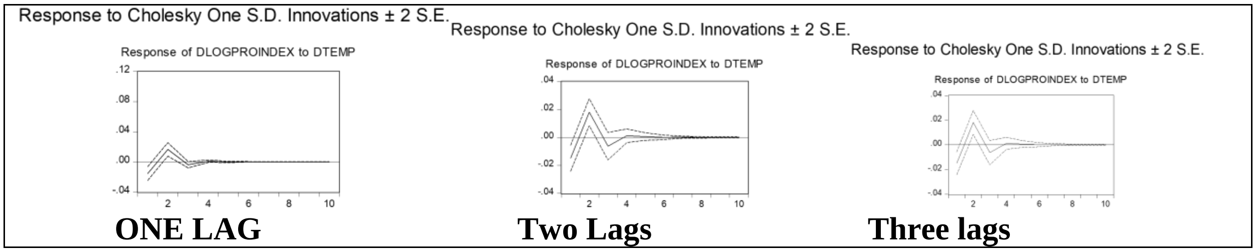

Figure A.4. The Response of Production Index to Temperature Shock with more lags

Precipitation Shocks

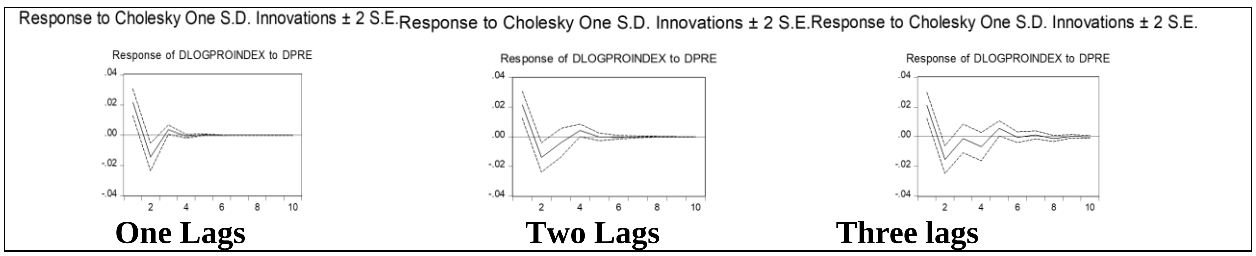

Figure A.5.The Response of Production Index to Precipitation Shock with more lags

Table A.13.

List of Countries of Model Two

Country Name	Country Name
1.Burundi	8. Niger
2.Burkina Faso	9. Nigeria
3.Cameroon	10. Zambia
4. Kenya	11.Senegal
5.. Mali	12. Ivory Coast
6.. South Africa	13.Gahana
7. Sudan	

Source: Own Calculations

Panel Autoregressive Model PVAR (Technical Notes)

To analyze the dynamic relationship between climate change and agriculture production, we compute impulse-response functions from an estimated Panel VAR in a similar manner as in Lof et al. (2013) estimated the relationship between aid and GDP in developing countries.

Using the first difference of agriculture output index as a dependent variable ($\boldsymbol{\Delta} Y_{it}$) and the first difference of other inputs as our variables of interest, we estimate the following PVAR:

$$V_{it} = \mu_i \quad + \mathrm{A} y_{it} - 1 + \varepsilon_{it},$$

in which Y_{it}= ($\boldsymbol{\Delta}$ D_{it}, $\boldsymbol{\Delta}$ Y_{it}) 0, μ_{it} is a 2 × 1 country-specific intercept term (fixed effect), A is a 2×2 coefficient matrix and ε_{it} is a 2×1 residual term. The subscripts i and t denote country and year, respectively. The VAR includes only first-order lags, which is selected using the Bayesian Information Criterion (BIC).

Before estimating the PVAR, we apply first-differencing, such that the fixed effect μ_{it} drops out of the model. Afterwards, we estimate the differenced model by GMM, while applying lagged values as instruments. This is a standard procedure for estimating dynamic models with panel data, since the standard fixed-effects estimator is generally inconsistent estimator for such models (Nickel 1981). The resulting estimate of A is used to compute the impulse-response functions. Confidence intervals for the impulse-response functions are computed by bootstrap simulation see Lof et al. (2013) for details. To identify the shocks, we impose a recursive ordering, which makes the order of the variables more relevant. As a robustness check, we will also consider changing the variables order.

In PVAR models, the results come in the form of impulse response functions (IRFs) and their coefficients analysis, as well as forecast error variance decompositions (FEVDs). The impulse response functions (IRFs) enable us to examine the impact of innovations or shocks of any variable to other variables in the system.

