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ANALYSIS OF CLIMATIC VARIABILITY AND ITS EFFECTS ON PRODUCTION OF SELECTED CROP IN ADA'A DISTRICT: MULTIVARIATE TIME SERIES APPROACH

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This is to certify that the thesis prepared by **Diribsa Tsegaye**, entitled: *Analysis of Climatic Variability and its Effects on Selected Crop Production: Multivariate Time Series Approach: The case of Ada'a district* and submitted in partial fulfillment of the requirements for the Degree of Master of Science in Statistics (Applied Statistics) complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

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ACRONYMS

AIC	Akaike information criterion
SBIC	Schwarz Bayesian information criterion
HQIC	Hannan-Quin information criteria
CRV	Central Rift Valley
NMA	National Meteorological Agency
FAO	Food Agriculture Organization
GDP	Gross Domestic Product
VAR	Vector Autoregressive
VEC	Vector Error Correction
VECM	Vector Error Correction Model
WMO	World Meteorological Organization
ARDL	Autoregressive Distributed Lag Model
DOLS	Dynamic Panel and Dynamic Ordinary Least Squares
SNNP	Southern Nations Nationalities and People
CSA	Central Statistical Agency
USAID	United States Agency for International Development
USHCN	United States Historical Climatology Network
LDCs	Least developed Countries
UNMDG	United Nations Millennium Development Goals
ADF	Augmented Dickey-Fuller

PP	Phillip-Perron
AR	Autoregressive
LM	Lagrange Multiplier
SVAR	Structural Vector Autoregressive
IPCC	Intergovernmental Panel on Climate Change

ABSTRACT

Analysis of Climatic Variability and its Effects on Production of Selected Crop in Ada'a District: Multivariate Time Series Approach.

Diribsa Tsegaye, 2016

Climate change affects all economic sectors to some degree, but the agricultural sector is perhaps the most sensitive and vulnerable. In the last three decades, Ethiopia has been affected by climate-related hazards. Agriculture, the most dominant sector in the national economy, has been most at risk because of its dependence on seasonal rainfall. Anticipated climate change has negatively impacted the agricultural sector due to increased temperatures and decreased or greater variability in precipitation, leading to increased food insecurity.

This study was carried out with the general objective of examining climate variability and its effects on selected crop production for the last three decades in Ada'a district of East Showa Zone of Oromia Regional State. The relevant data were obtained from the National Meteorological Agency (NMA) and district's agricultural office. Data on selected crop production, total rainfall and average temperature for the period of 1985 to 2015 were used. The vector autoregressive (VAR) model is employed for modeling.

The cointegration relations among the variables were identified by applying Johansen's cointegration tests, while potential causal relations were examined by employing Granger's causality tests. Moreover, the short run interactions among the variables were determined through the application of impulse response analysis.

The results of the research imply the existence of short term adjustments and long-term dynamics in crop productivity, total rainfall, minimum and maximum temperature. The result of Johansen test indicates the existence of one cointegration relation between the variables. The final result shows that a Vector Error Correction (VEC) model of lag two with one cointegration equations best fits the data.

Key words: *Vector Autoregressive, Climate variability and crop productivity.*

CHAPTER 1

1. INTRODUCTION

1.1 Background of the study

Global warming is considered to be major threat for life on our planet and its multifaceted impacts are affecting the whole world in various forms. Several scientific studies have suggested that developing countries in particular are suffering from the burden of the ever changing climatic conditions (UN-OHRLLS, 2009). Many low income countries are located in tropical, sub-tropical region, or in semi-arid zones, that are particularly vulnerable to shifting weather patterns and rising temperature (Joachim, 2008). Widespread research findings have revealed that climate variability and change have significant impacts on global and regional food productivity systems particularly on the performance of common staple food crops in the tropical sub-humid climatic zone (UN-OHRLLS, 2009). Climate variability and change have been implicated to have significant impacts on global and regional food productivity particularly the common staple food crops performance in tropical sub-humid climatic zone. For example, the most food insecure regions and most climate change vulnerable regions in Ethiopia are those that experience both the lowest and most variable rainfall patterns (UN-OHRLLS, 2009). Many African countries are vulnerable to climate change because their economies largely depend on climate-sensitive agricultural productivity system (Temesgen, 2000). This is particularly true in low-income countries like Ethiopia where adaptive capacity is low.

Ethiopia is characterized by diverse topographic features that have led to the existence of a range of agro-climatic zones each with distinctly variant climatic conditions which in turn have resulted in the evolution of a wide variety of fauna and flora agricultural productivity systems. Among these agro-climatic zones, the lowland (kola) that receives the lowest and most erratic rainfall rates notably the Central Rift Valley (CRV) region experiences frequent natural hazards such as sudden flood, recurrent droughts and chronic water stress that are aggravated by climate change and its variability. It was observed that climate variability of erratic rainfall and its uneven sequential and spatial distribution had created frequent flooding and drought in these areas (Lai et al., 1998).

In the CRV of Ethiopia, it was also observed that fluctuations in rainfall and temperature rates were among the variables affecting the productivity and productivity of the agricultural systems (Deschenes & Greenstone, 2006). Climate variability indirectly affects the agricultural productivity of the area through influencing the emergence and distribution of crop pests, livestock diseases, aggravating the frequency and distribution of adverse weather conditions, reducing water supplies and enhancing severity of soil erosion among other impacts (Watson et al, 1998). Climate variability and its associated impacts induce frequent crop failures, and declining livestock productivity and productivity leading to aggravated rural poverty in the region. Scientific evidences suggest that higher temperatures and changing rainfall levels as a result of the changing climate could further depress agricultural crop yields in many arid-and semi-arid parts of Ethiopia (Bezabih et. al; 2010).

Ethiopia has the most variable rainfall patterns. A number of professionals and organizations have documented scientifically interesting reports on Ethiopian rainfall variability by classifying the country into various and wide temporal and spatial rainfall categories (NMSA,1996a & b; FAO, 1984; FAO, 1989; Degefu, 1987; Gemechu, 1977; Ethiopian Delegation, 1984; Gonfa, 1996; NRRD/MOA, 2000). According to Haile (1986) drought occurs every 3-4 years in the northern and 6-8 years in other parts of Ethiopia. According to Kidson (1977) a steady downward trend of rainfall since the peaks of the 1950s has expanded more in 1980s covering almost the whole of Africa. In the Ethiopian context, opinions are also divergent regarding the arrival of the rainy season, which used to occur in March but is recently shifting to April through July and, therefore, there is a progressive shortening of the growing periods and the corresponding seasonal rainfall totals.

Agriculture sector is vulnerable to climate change. Climate change affects agriculture by altering yields and changing areas where crops can be grown. Increased variability in weather-related shocks and stresses, resulting from climate change, increases the risk of productivity failure for farmers particularly those engaged in rain-fed agriculture (IPCC, 2007). This is associated with the fact that agricultural productivity in developing countries is mostly based on rain-fed, whereas, in developed countries rain-fed agriculture is supplemented with irrigation facilities and other infrastructures. Increasing climate variability can put productivity at risk and is likely to further decrease farmer investment. Furthermore, risks in agriculture are associated with negative outcomes that arise from imperfectly predictable biological, climatic, and price variables. These variables include natural adversities such as, pests and diseases and, climatic factors which are not within the control of the farmers. Therefore, rainfall variability and other climatic risks account for a significant share of agricultural productivity risk (World Bank, 2001; FAO, 2008).

In Ethiopia, the average annual minimum temperature has increased by about 0.25 ^{o}C every ten years while the average annual maximum temperature has increased by about 0.1 ^{o}C. Moreover, the National Meteorological Agency (NMA) further showed that there was a very high variability of rainfall over 50 years starting from 1956-2006 (NMA, 2007).

Africa's rain-fed agricultural productivity including productivity of cereals could be reduced by up to 50% due to climate change. This situation was identified as a serious challenge for Africa, a region already having the highest proportion of people living in extreme poverty and the lowest level of agricultural productivity (Hellmuth et al., 2007). It was observed that the main environmental problems in Ethiopia include land degradation, soil erosion, and deforestation, loss of biodiversity, desertification, recurrent drought, flood and water and air pollution (NMA, 2007; MoFED, 2007). Furthermore, climate related hazards in the country include mainly drought, floods, heavy rains, strong winds, frost and heat waves (high temperatures).

Given the fact that the location of Ethiopia is in the Sahel Region, a region with erratic rainfall and unpredictable climate variability, the country has also suffered from extremes of climate, manifested in the form of frequent drought (1965, 1974, 1983, 1984, 1987, 1990, 1991, 1999, 2000, and 2002) along with recent flooding of 1997 and 2006 (Yesuf et al., 2008). In addition, as cited by Zewdie B., Negalign B. and Argaw A. (2015), in Southern Ethiopia, where Borana Zone is located, experienced severe droughts in 2000 (Angasse A. & Oba G., 2007), 2006, 2008 and 2010–2011 (USAID, 2011). During the drought of 2000, 80% of livestock died (Angasse A. & Oba G., 2007).

The main causes of most disasters are climate related for which deterioration of the natural environment due to unchecked human activities is the one and poverty has further exacerbated the situation. Moreover, according to NMA (2007) high dependence on rain fed agriculture which is very sensitive to climate variability and change, under-development of water resources; high population growth rate, weak institutions and lack of awareness are also among the other sources for vulnerability of Ethiopia to climate variability and change.

Recent climate variability is already imposing a significant challenge to Ethiopia by affecting food security, water and energy supply, poverty reduction and sustainable development efforts, as well as by causing natural resource degradation and natural disasters (Rediat Takele, 2012).

1.2. Statement of the problem

Ethiopian agriculture dominates the economy which accounts almost 50 % of GDP, and 85 % of total employment(World Bank, 2012). Thus, the country is highly dependent on the agricultural sector for income, foreign currency and food security. The sector is dominated by small-scale farmers who employ largely rain-fed and traditional practices a state which renders Ethiopia highly vulnerable to climate variability.

In addition agricultural economy in Ethiopia has features of subsistence economy, meaning provides sufficient food to last only from one harvest to the next. Therefore, a failure of one harvest means starvation for the ensuing year, shortage of seed for the next cropping season and loss of animal power to plough the fields (Abate, 1994).

Climate change affects agricultural production through shortening of maturity period and then decreasing crop productivity (NMA, 2007; PANE, 2009). It was indicated that there will be expected future area loss in teff and wheat productivity in Ethiopia and the pattern of teff and wheat species will be restricted to higher altitude due to future changes in climate (Yumbya *et al.*, 2011). High water stress and increase in temperature which in turn reflects on low crop productivity are among the challenges associated with the impact of climate change on an important crop like teff and wheat.

There have been limited scientific evidences on impacts of climate change on teff productivity in Ethiopia. For instance those pertinent literatures addressed the effects of climate variability in the country were based on general agricultural crops produced by farmers (Deressa and Hassan, 2009; Molla, 2009; Belay, 2012). Hence, such studies considered the lump sum of agricultural crops in to one category while in reality; climate change affects different crops differently as long as different crops have different climate requirements. Therefore, under such findings it is difficult to disaggregate the impact on teff and wheat productivity, as long as the impact is not solely referred for teff and wheat productivity.

Moreover, Study by Yumbya *et al.* (2011) assessed impact of climate change on teff productivity for three teff potential districts of Ethiopia in terms of expected future loss in current suitable area for teff through future projections. However, the study was limited in in-depth analysis on the effects of climate variability on teff and wheat productivity specially in Ada'a area though the well known indigenous teff in Ethiopia is produced in this district. Almost all farmers in Ada'a district majorly produce teff and wheat once a year. Therefore, assessments of climate variability on teff and wheat productivity with specific focus on the likely change in the magnitude of the impacts on crop productivity when the climate variables change and projected climate effect on productivity per hectare of teff and wheat due to future changes in temperature and rainfall are among the gaps which the study intends to bridge. This study was designed to investigate climate variability and its effects on selected crop productivity of Ada'a district area.

1.3. Objectives of the study

1.3.1. General Objective

The general objective of this study is to examine climate variability and its effects on crop productivity for the last three decades in Ada'a district of East Showa Zone of Oromia Regional State using Vector Autoregressive (VAR) and Error Correction models.

1.3.2. Specific objectives

- To asses annual rainfall and average temperature variability in the study area.
- To examine the effect of total rainfall variability on selected crop productivity in the study area.
- To examine the effect of average temperature variability on selected crop productivity in the study area.

1.4. Significance of the study

The study aimed at analyzing of climate variability and its effects on selected crop productivity. Identifying and quantifying the effects of climate variability on crop productivity is the main area of interest of this study.

The results of this research paper could be used:

- To provide information that would be helpful for decision makers in formulating policies to mitigate the problems of climate variability and improve crop productivity.
- To provide information for the early warning system in the region.
- As a basis for further study in East Showa zone area.

1.5. Limitation of the Study

Due to lack of data on major crops (lentils, maize, chickpea and etc), key climatic variables (humidity) and non-climatic variables (soil type), the analysis in this study was limited only to teff productivity, wheat productivity, total rainfall and average temperature.

CHAPTER 2

2. LITERATURE REVIEW

2.1 Definitions and concepts

Climate: Climate is usually defined as the “average weather” or more rigorously as the statistical description in terms of the mean and variability of relevant quantities over a period of time ranging from months to thousands or millions of years. The classical period is 30 years, as defined by the World Meteorological Organization (WMO, 2007).

Weather: Is a short-term phenomenon, describing atmosphere, daily air temperature, pressure, humidity, wind speed, and precipitation (IPCC, 2007).

Climate variability: Variations 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 (Fussel and Klein, 2006,).

Climate change: “A change in the state of the climate that can be identified (e.g., by 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. Climate change may be due to natural internal processes or external forcing or to persistent anthropogenic changes in the composition of the atmosphere or in land use” (IPCC, 2007).

2.2 Climate change and Agriculture

Higher temperatures, reduced rainfall and increased rainfall variability reduce crop productivity and as a result could lead to food security problem in low income and agriculture-based economies. Thus, the impact of climate change is detrimental to countries that depend on agriculture as the main livelihood (Edwards-Jones et al. 2009).

Plausible climate change scenarios include higher temperatures and changes in rainfall. Although temperature increases can have both positive and negative effects on crop productivity, in general, temperature increases have been found to reduce productivity and quality of many crops (Richard M. Adams, 1998). Increases in rainfall (i.e. level, timing and variability) may benefit semi-arid and other water short areas by increasing soil moisture, while a reduction in rainfall could have the opposite effect (Richard M. Adams, 1998).

Climate change causes climate variability of temperature and rainfall as well as the frequency and severity of weather events. Some indirect effect of climate change includes, changes in soil moisture, land and water condition, change in frequency of fire and pest infect and the distribution of diseases. The potential for a system to sustain adverse impact on agriculture is determined by its capacity to adapt to the changes (Mohan and Rob, 2005). Climate change will have wide-ranging effects on the environment, and on socio-economic and related sectors, including water resources, agriculture and food security, human health, terrestrial ecosystems and biodiversity.

Changes in rainfall pattern are also likely to lead to severe water shortages and/or flooding. Rising temperatures also will cause shifts in crop growing seasons which affects food security and changes in the distribution of disease vectors putting more people at risk from diseases such as malaria. Temperature increases will potentially severely increase rates of extinction for many habitats and species (UNFCCC, 2007).

Climate change has the potential to undermine sustainable development, increase poverty, and delay or prevent the realization of the Millennium Development Goals (IPCC, 2007). An effective way to address the impacts of climate change is by integrating adaptation measures into sustainable development strategies so as to reduce the pressure on natural resources, improve environmental risk management, and increase the social well-being of the poor. Climate change can influence humans directly, through impacts on health and the risk of extreme events on lives, livelihoods and human settlements, and indirectly, through impacts on food security and the viability of natural resource-based economic activity. The biophysical effects of climate change on agriculture induce changes in productivity and prices, which play out through the economic system as farmers and other market participants adjust autonomously, altering crop mix, input use, productivity, food demand, food consumption, and trade (Oxfam, 2006).

Climatic variabilities are the types of changes (temperature, rainfall, occurrence of extremes); magnitude and rate of the climate change that causes the impacts on the area of public health, agriculture, food security, forest hydrology and water resources, coastal area, biodiversity human settlement, energy, industry, and financial services. Changes in physical and socio-economic system have been identified in many regions (UNFCCC, 2007). Detecting these changes and associating them with climate change poses huge problems since these systems are usually subject to many stress factors other than climate change too. Vulnerability is the degree to which a system (such as a social-ecological system) is likely to be wounded or experience harm or stress in the natural or social and environment (Kaspersonet al., 2001).

Vulnerability results from a combination of processes that shape the degrees of exposure to a hazard, sensitivity to its stress and impacts, and resilience in the face of those effects. It is also considered a characteristic of all people, ecosystems, and regions confronting environmental or socioeconomic stresses and, although the level of vulnerability varies widely, it is generally higher among poorer people (Kasperson et al., 2001).

In recent years, climate changes had affected all regions around the world and its effects had been observed in many parts of the world in recent decades and are expected to be intensified in the coming decades. In fact, climate change is one of the phenomena that the current world is experiencing it (Gafari *et al.,* 2014). Agriculture and natural resources are extremely dependent on weather and hence climate variability and changes, both in short-term (during the growing season) and long-term have a decisive role in its production and sustainability (Gafari *et al.,* 2014).

Agriculture sector is economically and physically vulnerable to changes in climate factors such as temperature and rainfall. In addition, the semi-arid nature of some countries with the rise of agriculture on marginal land, frequent droughts, scarce water resources and frequent fluctuations in rainfall would intensify this damage (Benhin, 2008). So according to what was said, changes in climate variables such as temperature and rainfall have an important role in agricultural productivity and rising in temperature and reducing in rainfall are the main variables in the phenomenon of climate change, which Changes in the pattern of these two variables can reduce yield during harvest time (Ben Zaied, 2013). Therefore, it is expected that climate change could influence the food production, food prices and potentially food security (Jayatilleke and Yiyong, 2014).

As cited by Maryam Asadpour Kordi, Hamid Amirnejad and Seyyed Mojtaba Mojaverian (2015), many studies have been done regarding climate change and its effects on crop productivity, which some examples of these studies are mentioned here.

Aligani *et al* (2011) in a study evaluated the effect of temperature and rainfall on yield of Iran's irrigated wheat based on combined time-series data from 1991 to 2006 and 14 provinces with high yield, and the results showed that for each provinces, physical variables (inputs) of model except the used pesticide had a significant positive effect on wheat yield and rainfall and temperature had positive and negative effects on wheat yield, respectively. Zarekani *et al* (2014) studied the effects of climate change on the economy of irrigated wheat in North Khorasan, Iran. Their results showed that climate change had been occurred in the last 30 years in this province and a significant relationship was observed between the logarithm of the parameters of minimum temperature, maximum temperature and annual rainfall with the yield of irrigated wheat.

As cited by Naveed Mehmood and Samina Khalil (2013), Janjua *et al.* (2010) investigated the impact of climate change on wheat productivity. They use simulations models for the expected impact of the climate change on wheat productivity accompanied by the VAR technique. Climate variables are represented by the average annual temperatures and rainfall. The result of the VAR model indicates that there is no significant negative impact of climate change on wheat productivity in Pakistan but through simulation techniques they showed an increase in the temperature by 2 to 3°C in 2050 and 2060 will definitely lower the productivity across the country. They conclude that the policy makers should take care of the issue of rising temperature which is being a long run consequence for wheat productivity in Pakistan.

Mirza and Schmitz (2011) study the economic assessment of the effects of climate change on crop productivity in Pakistan. They developed a panel model for modeling climate change and its impact on crop productivity in Pakistan. Their study shows, how changes in climate affects crop productivity in Pakistan measured as weighted food crop wheat, maize and rice. They conclude that areas with greater climatic pressures will be affected and hence lower level of crop productivity in the arid zone. The proposed hypothesis is that changing climatic variables have reduced and are reducing crop productivity and posing a threat to long term food security.

Nicholas (1997) examined the effects of climate change on wheat yield in Australia and concluded that by increasing one degree in temperature, wheat yield increased as much as 3-5 percent. Sultana *et al* (2009) by studying the vulnerability and adaptation of wheat production to the climate change in four climatic regions of Pakistan concluded that increasing in temperature would reduce the crop yield in arid, semiarid and semi-humid areas, but in the wet area with a gradual increase in temperature of 4 °C compared to the current situation, wheat yield would have an increasing trend. Luo *et al* (2009) by investigating the potential effects of climate change on wheat yield in area located in the southern part of Australia, suggested that the antedating of cultivation time is the most effective strategy for adaption to this phenomenon.

Ben Zaied (2013) examined the effects of climate change of annual rainfall and temperature on agricultural sector in Tunisia using the dynamic panel method and fully modified ordinary least squares (FMOLS). The results showed that the annual temperature and rainfall had negative and positive impact, respectively on crop production and total agricultural production in Tunisia. The effect of climate in the short-term was also estimated smaller than long-term.

Janjua *et al.* (2014) in a study titled "climate change and wheat production in Pakistan" examined the effects of climate change on wheat production using the autoregressive distributed lag model (ARDL) during 1960-2009. The results showed that climate change did not affect wheat production in Pakistan and only variables of fertilizer and cultivation land had a significant effect on wheat production in a short-term. Aditya *et al* (2014) studied the effect of climate change hazard on harvest intensity using the dynamic panel and dynamic ordinary least squares (DOLS) for 42 years. Their results showed that the effect of climate change hazard was negative on harvest intensity in a short-term in rural area in India, while this effect was positive in long-term.

Zerihun G. Kelbore (2012) studied the impacts of climate change on crop yield and yield variability in Ethiopia using Stochastic production function and the results showed that an increase in kiremt rain increases mean teff, wheat productivity in the SNNP region, whereas it has a relative decreasing effect on teff and wheat productivity in Amhara and Oromia regions. An increase in belg rain reduces mean teff and wheat productivity in SNNP region. An increase in kiremt rainfall decreases variability of teff and wheat productivity in SNNP region. An increase in belg rainfall decreases variability of average teff productivity in SNNP region.

Bezabih Emana and Mengistu ketema (2012) studied a time series analysis of climate variability and its effects on food productivity in North Shewa zone in Ethiopia using the Co-integrated Vector Autoregressive and Error Correction model. They concluded that food production was significantly affected by rainfall and temperature and it have also significant effect on crop productivity.

2.3 Ethiopian agriculture

Ethiopian agriculture is predominantly characterized by traditional methods of farming with very little change in farming practice over the past few centuries. The continuous use of such farming practice over a long period of time with little or no soil conservation measures has significantly eroded the fertility of the soil and agricultural outputs (Degefe, 2000).

The major factors behind the poor performance of Ethiopian agriculture are diminishing farm size and subsistence farming, soil degradation, inadequate and variable rainfall, climate-related disasters, tenure insecurity, weak agriculture research base and extension system, lack of financial system, imperfect agriculture markets and poor infrastructure. Ethiopian farming largely produces only enough food for the peasant holders and their family for consumption, leaving little to sell. Crops are the major productivity and sources of food in the country since most of the population depend on agriculture (Degefe, 2000).

Therefore, all famines that occurred in Ethiopia were attributed to crop failure due to climate variability effects. The major problem of crop productivity in Ethiopia is the low productivity due to lack of integrated disease and insect pests control, heavily dependence on the rain-fed agriculture and shortage of technique for proper conservation and utilization of water for full and supplemental irrigation at critical stage of crops.