IRFs model the dynamics of the response; the coefficients represent the average effects of IRFs and permit recognizing the significance of the overall response, while variance decompositions (FEVDs) gives information about the variation in one variable due to shock to the others. The impulse response function corresponds to a one-time shock in other variables, holding all the other shocks constant at zero. In other words, orthogonalizing the response allows us to identify the effect of one shock at a time, while holding other shocks constant.

This study particularly interested in the impact of climate shocks to agriculture production variables and the response of such variables to climate. To obtain orthogonalized impulse response functions, the model decomposes the residuals in a way that makes them orthogonal. This work requires applying a careful VAR identification procedure (ordering). The most common way to deal with this problem is to choose a causal ordering.

The model adopts the Chomsky decomposition of variance-covariance matrix of residuals which is well documented in the literature. This process is called VAR identification and involves an ordering of variables in the VAR system. We allocate any correlation between the residuals to the variable that appears earlier in the ordering. The identifying assumption is that the variables that appear earlier in the systems are more exogenous, and those which appear later are more endogenous, which implies that the variables that appear earlier (exogenous) affect the following variables contemporaneously and with lags, while the variables that appear later (endogenous) only affect the previous variables with lag. In this study the simple model has five variables: Agricultural output, machinery, fertilizers, livestock, land, temperature and precipitation. Here is order we choose for the identification of the VAR system in our model

Z_{it}= (Temperature, Precipitation, livestock, land, machinery, fertilizers (Agriculture output)

Temp =>Precipitation => Factor Inputs (productivity) => agricultural output

We believe that, Temperature and Precipitation affect major inputs factors and that will in turns affect ***agricultural output***. This identification strategy based on the assumption that climate change; specifically heat stress can have drastic effect on agriculture production and productivity. These impacts can take the form of damage to human health, reductions in labor productivity and labor supply, and possible reductions in the rate of human capital accumulation—all of which may decreases ***agricultural output*** and overall social welfare in both the short and long run. The simple VAR model is presented below with three variables: temperature (T), Land (L) and agriculture output (agriculture). A model of five variables which will include, temperature, precipitation, labor, livestock, land, machinery, fertilizers and Agriculture output will be presented in the same manner in the baseline model (for robustness check a model of three will be estimated).

For simplification, the three variable PVAR model is presented below to show the dynamics of the model and its identification strategy;

$$\begin{pmatrix} 1 & \alpha_{12} & \alpha_{13} \\ \alpha_{21} & 1 & \alpha_{23} \\ \alpha_{31} & \alpha_{32} & 1 \end{pmatrix} \begin{pmatrix} \Delta T \\ \Delta L \\ \Delta Y \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{pmatrix} \begin{pmatrix} L_{11} & L_{12} & L_{13} \\ L_{21} & L_{22} & L_{11} \\ L_{31} & L_{32} & L_{33} \end{pmatrix} \begin{pmatrix} \Delta T_{i,t-p} \\ \Delta L_{i,t-p} \\ \Delta Y_{i,t-p} \end{pmatrix} + \begin{pmatrix} u_1 \\ u_2] \\ u_3 \end{pmatrix}$$

where, T is temperature L, is land input and Y is agricultural output variables. This is an ordering strategy in which the variables appearing first in the ordering (leftist in vector Z) affect the variables later in the ordering (rightist in vector Z) both contemporaneously and with a lag, while the variables appear later in the ordering only affect the first variables with a lag. In other words, temperature and precipitation as climatic variables are assumed to be least endogenous and most exogenous [Raddatz (2009) calls them 'acts of God']. These variables are assumed to be major inputs in agriculture production in SSA consequently affect largely the agricultural ***output*** estimates, contemporaneously and with a lag. As it is a set of endogenous equations, all variables influence each other. Land, machinery (capital) and livestock are contemporaneously affected by GDP. In fact, all major agriculture input factors will be affected (with lags) by agriculture output which is major component of GDP in most SSA, as lower GDP this year will result in lower input factors(next year).

The theoretical explanation of our model requires a delay in the indirect effect of climatic variables on agricultural output and on other inputs, thus agriculture output responds to climatic variables with lag. Based on the impulse response function described above, we can evaluate the relative importance of different structural shocks to endogenous variables by measuring the contributions of shocks on the variance changes of variables. The variance decompositions display the proportion of movements in the dependent variables that are due to their own shocks versus shocks to the other variables.

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