2.4 Climatic Change and Agriculture in Ethiopia

A recent mapping on vulnerability and poverty in Africa put Ethiopia as one of the countries most vulnerable to climate change with the least capacity to respond (Bezu and Holden, 2008). Indeed, Ethiopia has experienced at least five major national droughts since 1980 (Yosuf et al; 2008). Cycles of drought create poverty traps for many households, constantly uneasy task to build up assets and increase income. Survey data show that between 1999 and 2004 more than half of all households in the country experienced at least one major drought shock. These shocks are a major cause of transient poverty had households been able to smooth consumption, and then poverty in 2004 would have been at least 14% lower, a figure that translates into 11 million fewer people below the poverty line. Food shortage and famine associated with rainfall variability cause a situation of high dependency on international food aid. And Ethiopia is one of the biggest food aid receipt countries in Africa that accounts to 20-30% of all food aid to sub-Saharan Africa (Bezu and Holden, 2008).

Climate change, climate change vulnerability and climate shocks negatively impact crop productivity; Rising temperatures, increasingly erratic rainfall, shortened rainy seasons, and lower amounts of seasonal rains are reducing crop productivity (USAID, 2015).

Analysis of historical climate trends can provide useful insights into the current trajectory of various climate variables, particularly on shorter-term planning horizons (USAID, 2015). As cited by USAID (2015), changes observed in the seasonal climate of Ethiopia during the 1981-2014 period were examined across the three predominant rainy seasons: *kiremt* (June through September), *bega* (October through December) and *belg* (March through May) using rainfall and temperature data from Climate Hazards Group Infrared Rainfall with Stations (CHIRPS) (Peterson et al., 2013) and Climate Research Unit Time Series 3.21 (University of East Anglia, 2013; Harris, Osborn, & Lister, 2014).

Climate variability and extreme events (rainfall and temperature variability, droughts, floods, etc.) are already impacting the health, life and livelihoods of Ethiopia‟s population, whose reliance on resource dependent activities makes them more vulnerable. Current trends, coupled with projected changes in climate for the coming decades could have serious repercussions for both people and the ecosystems on which they depend by adversely impacting crop productivity, food access, energy security and the availability of fuel wood (USAID, 2015).

2.5 Climate variability and observed trends in Ethiopia

Baseline climate that was developed using historical data of temperature and rainfall from 1971-2000 for selected stations in Ethiopia showed the year-to-year variation of rainfall for the period between 1951 to 2005 over the country expressed in terms of normalized rainfall anomaly averaged for 42 stations (NMA2007). The country during those periods (1951 to 2005) has experienced both dry and wet years.

Annual rainfall is likely to decrease throughout most of the African region, with the exception of Eastern Africa, where annual rainfall is projected to increase. These changes in the physical environment are expected to have an adverse effect on agricultural productivity, including staple crops such as wheat and maize. Trend analysis of annual rainfall in Ethiopia shows that rainfall remained more or less constant when averaged over the whole country while a declining trend has been observed over the Northern and Southwestern Ethiopia (IPCC, 2007).

2.6 Rainfall and temperature variability

The rainfall is highly variable both in amount and distribution across regions and seasons (Tesfaye, 2003, Mersha, 1999). Climate trends and climatic extreme indices derived from empirical, observed data indicate that global average surface temperatures have been increasing since the mid-19th century with the greatest rate of change observable since the mid-1970s (IPCC, 2014). Recent climatological studies have shown an increase in global surface air temperature by 0.76°C from 1850 to 2005 (Bakri and Abou-Shleel, 2013). The study reveals the extent to which global temperatures increased over the last century. However, it fails to add to the discourse about the causes of the phenomenon which is fundamentally critical in analyzing issues of climate variability and change.

A research carried out by Poulter *et al.* (2013) in the inner Asia which includes the semi-arid regions of northern China, Mongolia, and parts of southern Russia reveals an increase in mean annual air temperature. A similar research conducted by Cinco *et al*. (2014) on temperature anomalies in the Philippines for the period 1951–2010 against the baseline period of 1961–1990 demonstrates an overall increasing trend with values becoming positive in 1977 and 'peaking' in 1998 with a +1.0 °C anomaly. From 1996 to 2010, the end of the observed period, positive anomalies were consistently greater than 0.5 °C with 2005 and 2006 marking the peak warm years of the first decade of the 21st century. The temperature anomaly as revealed in the research gives evidence which is consistent with a warming global climate. Further studies in Asia have also shown an increase in mean annual temperature. For instance, according to a study by Chen *et al*. (2014), the mean annual temperature (MAT) in the whole Yangtze basin of China over the period 1955–2011 was 14.0 ^{o}C ranging from 13.4 ^{o}C to 14.9 ^{o}C. The MAT increased from 12.7 ^{o}C in the upper section of the catchment to 16.0 ^{o}C in the lower basin. The study shows a variation in the increase in the annual mean temperature of the upper and lower basins.

Boyles and Raman (2003) cited in Sayemuzzaman, *et al.* (2014), studied temperature and rainfall trends on seasonal and annual time scales in North Carolina, United States between 1949–1998. The study analyzed, using the linear time series slopes to investigate the spatial and temporal trends of rainfall. The study in the final analysis revealed a warmer temperature trend during the 1990s and the warmest being 1950. It can be noted from the analysis that, even though temperature increased within the stipulated duration, the early years experienced much more increase than the latter years and hence, temperature increased at a decreasing rate.

The study of Chen *et al*. (2014) indicates that rainfall across the whole Yangtze basin of China is very high in comparison to many rivers elsewhere. Annual rainfall across the whole basin averages 1024 mm and even in the driest section, the upper basin, the average is still 854 mm. The study however attributes the high rainfall in the Yangtze basin to the relatively small net consumption of water in relation to total annual flow in the region. In the same vein, Petrie *et al.* (2014) demonstrated in their study at northern Chihuahuan Desert, United States, that regional rainfall exhibits trends in average event timing and magnitude. Their study however indicated that the compensating changes did not induce change in the total average monsoon rainfall at the United States Historical Climatology Network (USHCN) sites over the last 100 years. The major reason given for no change in average total rainfall was explained to the effect that small number of very large events could account for the majority of total rainfall and that smaller events may often be insignificant in terms of total rainfall. Contrary, the findings of Afzal (2011) reveals that the increasing trends in rainfall have not been temporally continuous. Rather, the findings show an abrupt change in rainfall amounts around 1980 in Western Scotland. The study further notes that there was a spatial pattern in average rainfall variability. For instance, the West and South-west regions experienced the highest rainfall variability pattern. The study is deficient as to why the increasing trend in rainfall has not been temporally continuous. In the analysis of Tao *et al.* (2011) on the characteristics of hydro-climatic changes in the Tarim River Basin in China. They noted that the stations with significant increasing trends in annual stream flow were mainly distributed at the southern slope of Tianshan Mountain, which can only be explained by climatic changes.

The seasonal and annual rainfall variations are results of the macro-scale pressure systems and monsoon flows which are related to the changes in the pressure systems (Haile, 1986). The spatial variation of the rainfall is influenced by the changes in the intensity, position, and direction of movement of these rain-producing systems over the country (Temesgen, 2000). Moreover, the spatial distribution of rainfall in Ethiopia is significantly influenced by topography which also has many unexpected changes in the Rift Valley. Central rift valley is one of the environmentally very vulnerable areas in Ethiopia. Being a closed basin, relatively small interventions in land and water resources can have far reaching consequences for ecosystems goods and services, and potentially undermine the sustainable use of the area. Water resources in the CRV are increasingly over-exploited due to water extraction for agriculture and industry (soda ash productivity). The water level of lake Abijata has dropped about 5 m since the late 1960s and its shore has retreated 5 to 6 km, thus reducing the lake's size is about half of its original size (Attia and Abulhoda, 1992). In addition, land resources in the CRV are visibly over-grazed by an abundant livestock population while productivity of rain fed cropping is very low.

CHAPTER 3

3. DATA AND METHDOLOGY

3.1. Data

The study mainly depends on the analysis of secondary data at district level for the region. The relevant data was obtained from the National Meteorological Agency (NMA) and district‟s agricultural offices. Data on selected crop productivity, rainfall and temperature for the period of 1985 to 2015 was used.

3.2. Description of the study area

The study district is located at 45 km south east of Addis Ababa, Ethiopia. The district is the most important agricultural area in the central highlands of Ethiopia. The area receives an annual rainfall of around 1152mm (NMA 2006) with medium seasonal variability and bimodal pattern. The “Belg” or the shorter season‟s rain, which is quite small to support crop productivity, usually occurs during the periods from March to May. The long rainy season extends from June to September. The mean annual maximum and minimum temperatures are 30^{o}c and 8.5^{o}c respectively and the mean relative humidity is 61.3% (NMSA 2006). The area is located at 9^{0}N latitude and 40^{0}E longitude, with an altitude of 1880 meter above sea level in the central highland of Ethiopia. The area is intensively cultivated for crop productivity. The major crop types grown in the district are wheat, chickpea and indigenous Ethiopian crop, “teff”.

3.3. Variables in the study

Climate variability is partially explained by its key indicators that are rainfall and temperature. Climate change impact on agricultural productivity can be seen from the historical effects of rainfall and temperature on crop productivity. Crop productivity is also affected by several other climatic and non-climatic variables like type and amount of fertilizer used, improved seed, type of technology and etc. In case of this study, type of fertilizer used and seed type were not changed and the system and approach of farming was also constant. Therefore, the variables of interest are teff productivity (Quintal/hectare), wheat productivity (Quintal/hectare), total rainfall (mm), maximum average temperature (^{o}C) and minimum average temperature (^{o}C).

3.4. METHODOLOGY

Time series is broadly defined as a sequence of data points measured typically at successive points in time spaced at uniform time intervals. It can be divided into two major parts: univariate and multivariate time series. The term "univariate time series" refers to a time series that consists of single observations recorded sequentially over equal time increments. Autoregressive integrated moving average (ARIMA) modeling is a specific subset of univariate modeling in which a time series is expressed in terms of past values of itself (the autoregressive component) plus current and lagged values of a 'white noise' error term (the moving average component).

On the other hand, multivariate time series analysis involves statistical analysis of more than one statistical outcome variable at a time. In design and analysis, the technique is used to perform studies across multiple dimensions while taking into account the effects of all variables on the responses of interest. Multivariate time series analysis is used when one wants to model and explain the interactions and co-movements among a group of time series variables. This paper is concerned with modeling multivariate time series data.

3.4.1. Vector autoregressive (VAR) models

The VAR model is one of the most successful, flexible, and easy to use models for the analysis of multivariate time series. It is a natural extension of the univariate autoregressive model to dynamic multivariate time series. The VAR model has proven to be especially useful for describing the dynamic behavior of economic and financial time series and for forecasting. Forecasts from VAR models are quite flexible because they can be made conditional on the potential future paths of specified variables in the model.

In addition to data description and forecasting, the VAR model is also used for structural inference and policy analysis. In structural analysis, certain assumptions about the causal structure of the data under investigation are imposed, and the resulting causal impacts of unexpected shocks or innovations to specified variables on the variables in the model are summarized. These causal impacts are usually summarized with impulse response functions.

3.4.1.1. Stationary vector autoregression model

Let $Y_t = \left(Y_{1t}, Y_{2t} ..., Y_{nt}\right)'$ denote an (n×1) vector of time series variables. The basic p-lag vector autoregressive (VAR (p)) model has the form (Hamilton, 1994):

$$Y_t = C + \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + \ldots + \Pi_p Y_{t-p} + \varepsilon_t, t = 1,2,\ldots,T \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [3.1]$$

where C denotes an *n* x 1 vector of constants and Π_j is an *n* x *n* matrix of autoregressive coefficients for *j* = 1, 2, . . . , *p*. The *n* x 1 vector ε_t is a vector generalization of white noise:

$$E(\varepsilon_t) = 0, \text{ and } E(\varepsilon_t \varepsilon_s) = \begin{cases} \Sigma, s = t \\ 0, s \neq t \end{cases} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [3.2]$$

where Σ is an (n x n) symmetric positive definite matrix.

Let C_i denote the i^{th} element of the vector C and $\Pi_{k,ij}$ denote the row *i* and column *j* element of the matrix Π_k. Then the first row of the vector system in [3.1] specifies that:

$$\begin{aligned} Y_{1t} &= C_1 + \Pi_{1,11} Y_{1,t-1} + \Pi_{1,12} Y_{2,t-1} + \ldots + \Pi_{1,1n} Y_{n,t-1} + \Pi_{2,11} Y_{1,t-2} + \Pi_{2,12} Y_{2,t-2} \\ &+ \ldots + \Pi_{2,1n} Y_{n,t-2} + \ldots + \Pi_{p,11} Y_{1,t-p} + \Pi_{p,12} Y_{2,t-p} + \ldots + \Pi_{p,1n} Y_{n,t-p} + \varepsilon_{1t} \ldots\ldots\ldots\ldots [3.3] \end{aligned}$$

Thus, a vector auto regression is a system in which each variable is regressed on a constant and *p* of its own lags as well as on *p* lags of each of the other variables in the VAR. Note that each regression has the same explanatory variables. Using lag operator notation, [3.1] can be written in the form:

$$\Pi(B) Y_t = C + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [3.4]$$

where $\Pi(B) = I_n - \Pi_1 B - \cdots - \Pi_p B^P$ and B is the lag (backward shift) operator.

The VAR (p) is stable if the roots of $det(I_n - \Pi_1 B - \cdots - \Pi_p B^P) = 0$ lie outside the complex unit circle (have modulus greater than one) or equivalently, if the eigenvalues of the companion matrix:

$$F = \begin{pmatrix} \Pi_1 & \Pi_2 & . & . & . & \Pi p \\ I_n & 0 & . & . & . & 0 \\ 0 & . & & & & . \\ & & . & & & . \\ & & & . & & . \\ 0 & 0 & & 0 & I_n & 0 \end{pmatrix} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.5)$$

have modulus less than one. Assuming that the process has been initialized in the infinite past, then a stable VAR (p) process is stationary with time invariant means, variances and auto covariances.

If Y_t in [3.1] is covariance stationary (i.e. if the covariance doesn‟t depend on t), then the unconditional mean is given by:

$$\mu = (I_n - \Pi_1 B - ... - \Pi_P B^p)^{-1} C = (\Pi(B)^{-1})\ C$$

The mean-adjusted form of the VAR (p) is then:

$$Y_t - \mu = \Pi_1(Y_{t-1} - \mu) + \Pi_2(Y_{t-2} - \mu) + ... + \Pi_p(Y_{t-p} - \mu) + \varepsilon_t \text{.......................................[3.6]}$$

The basic VAR (p) model may be too restrictive to represent sufficiently the main characteristics of the data. In particular, other deterministic terms such as a linear time trend or seasonal dummy variables may be required to represent the data properly. Additionally, exogenous variables may be required as well. The general form of the VAR (p) model with deterministic terms and exogenous variables is given by:

$$Y_t = \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + ... + \Pi_p Y_{t-p} + \beta D_t + GX_t + \varepsilon_t \text{.......................................[3.7]}$$

where D_t represents an ($l \times 1$) matrix of deterministic components, X_t represents an m × 1vector of exogenous variables, β and G are parameter matrices, and l and m are number of time trend and exogenous variables respectively.

3.4.1.2. Testing Stationarity: unit root test

A time series is said to be stationary when the mean and autocovariances of the series remain constant over time. In other words, the stochastic process Y_t is said to be stationary if:

$E(Y_t) = \mu$, constant for all value of t ………………………………. [3.8]

$\text{cov}(Y_t, Y_{t-j}) = \Gamma_j$, for all t and j=0, 1, 2, …………………............ [3.9]

Condition [3.8] means that all Y_t have the same finite mean vector μ and [3.9] requires that the autocovariances of the process do not depend on t but just on the time period j that the two vectors Y_t and Y_{t-j} are apart. Therefore, a process is stationary if its first and second moments are time invariant.

A time series variable Y_t is said to be integrated of order d, denoted by I(d) where d is an integer with d ≥ 1, if the stochastic trends can be removed by differencing the variable d times or time series are non-stationary in level and become stationary after dth difference. Using the differencing operator Δ which is defined as $\Delta^d Y_t = (1-B)^d Y_t$, the variable Y_t is I (d) if $\Delta^d Y_t$ is stationary, where B is the lag operator. A series is said to be integrated of order zero, denoted by I (0), if the series is stationary in level.

To test for stationarity of a series several procedures have been developed. The most popular ones are Augmented Dickey-Fuller (ADF) test due to Dickey and Fuller (1979, 1981) and the Phillip-Perron (PP) due to Phillips (1987) and Phillips and Perron (1988). The following discussion outlines the basic features of unit root tests Hamilton (1994).

Consider a simple AR (1) process:

$$Y_t = \rho Y_{t-1} + X_t'\delta + \varepsilon_t \text{..} [3.10]$$

where X_t are optional exogenous regressors which may consist of constant or a constant and trend, ρ and δ are parameters to be estimated, and ε_t is assumed to be white noise. If |ρ| ≥ 1, Y_t is a non-stationary series and the variance of Y_t increases with time. If |ρ|<1, Y_t is a stationary series. Thus, the hypothesis of Stationarity can be evaluated by testing whether ρ is strictly less than one i.e. H_0: ρ=1 versus H_1: ρ<1.

3.4.1.2.1. Augmented Dickey-Fuller (ADF) test

The standard Dickey-Fuller test is conducted by estimating equation [3.10] after subtracting Y_{t-1} from both side of the equation:

$$\Delta Y_t = \alpha Y_{t-1} + X_t'\delta + \varepsilon_t \text{..} [3.11]$$

where $\alpha = \rho - 1$ and $\Delta Y_t = Y_t - Y_{t-1}$. The null and alternative hypotheses may be re-expressed as H_0: α=0 versus H_1: α<0 and evaluated using the conventional t-ratio:

$$t_\alpha = \frac{\hat{\alpha}}{(s.e(\hat{\alpha}))} \text{..[3.12]}$$

Where $\hat{\alpha}$ is the OLS estimate of α, and $s.e(\hat{\alpha})$ is the standard error of $\hat{\alpha}$.

Dickey and Fuller (1979) show that under the null hypothesis of a unit root, this statistic does not follow the conventional Student‟s t-distribution, and they derive asymptotic results and simulate critical values for various test and sample sizes. MacKinnon (1991, 1996) implements a much larger set of simulations than those tabulated by Dickey and Fuller. In addition, MacKinnon estimates response surfaces for the simulation results, permitting the calculation of Dickey-Fuller critical values and p-values for arbitrary sample sizes. The simple Dickey-Fuller unit root test described above is valid only if the series is an AR (1) process. If the series is correlated at higher order lags, the assumption of white noise disturbances ε_t is violated.

The Augmented Dickey-Fuller (ADF) test constructs a parametric correction for higher-order correlation by assuming that the series follows an AR (p) process and adding lagged difference terms of the dependent variable to the right-hand side of the test regression:

$$\Delta Y_t = \alpha Y_{t-1} + X_t'\delta + \beta_1 \Delta Y_{t-1} + \beta_2 \Delta Y_{t-2} + ... + \beta_p \Delta Y_{t-p} + U_t \text{......................[3.13]}$$

This augmented specification is then used to test for the presence of a unit root. An important result obtained by Fuller (1976) is that the asymptotic distribution of the t-ratio for α is independent of the number of lagged first differences included in the ADF regression. Moreover, while the assumption that Y_t follows an autoregressive (AR) process may seem restrictive, Said and Dickey (1984) demonstrate that the ADF test is asymptotically valid in the presence of a moving average (MA) component, provided that sufficient lagged difference terms are included in the test regression.

3.4.1.2.2. The Phillips-Perron (PP) Test

Phillips and Perron (1988) propose an alternative (nonparametric) method of controlling for serial correlation when testing for a unit root. The PP method estimates the non-augmented DF test equation and modifies the t -ratio of α coefficient so that serial correlation does not affect the asymptotic distribution of the test statistic. The PP test is based on the statistic:

$$\hat{t}_{\alpha} = t_{\alpha}\left(\frac{\gamma_0}{f_0}\right)^{\frac{1}{2}} - \frac{T\left(f_0 - \gamma_0\right)\left(s.e(\hat{\alpha})\right)}{2 f_0^{\frac{1}{2}} * s} \qquad [3.14]$$

where $\hat{\alpha}$ is the OLS estimate of α, t_{α} is the t -ratio, $s.e\ (\hat{\alpha})$ is the standard error of $\hat{\alpha}$ and s is the standard deviation of the test regression. In addition, γ_0 is a consistent estimate of the error variance in [3.11] (calculated as $(T-n)\frac{S^2}{T}$, where n is the number of regressors). The remaining term f_0 is an estimator of the residual spectrum at frequency zero. The asymptotic distribution of the PP modified t-ratio is the same as that of the ADF statistic.

3.4.1.3. Estimating the order of the VAR

The lag length for the VAR model may be determined using model selection criteria. The general approach is to fit VAR models with orders $m = 0,\dots,p_{\max}$ and choose the value of m which minimizes some model selection criteria Lutkepohl (2005). The general form of model selection criteria is:

$$C(m) = \ln\left|\hat{\sum}_m\right| + C_T.\varphi(m,n) \qquad [3.15]$$

where $\hat{\sum}_m = T^{-1}\sum_{t=1}^{T}\hat{\varepsilon}_t\hat{\varepsilon}_t'$ is the residual covariance matrix estimator for a model of order m, $\varphi(m,n)$ is a function of order m which penalizes large VAR orders and C_T is a sequence which may depend on the sample size and identifies the specific criteria.

The term $\ln\left|\hat{\sum}_m\right|$ is a non-increasing function of the order m, while $\varphi(m,n)$ increases with order m. The lag order is chosen which optimally balances these two forces.

The three most commonly used information criteria for selecting the lag order are the Akaike information criterion (AIC), Schwarz-Bayesian information criterion (SBIC), Hannan-Quin information criteria (HQIC):

$$AIC(m) = \ln\left|\hat{\sum}_m\right| + \frac{2}{T} mn^2 \qquad [3.16]$$

$$SBIC(m) = \ln\left|\hat{\sum}_m\right| + \frac{\ln T}{T} mn^2 \qquad [3.17]$$

$$HQIC(m) = \ln\left|\hat{\sum}_m\right| + \frac{2\ln\ln T}{T} mn^2 \qquad [3.18]$$

In each case $\varphi(m,n) = mn^2$ is the number of VAR parameters in a model with order m and n is number of variables. The AIC criterion asymptotically overestimates the order with positive probability. On other hand, the HQIC and SBIC criteria are both consistent, that is, the order estimated with these criteria converges to the true VAR order p under quite general conditions if the true order (p) is less than or equal to $p_{\max}$.

3.4.2. Cointegration analysis and vector error correction model (VECM)

Two series Y_{1t} and Y_{2t} are said to be cointegrated if Y_{1t} and Y_{2t} have unit roots, but some linear combination of them is stationary. The variables in the VAR system may have a long-run equilibrium relationship to which any deviating variable is gradually pulled over time. The long-run equilibrium relationship is called the cointegrating vector. When there is a cointegrating vector, the VAR model should be augmented with an error correction term. In other words, pure VAR can be applied only when there is no cointegrating relationship among the variables in the VAR system. Hence, a prerequisite before running any VAR model is to run a cointegration test.

The role of cointegration is to link between the relations among a set of integrated (nonstationary) series and the long-term equilibrium. The presence of a cointegrating equation is interpreted as a long-run equilibrium relationship among the variables. If there is a set of n integrated variables of order one (I (1)), there may exist up to (n-1) independent linear relationships that are I (0). In general, there can be r ≤ n-1 linearly independent cointegrating vectors, which are gathered together into the (n x r) cointegrating matrix.

3.4.2.1 Testing for cointegration using Johansen's methodology

The starting point in Johansen"s procedure (1988, 1991) in determining the number of cointegrating vectors is the VAR representation of Y_t. A vector autoregressive model of order p VAR (p) is assumed:

$$Y_t = \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + ... + \Pi_p Y_{t-p} + \beta D_t + \varepsilon_t \text{...[3.19]}$$

where Y_t is an (n x 1) vector of non-stationary (I (1)) variables, D_t is a d-vector of deterministic components, and ε_t is a vector of innovations. The VAR in [3.19] can be reparametrized as a vector error correction model as (Hamelton, 1994):

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + \beta D_t + \varepsilon_t \text{..[3.20]}$$

where $\Pi = \sum_{i=1}^{p} \Pi_i - \mathrm{I}$ and $\Gamma_i = -\sum_{j=i+1}^{p} \Pi_j$, i=1, 2, …, p-1.

Granger"s representation theorem asserts that if the coefficient matrix *Π* has reduced rank r < n, then there exist n *x r* matrices *α* and ***β*** each with rank *r* such that Π=α***β***" and $\beta' Y_t$ is I (0), where *r* is the number of cointegrating relations and each column of *β* is a cointegrating vector. The elements of *α* are known as the adjustment parameters in the vector error correction (VEC) model. A vector error correction (VEC) model is a restricted VAR designed for use with nonstationary series that are known to be cointegrated. The VEC has cointegration relations built into the specification so that it restricts the long-run behavior of the endogenous variables to converge to their cointegrating relationships while allowing for short-run adjustment dynamics.

The cointegration term $\Pi Y_{t-1} = \alpha\beta' Y_{t-1}$ is known as the *error correction* term since the deviation from long-run equilibrium is corrected gradually through a series of partial short-run adjustments. When rank (Π) = 0, then there are no cointegrating variables, i.e., all rows (columns) of Π are linearly dependent and the system is nonstationary in level. When Π has full rank (rank (Π) = n), then Y_t has no unit root, i.e., Y_t is stationary in level.

Johansen (1988) proposed two tests for estimating the number of cointegrating vectors: the trace test and the maximum eigenvalue test. Trace statistic tests the null hypothesis of r cointegrating relations against the alternative of (r+1) cointegrating relations for r = 0, 1, 2…, n-1. Define $\hat{\lambda}_i$, i=1, 2, …, n to be a complex modulus of eigenvalues of $\hat{\Pi}$ and let they be ordered such that $\hat{\lambda}_1 > \hat{\lambda}_2 ... > \hat{\lambda}_n$. The trace statistic is computed as:

$$\lambda_{trace}(r) = -T\sum_{i=r+1}^{n}\log\left[1-\hat{\lambda}_i\right] \text{...} [3.21]$$

The maximum eigenvalue statistic tests the null hypothesis of r cointegrating relations against the alternative of n cointegrating relations for r = 0, 1, 2…n-1 where n is the number of variables. This test statistic is computed as:

$$\lambda_{\max}(r, r+1) = -T\log\left(1-\hat{\lambda}_{r+1}\right) \text{..} [3.22]$$

where $\hat{\lambda}_{r+1}$ is the $(r+1)^{th}$ ordered eigenvalue of $\hat{\Pi}$, and T is the sample size. The asymptotic critical values tabulated by Johansen and Juselius (1990) will be used for these tests.

3.4.2.2. Estimation of the vector error correction model

In order to estimate a vector error correction model without deterministic terms, subtracting Y_{t-1} from both side of equation (3.1) and rearranging terms gives the so-called error correction model form of the process:

$$\Delta Y_t = -\Pi Y_{t-1} + \beta_1\Delta Y_{t-1} + ... + \beta_{p-1}\Delta Y_{t-p+1} + \varepsilon_t \text{...} [3.23]$$

where $\Pi = I - \Pi_1 - ... - \Pi_p$ and $\beta_i = -\Pi_{i+1} - ... - \Pi_p$ for i= 1,2,…,p-1. In this representation of the process, all terms are stationary because ΔY_t and ε_t are stationary.

Hence, the term ΠY_{t-1} is the only one which includes I (1) variables and, consequently, ΠY_{t-1} must also be I (0). In other words, ΠY_{t-1} must contain the cointegrating relations of the system. It is also possible to obtain the Π_j parameter matrices from the coefficients of the error correction model as: $\Pi_1 = \beta_1 - \Pi + I$, $\Pi_i = \beta_i - \beta_{i-1}$ for i=2,3,…,p-1, and $\Pi_p = -\beta_{p-1}$. In deriving an estimator for the parameters of [3.23], we will use the following additional notation:

$$\Delta Y = [\Delta Y_1, \Delta Y_2, ..., \Delta Y_T]_{n\ x\ T} \quad , \quad Y = [Y_1, Y_2, ..., Y_T]_{n\ x\ T} \quad , \quad \beta = [\beta_1, \beta_2, ..., \beta_{p-1}]_{n\ x\ p-1}$$

$$X = [X_1, X_2, ..., X_T]_{p-1\ x\ T} \text{ with } X_{t-1} = \begin{bmatrix} \Delta Y_{t-1} \\ . \\ . \\ . \\ \Delta Y_{t-p+1} \end{bmatrix}_{p-1\ x\ 1} \text{ and } U = [u_1, u_2, ..., u_T]_{n\ x\ T}.$$

For t=2, 3,…, T, the error correction model in (3.23) can be written as:

$$\Delta Y + \Pi Y = \beta X + U \text{..} [3.24]$$

If Π were known, the least square (LS) estimator of β would be:

$$\hat{\beta} = (\Delta Y + \Pi Y) X'(XX')^{-1} \text{..} [3.25]$$

Substituting this estimator in [3.24] gives the multivariate regression model:

$$\Delta YM = -\Pi YM + \hat{U} \text{..} [3.26]$$

where $M = I - X'(XX')^{-1} X$. Now an estimator of Π can be obtained by a reduced rank regression. A feasible estimator of β is then obtained by replacing Π in [3.25] by $\hat{\Pi}$. If the process is normally distributed, the estimators obtained in this way are in fact ML estimators (Johansen (1988, 1991)).

Under general assumptions, the estimators of β and Π are consistent and asymptotically normal, that is,

$$\sqrt{T}(\hat{\beta} - \beta) \xrightarrow{d} N(0,\ \Sigma_{\hat{\beta}}) \text{..} [3.27]$$

$$\sqrt{T}(\hat{\Pi} - \Pi) \xrightarrow{d} N(0,\ \Sigma_{\hat{\Pi}}) \text{..} [3.28].$$

The asymptotic distribution of $\hat{\beta}$ is nonsingular, and hence, standard inference may be used. In contrast, $\Sigma_{\hat{\Pi}}$ in [3.28] has rank nr and is singular if r < n, where r is the number of cointegrated vectors.

3.4.3. Model checking

A wide range of procedures is available for checking the adequacy of VAR and VEC models. They should be applied before a model is used for specific purpose to ensure that it represents the data adequately.

3.4.3.1. Test of residual autocorrelation

3.4.3.1.1. Portmanteau autocorrelation test

The portmanteau test for residual autocorrelation checks the null hypothesis that all residual autocovariances are zero, that is:

$$H_0 : E(\varepsilon_t \varepsilon'_{t-j}) = 0, \quad j = 1,2,\ldots,h \text{...[3.29]}$$

It is tested against the alternative that at least one auto covariance and, hence, one autocorrelation is nonzero. The test statistic is based on the residual autocovariances and has the form:

$$Q_h = T \sum_{j=1}^{h} tr\left(\hat{\gamma}'_j \hat{\gamma}_0'^{-1} \hat{\gamma}_j \hat{\gamma}_0^{-1}\right) \text{...[3.30]}$$

where $\hat{\gamma}_j = T^{-1} \sum_{t=j+1}^{T} \hat{\varepsilon}_t \hat{\varepsilon}'_{t-j}$, tr(.) is the trace operator and the $\hat{\varepsilon}_t$ "s are the estimated residuals. If $\hat{\varepsilon}_t$ are residuals from a stable VAR (p) process, Q_h has an approximate $\chi^2\left(n^2(h-p)\right)$ distribution under the null hypothesis, where T is the length of the series, h denotes the order of the autocorrelation, p is the maximum lag in the VAR model and n is the number of regressors. The limiting χ^2 distribution is strictly valid only if $\frac{h}{T} \to 0$ with growing sample size.

Alternatively (especially in small samples), a modified statistic is given by:

$$Q^*{}_h = T^2 \sum_{j=1}^{h} \frac{1}{T-j} t_r \left(\hat{\gamma}'_j \hat{\gamma}'^{-1}_0 \hat{\gamma}_j \hat{\gamma}_0^{-1} \right) \text{.........} [3.31]$$

This statistic may have better small sample properties than the unadjusted version. The choice of h is important for the test performance. If h is chosen too small, the χ^2 approximation to the null distribution may be very poor whereas a large h may result in a loss of power.

3.4.3.1.2. Autocorrelation LM test

This test was developed by Breusch and Godfrey (1978). Assume a VAR model for the error u_t given by:

$$u_t = B_1 u_{t-1} + ... + B_h u_{t-h} + v_t \text{.........} [3.32]$$

The quantity v_t denotes a vector of white noise error terms. To test for autocorrelation in u_t, the null and alternative hypotheses are:

$$H_0 : B_1 = B_2 = ... = B_h = 0$$

$H_1 : B_j \neq 0$ for at least one $j \leq h$

We use the Lagrange Multiplier method to perform the test. This method is very useful for finding optimal estimates under constraint conditions.

Under H_0, we only need to check the regular VAR model $u_t = v_t$. To determine the test statistic we begin with the auxiliary regression:

$$\hat{u} = \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + ... + \Pi_p Y_{t-p} + B_1 \hat{u}_{t-1} + B_2 \hat{u}_{t-2} + ... + B_h \hat{u}_{t-h} + \beta D_t + v_t \text{.........} [3.33]$$

where D_t represents an ($l \times 1$) matrix of deterministic components, β is a parameter matrix of suitable dimension and v_t is an auxiliary error term.

The model is estimated by the same method as original model[3.32]with $\hat{u}_t$, $t \le 0$, replaced by zero. Denoting the residuals from the estimated auxiliary model by $\hat{v}_t$ (t = 1, . . . , T), the residual covariance matrix estimator obtained from the auxiliary model is:

$$\hat{\Sigma}_v = \frac{1}{T}\sum_{t=1}^{T} \hat{v}_t \hat{v}_t'.$$

Moreover, re-estimating the relevant auxiliary model without the lagged residuals $\hat{u}_{t-i}$, that is, imposing the restriction $\mathrm{B}_1 = \mathrm{B}_2 = \ldots = \mathrm{B}_h = 0$, and denoting the resulting residuals by $\hat{v}^R{}_t$, the corresponding covariance matrix estimator is:

$$\hat{\Sigma}_R = \frac{1}{T}\sum_{t=1}^{T} \hat{v}^R{}_t \hat{v}^{R'}{}_t.$$

The LM statistic is:

$$\lambda_{LM}(h) = T\{n - tr[(\hat{\Sigma}_R)^{-1}\hat{\Sigma}_v]\}.$$

This statistic has an asymptotic $\chi^2(hn^2)$ distribution under the null hypothesis.

3.4.3.1.3. Test of multivariate normality

The multivariate version of the Jarque-Bera test is used to test the normality of the residual vector such that its components are independent and then check the compatibility of the third and fourth moments with those of a normal distribution. In a first step, the residual covariance matrix is estimated as: $\hat{\Sigma}_u = \frac{1}{T}\sum_{t=1}^{T}(\hat{u}_t - \bar{\hat{u}})(\hat{u}_t - \bar{\hat{u}})'$ and the square root of covariance matrix $((\hat{\Sigma}_u)^{\frac{1}{2}})$ is computed.

The tests for non-normality may be based on the skewness and kurtosis of the standardized residuals $(\hat{u}_t)^s = \{(\hat{u}_{1t})^s, \ldots, (\hat{u}_{nt})^s\}' = (\hat{\Sigma}_u)^{-\frac{1}{2}}(\hat{u}_t - \bar{\hat{u}})$:

$$b_1 = (b_{11}, \ldots, b_{1n})' \text{ with } b_{1n} = T^{-1}\sum_{t=1}^{T}((\hat{u}_{nt})^s)^3$$

$$b_2 = (b_{21}, \ldots, b_{2n})' \text{ with } b_{2n} = T^{-1}\sum_{t=1}^{T}((\hat{u}_{nt})^s)^4$$

Defining $s_3 = \frac{1}{6} T \hat{b}_1' \hat{b}_1$ and $s_4 = \frac{1}{24} T \left(\hat{b}_2 - \underset{\sim}{3}\right)' \left(\hat{b}_2 - \underset{\sim}{3}\right)$ where $\underset{\sim}{3} = (3,3,...,3)'$ is an (n x 1) vector, a multivariate version of the Jarque-Bera statistic is:

$JB_n = s_3 + s_4$.

The statistics s_3 and s_4 have $\chi^2(n)$ limiting distributions and JB_n has a $\chi^2(2n)$ asymptotic distribution if the normality null hypothesis holds. The latter statistic was proposed by Doornik and Hansen (1994).

3.4.4. Structural vector autoregressive (SVAR) analysis

The general VAR(p) model has many parameters, and they may be difficult to interpret due to complex interactions and feedback between the variables in the model. As a result, the dynamic properties of a VAR (p) are often summarized using various types of structural analysis.

The three main types of structural analysis summaries are:

- Granger causality tests;
- Impulse response functions; and
- Forecast error variance decompositions.

The following sections give brief descriptions of these summary measures.

3.4.4.1. Granger causality tests

One of the main uses of VAR models is forecasting. The structure of the VAR model provides information about a variable‟s or a group of variables‟ forecasting ability for other variables.

The following intuitive notion of a variable‟s forecasting ability is due to Granger (1969). If a variable, or group of variables, Y_1 is found to be helpful for predicting another variable, or group of variables, Y_2 then Y_1 is said to Granger-cause Y_2; otherwise it is said to fail to Granger-cause Y_2. Formally, Y_1 fails to Granger-cause Y_2 if for all s > 0 the MSE of a forecast of $Y_{2,t+s}$ based on $(Y_{2,t}, Y_{2,t-1},...)$ is the same as the MSE of a forecast of $Y_{2,t+s}$ based on $(Y_{2,t}, Y_{2,t-1},...)$ and $(Y_{1,t}, Y_{1,t-1},...)$. Clearly, the notion of Granger causality does not imply true causality. It only implies forecasting ability. If Y_1 causes Y_2 and Y_2 also causes Y_1 the process $\left(Y_{1t}', Y_{2t}'\right)'$ is called a feedback system.

In a bivariate VAR (p) model for $Y_t = \left(Y_{1t}, Y_{2t}\right)'$, Y_2 fails to Granger-cause Y_1 if all of the p VAR coefficient matrices $\Pi_1, \Pi_2, ..., \Pi_P$ are lower triangular. That is, the VAR (p) model has the form:

$$\begin{pmatrix} Y_{1t} \\ Y_{2t} \end{pmatrix} = \begin{pmatrix} C_1 \\ C_2 \end{pmatrix} + \begin{pmatrix} \Pi_{11}^1 & 0 \\ \Pi_{21}^1 & \Pi_{22}^1 \end{pmatrix} \begin{pmatrix} Y_{1,t-1} \\ Y_{2,t-1} \end{pmatrix} + ... + \begin{pmatrix} \Pi_{11}^p & 0 \\ \Pi_{21}^p & \Pi_{22}^p \end{pmatrix} \begin{pmatrix} Y_{1,t-p} \\ Y_{2,t-p} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$$

so that all of the coefficients on lagged values of Y_2 is zero in the equation for Y_1. Similarly, Y_1 fails to Granger-cause Y_2 if all of the coefficients on lagged values of Y_1 are zero in the equation for Y_2.

The p linear coefficient restrictions implied by Granger non-causality may be tested using the Wald statistic. Notice that if Y_2 fails to Granger-cause Y_1 and Y_1 fails to Granger-cause Y_2, then the VAR coefficient matrices $\Pi_1, \Pi_2, ..., \Pi_P$ are diagonal. Testing for Granger non-causality in the general n variable VAR (p) models follows the same logic used for bivariate models.

3.4.4.2. Impulse response functions

Any covariance stationary VAR (p) process has a Wold"s representation of the form:

$$Y_t = \mu + \varepsilon_t + \Psi_1 \varepsilon_{t-1} + \Psi_2 \varepsilon_{t-2} + ... + \Psi_p \varepsilon_{t-p} \text{...[3.49]}$$

where the (n × n) moving average matrices Ψ_s are determined recursively. It is tempting to interpret the $(i, j)^{th}$ element Ψ_{ij}^s of the matrix Ψ_s as the dynamic multiplier or impulse response:

$$\frac{\partial Y_{i,t+s}}{\partial \varepsilon_{j,t}} = \frac{\partial Y_{i,t}}{\partial \varepsilon_{j,t-s}} = \Psi_{ij}^s \text{ ....[3.50]}$$

However, this interpretation is only possible if $Var(\varepsilon_t) = \Sigma$ is a diagonal matrix so that the elements of ε_t are uncorrelated. One way to make the errors uncorrelated is to follow Sims (1980) recursive VARmodel and estimate the triangular structural VAR (p) model:

$$\left.\begin{aligned}
Y_{1t} &= C_1 + \gamma'_{11}Y_{t-1} + \ldots + \gamma'_{1p}Y_{t-p} + \eta_{1t} \\
Y_{2t} &= C_1 + \beta_{21}Y_{1t} + \gamma'_{21}Y_{t-1} + \ldots + \gamma'_{2p}Y_{t-p} + \eta_{2t} \\
Y_{3t} &= C_1 + \beta_{31}Y_{1t} + \beta_{32}Y_{2t} + \gamma'_{31}Y_{t-1} + \ldots + \gamma'_{3p}Y_{t-p} + \eta_{3t} \\
&. \\
&. \\
&. \\
Y_{nt} &= C_1 + \beta_{n1}Y_{1t} + \ldots + \beta_{n,n-1}Y_{n-1,t} + \gamma'_{n1}Y_{t-1} + \ldots + \gamma'_{np}Y_{t-p} + \eta_{nt}
\end{aligned}\right\} \ldots\ldots\ldots\ldots\ldots\ldots\ [3.51]$$

In matrix form, the triangular structural VAR (p) model is:

$$BY_t = C + \Gamma_1 Y_{t-1} + \Gamma_2 Y_{t-2} + \ldots + \Gamma_p Y_{t-p} + \eta_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [3.52]$$

where B = $\begin{pmatrix} 1 & 0 & 0 & . & . & . & 0 \\ -\beta_{21} & 1 & 0 & . & . & . & 0 \\ . & . & . & & & & . \\ . & . & & . & & & . \\ . & . & & & . & & . \\ -\beta_{n1} & -\beta_{n2} & -\beta_{n3} & . & . & . & 1 \end{pmatrix}$ ....[3.53] is a lower triangular matrix with 1"s along the diagonal. The algebra of least squares will ensure that the estimated covariance matrix of the error vector η_t is diagonal. The uncorrelated/orthogonal errors η_t are referred to as structural errors.

The triangular structural model [3.51] imposes the recursive causal ordering:

$$Y_1 \to Y_2 \to \ldots \to Y_n \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [3.54]$$

For example, the ordering $Y_1 \to Y_2 \to Y_3$ imposes the restrictions: Y_{1t} affects Y_{2t} and Y_{3t} but Y_{2t} and Y_{3t} do not affect Y_1; Y_{2t} affects Y_{3t} but Y_{3t} does not affect Y_{2t} .Similarly, the ordering $Y_2 \to Y_3 \to Y_1$ imposes the restrictions: Y_{2t} affects $\mathbf{Y}_{3t}$ and $\mathbf{Y}_{1t}$ but Y_{3t} and Y_{1t} do not affect Y_2; Y_{3t} affects Y_{1t} but Y_{1t} does not affect Y_{3t}.

For a VAR (p) with n variables there are n! possible recursive causal orderings. Which ordering to use in practice depends on the context and whether prior theory can be used to justify a particular ordering. Results from alternative orderings can always be compared to determine the sensitivity of results to the imposed ordering.

Once a recursive ordering has been established, the Wold"s representation of Y_t based on the orthogonal errors η_t is given by:

$$Y_t = \mu + \Theta_0 \eta_t + \Theta_1 \eta_{t-1} + ... + \Theta_p \eta_{t-p} \text{..[3.55]}$$

where $\Theta_0 = B^{-1}$ is a lower triangular matrix. The impulse responses to the orthogonal shocks η_{jt} are:

$$\frac{\partial Y_{i,t+s}}{\partial \eta_{j,t}} = \frac{\partial Y_{it}}{\partial \eta_{j,t-s}} = \theta_{ij}^s, \; i, j = 1,2,...,n; \; s > 0 \text{...[3.56]}$$

where θ_{ij}^s is the $(i, j)^{th}$ element of Θ_s. A plot of θ_{ij}^s against s is called the orthogonal impulse response function (IRF) of Y_i with respect to η_j. With n variables there are n^2 possible impulse response functions.

CHAPTER 4

4. RESULTS AND DISCUSSION

The study is based on thirty one years total rainfall in mm, maximum and minimum average temperature in degree centigrade (°C) and selected crop productivity in quintal per hectare (Q/h) of Ada'a districts. The time period included is from 1985 to 2015 G.C. The discussion begins by describing the data set and the results from the model selection procedure. Data analysis was performed by STATA12 and Eviews 7.

4.1. Descriptive Analysis

Table 4.1 below shows the summary of climatic variables and crop productivity. From the table, it can be seen that the mean of teff, wheat, total rainfall, maximum average temperature and minimum average temperature are 13.65 Q/hec, 22.99 Q/hec, 713.37 mm, 26.27 ^{0}C and 11.16 ^{0}C respectively. The total amount of rainfall ranged from 329.90 mm to 1033.50 mm which indicate a high inter-annual variability of the total rainfall. The standard deviation of total rainfall is 181.84 mm indicating higher variability of the annual rainfall. Also crop productivity exhibits the highest variability from year to year, with the range of 5.43 Q/hec to 35.00 Q/hec for teff productivity and 2.68 Q/hec to 53.00 Q/hec for wheat productivity. Standard deviation of maximum and minimum average temperature is 0.34 and 0.46 respectively. This shows the year to year variability in average temperature is not large.

Table 4.1. Descriptive Statistics of the series: 1985 to 2015

Descriptive Statistics	Teff (Q/hec)	Wheat (Q/hec)	Rainfall (mm)	Maximum Temperature (^{0}C)	Minimum Temperature (^{0}C)
Mean	13.65	22.99	713.37	26.27	11.16
Median	9.23	17.98	13.67	26.26	11.13
Maximum	35.00	53.00	1033.50	26.88	12.14
Minimum	5.43	2.68	329.90	25.75	10.18
Std. Dev.	8.29	13.15	181.84	0.34	0.46

Skewness	1.06	0.68	1.35	0.07	0.16
Kurtosis	-0.84	-0.44	0.30	1.89	2.68
Observations	31	31	31	31	31

4.2. Unit root properties of Individual series

The time series under consideration should be checked for stationarity before one can attempt to fit a suitable model. That is, variables have to be tested for the presence of unit root(s) thereby the order of integration of each series is determined. The time series plots of the series under consideration are shown in Figure 4.1 through Figure 4.4. Figure 4.2, 4.3 and 4.4 shows a stationary behavior of the series. Figure 4.1. shows non-stationarity of the series.

Figure 4.1. Time series plot of teff productivity (original series)

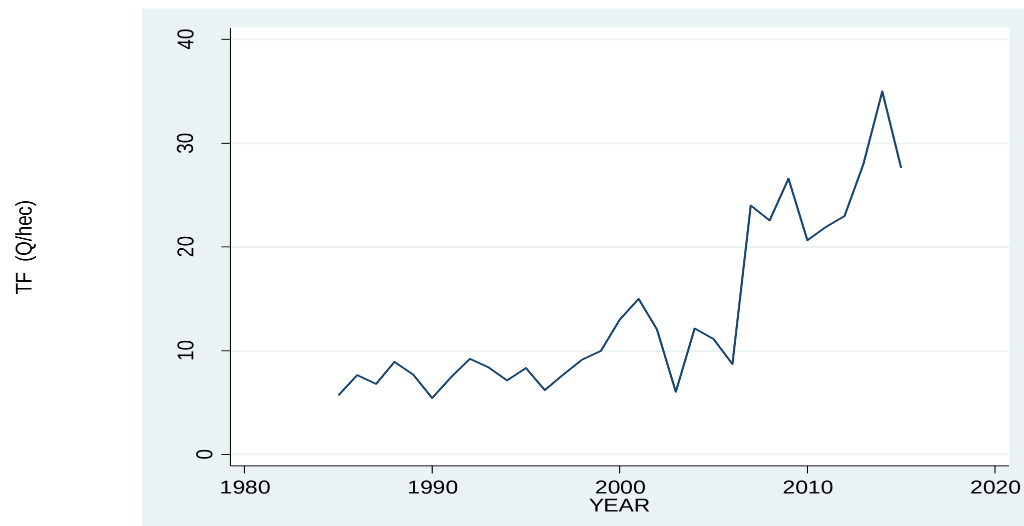


Figure 4.2. Time series plot of wheat productivity (original series)

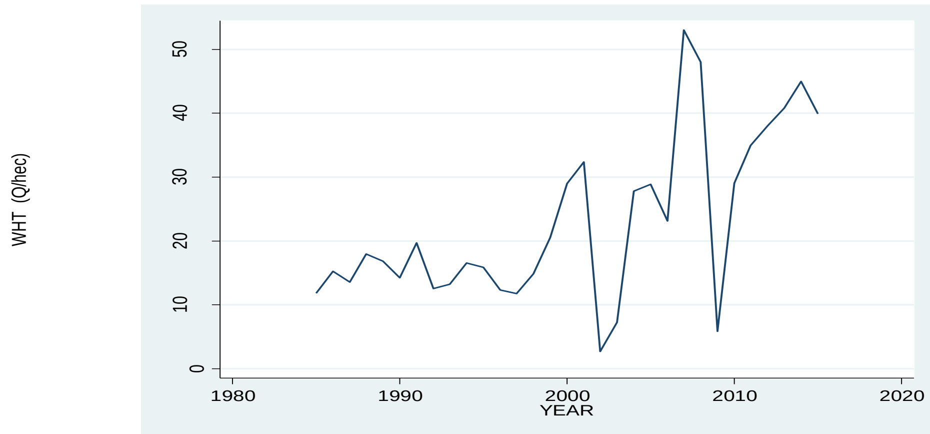


Figure 4.3. Time series plot of total rainfall (original series)

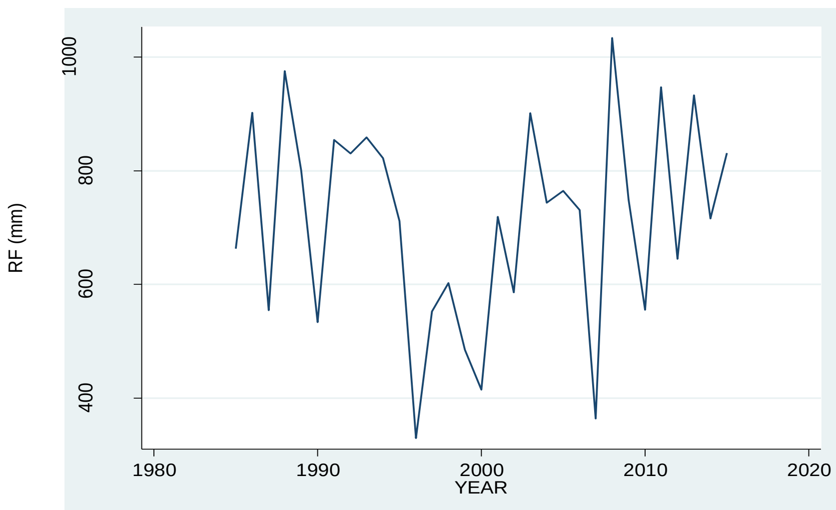


Figure 4.4. Time series plot of maximum average temperature (original series)

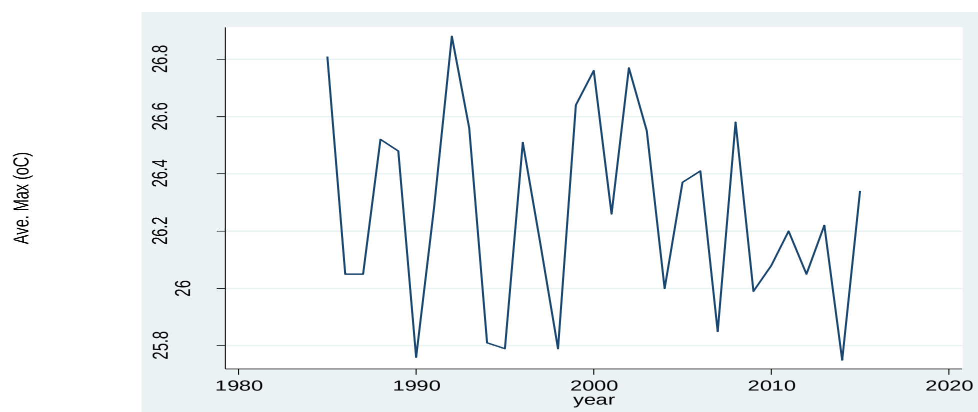


Figure 4.5. Time series plot of minimum average temperature (original series)

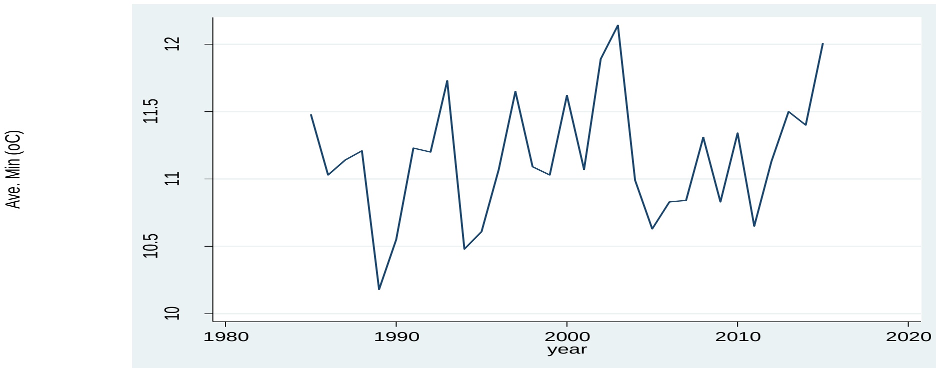


Figure 4.6. Time series plot of teff productivity (differenced series)

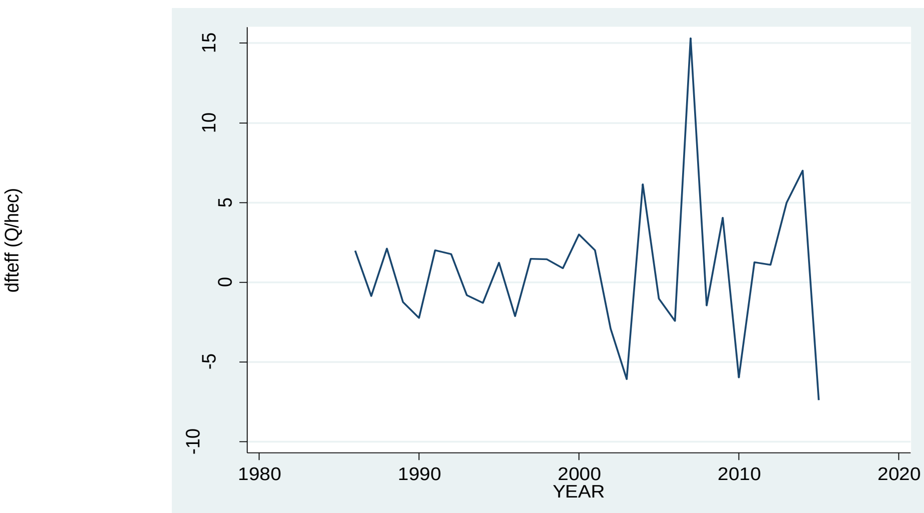


Figure 4.7. Time series plot of wheat productivity (differenced series)

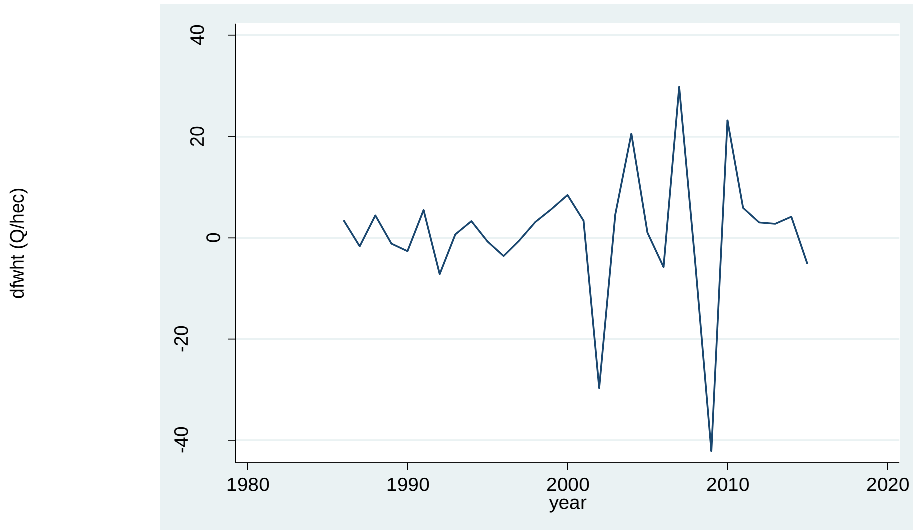


Figure 4.8. Time series plot of total rainfall (differenced series)

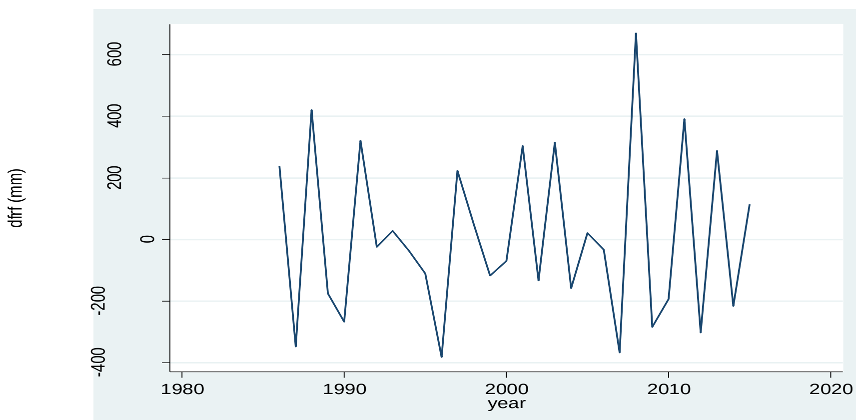


Figure 4.9. Time series plot of maximum average temperature (differenced series)

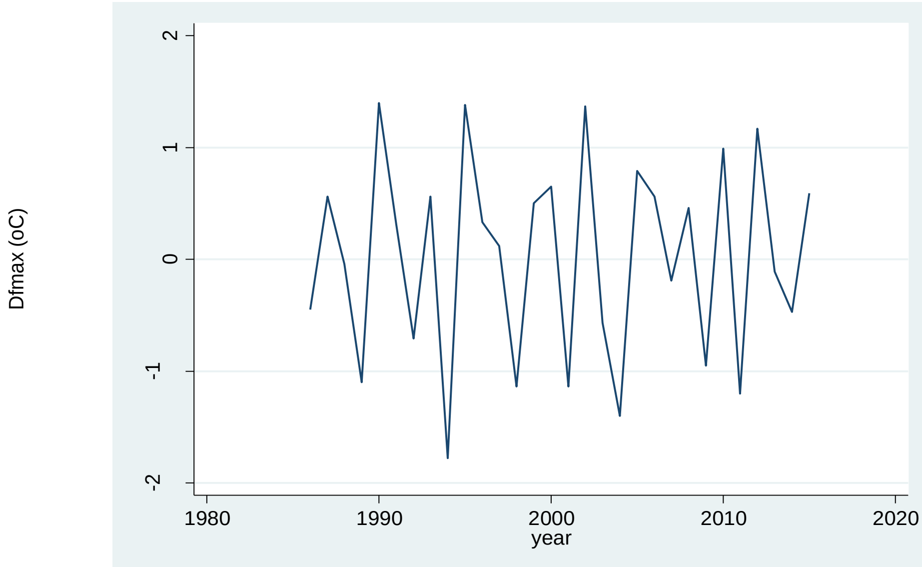
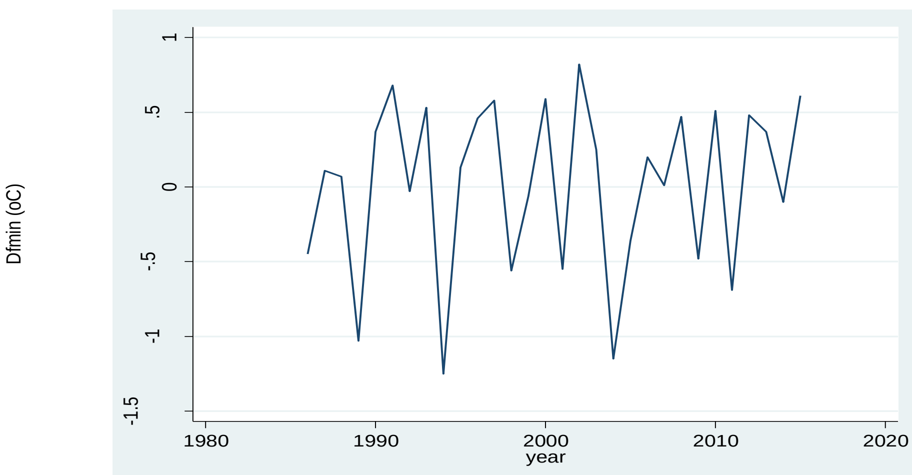


Figure 4.10. Time series plot of minimum average temperature (differenced series)



The stationarity of the series can be tested by using an Augmented Dickey-Fuller test and a Phillips and Perron test. The hypothesis to be tested is:

H_o: the series is non stationary against

H_1: the series is stationary

The results of ADF and PP tests, with intercept and trend both at level and first difference for each series are presented in Table 4.2 and 4.3. The critical values used for the tests are the McKinnon (1996) critical values. Test results, presented in Table 4.2, indicate that the null hypothesis that the series in levels contain unit root could be rejected for all the series except teff productivity. That is, the respective p-values are less than conventional significance levels α = 0.05 and 0.01 for all the series except teff productivity.

Since the null hypothesis cannot be rejected for teff, in order to determine the order of integration of the non stationary time series, the same tests were applied to its first difference (Table 4.3). The order of integration is the number of unit roots that should be contained in the series so as to be stationary. The result indicates that we reject the null hypothesis for the first differenced series with intercept and trend at the 5% level of significance for teff productivity. Since wheat productivity, total rainfall and average temperature are stationary in levels, their first differencing is also stationary. Thus, we can say the series are all integrated of order one (I (1)).

Table 4.2: Unit root test results (original series)

Series	**Level with intercept and trend**			
	Test Statistic		**Prob.***	
	ADF	**PP**	**ADF**	**PP**
Teff	**-2.872**	**-2.816**	**0.172**	**0.191**
Wheat	**-4.420**	**-4.332**	**0.002**	**0.003**
Total Rainfall	**-5.580**	**-5.615**	**0.000**	**0.000**
Ave. Max. Temp	**-5.73**	**-5.82**	**0.000**	**0.000**
Ave. Min. Temp	**-4.17**	**-4.07**	**0.005**	**0.007**
Critical value (5 %)	**-3.580**			

Table 4.3: Unit root test results (first difference)

Series	**First difference with intercept and trend**			
	Test Statistic		**Prob.***	
	ADF	**PP**	**ADF**	**PP**
Teff	**-6.836**	**-7.383**	**0.000**	**0.000**
Critical value (5 %)	**-3.584**			

*MacKinnon (1996) one-sided p-values.

4.3. VAR Model Specification

4.3.1. Estimating for Order of the VAR

Specifying the lag length has strong implications for subsequent modeling choices. Choosing too few lags could lead to systematic variation in the residuals whereas if too many lags are chosen it comes with the penalty of fewer degrees of freedom (as adding another lag, adds p x p variables). For determining the appropriate lag length for the VAR model the Akaike information criterion (AIC), Schwarz Bayesian information criterion (SBIC), Hannan-Quin information criteria (HQIC) were used.

In Table 4.4 below, the lag length selection criterion is tabulated. The AIC, SBIC and HQIC test suggest appropriate lag length for the VAR model is two (2). That is, the best fitting model is the one that minimize AIC or SBIC or HQIC.

Table 4.4: VAR lag order selection results

Lag	AIC	HQIC	SBIC
0	27.573	27.745	28.149
1	27.109	27.508	28.453
2	**25.813***	**26.441***	**27.924***
3	25.910	26.767	28.790

*indicates lag order selected by the criterion

As can be seen from Table 4.4, the three lag order selection criteria attain their minimum at lag two. Thus, we choose two lags to be included in Johansen test of co-integration.

The general form of the VAR model:

Let $Y_t = (Y_{1t}, Y_{2t}, \dots, Y_{nt})'$ denote an (nx1) vector of time series variables. The basic p-lag vector autoregressive (VAR(p)) model has the form (Hamilton, 1994):

$Y_t = C + \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + \cdots + \Pi_p Y_{t-p} + \varepsilon_t$, t = 1,2,...,T

where C denotes an nx1 vector of constants and Π_j is an nxn matrix of autoregressive coefficients for j = 1,2,...,p. The nx1 vector ε_t is a vector generalization of white noise.

The estimated model for teff productivity, wheat productivity, total rainfall and average temperature is respectively given by:

$\hat{Y}_{1t} = C_1 + \hat{\Pi}_1 Y_{1,t-1} + \hat{\Pi}_2 Y_{1,t-2} + \hat{\Pi}_3 Y_{3,t-1} + \hat{\Pi}_4 Y_{3,t-2} + \hat{\Pi}_5 Y_{4,t-1} + \hat{\Pi}_6 Y_{4,t-2}$

$$\hat{Y}_{2t} = C_2 + \hat{\Pi}_7 Y_{2,t-1} + \hat{\Pi}_8 Y_{2,t-2} + \hat{\Pi}_9 Y_{3,t-1} + \hat{\Pi}_{10} Y_{3,t-2} + \hat{\Pi}_{11} Y_{4,t-1} + \hat{\Pi}_{12} Y_{4,t-2}$$

$$\hat{Y}_{3t} = C_3 + \hat{\Pi}_{13} Y_{3,t-1} + \hat{\Pi}_{14} Y_{3,t-2} + \hat{\Pi}_{15} Y_{4,t-1} + \hat{\Pi}_{16} Y_{4,t-2}$$

$$\hat{Y}_{4t} = C_4 + \hat{\Pi}_{17} Y_{3,t-1} + \hat{\Pi}_{18} Y_{3,t-2} + \hat{\Pi}_{19} Y_{4,t-1} + \hat{\Pi}_{20} Y_{4,t-2}$$

The coefficient matrix Π_1 and Π_2 and vector of constants C were successfully estimated by the method of least squares using EVIEWS 7 software and the following results were obtained.

$$\begin{aligned} \Delta TEFF_t = {} & 1.032812 - 0.227673\Delta TEFF_{t-1} - 0.117656\Delta TEFF_{t-2} + 0.002227\Delta RF_{t-1} \\ & - 0.003057\Delta RF_{t-2} - 0.654700\Delta TEMP_{t-1} - 3.959944\Delta TEMP_{t-2} \end{aligned}$$

$$\begin{aligned} \Delta WHT_t = {} & 1.160246 - 0.052122\Delta WHT_{t-1} - 0.605250\Delta WHT_{t-2} + 0.003347\Delta RF_{t-1} \\ & - 0.21621\Delta RF_{t-2} - 1.486891\Delta TEMP_{t-1} - 14.73398\Delta TEMP_{t-2} \end{aligned}$$

$$\begin{aligned} \Delta RF_t = {} & -8.646047 - 1.055281\Delta RF_{t-1} - 0.604395\Delta RF_{t-2} + 215.6049\Delta TEMP_{t-1} \\ & + 136.0415\Delta TEMP_{t-2} \end{aligned}$$

$$\begin{aligned} \Delta TEMP_t = {} & -0.021962 - 0.247803\Delta TEMP_{t-1} - 0.370496\Delta TEMP_{t-2} - 0.000116\Delta RF_{t-1} \\ & - 0.000247\Delta RF_{t-2} \end{aligned}$$

4.3.2. Co-integration Analysis

Since all variables are integrated of the same order, we proceed to test for co-integration. Johansen (1995) co-integration test is applied at the predetermined lag 2 by assuming linear deterministic trend in data. In these tests, maximum eigenvalue and trace test statistics are compared to their corresponding special critical values. The trace test statistic proceed sequentially from the first hypothesis of no co-integration to an increasing number of co-integrating vectors whereas maximum eigenvalue test checks for r co-integrating relationships versus n co-integrating relationships, where n is the number of variables. The results of co-integration test for the series is given in Table 4.4 below. The trace statistic for the series indicates that at least one co-integrating vector ($r \geq 1$) exists in the system at the 95 percent confidence level (estimated LR statistic, 50.814 > 29.797, 95 per cent critical value). In order to cross check for identifying the specific number of co-integrating vectors, the maximam eigenvalue statistic is further employed. This statistic confirms the existence of one co-integrating relationship at the 95 per cent confidence level in this system (estimated LR statistic, 23.014 > 21.132, 95 percent critical value).

Table 4.5: Johansen co-integration test results

Hypothesized No. of CE(s)	Eigenvalue	Trace test statistic	0.05 critical value	Prob.**	Maximum Eigenvalue test statistic	0.05 critical value	Prob. **
None*	0.574	50.814	29.797	0.0001	23.014	21.132	0.0269
At most 1	0.464	17.799	25.495	0.4121	12.816	14.265	0.1931
At most 2	3.841	10.983	0.0912		3.841	10.983	0.0912

* denotes rejection of the null hypothesis,
** denotes MacKinnon-Haug-Michelis (1999) p-values.

From the Johansen co-integration test, it was determined that the rank of co-integration matrix to be equal to one.

4.4. Vector error correction model (VECM) estimation

Having concluded that variables in the VAR model appeared to be co-integrated, we proceed to estimate the short run behavior and the adjustment to the long run models, which is represented by VECM. The estimated results of the vector error correction model are presented in Table 4.6. The VEC model has the following structure:

$$Y_t = \mu + \sum_{i=1}^{p} \boldsymbol{\Gamma}_i \boldsymbol{\Delta} Y_{t-i} + \alpha \boldsymbol{B}\boldsymbol{X}_{t-1} + \boldsymbol{\varepsilon}_t$$

where $\boldsymbol{BX_t}$ is the error correction term given by $\beta' Y_t$ and β is the co-integrating vector. The responses of crop productivity, rainfall and temperature to short-term output movements are captured by the $\boldsymbol{\Gamma}_i$ coefficient matrices. The α coefficient vector reveals the speed of adjustment to the equilibrium, which measures the deviation from the long-run relationship between the variables.

Table 4.6 Estimated coefficients of Vector Error Correction Model

Vector error correction estimates

Sample (adjusted): 1988 - 2015

Standard errors in () & t-statistics in []

Cointegrating Eq:	CointEq1	Standard error	T-Statistics	
TF_t	1.000000			
RF_t	0.04754	0.00554	0.85779	
$TEMP_t$	4.903566	2.99995	1.63455	
C	85.46261			
Error Correction:	ΔTF	ΔWHT	ΔRF	ΔTEMP
CointEq1	-0.655497	0.259772	-5.492650	-0.011676
	(0.20633)	(0.56267)	(12.9927)	(0.02588)
	[-3.17690]	[0.46168]	[-0.42275]	[0.45119]
ΔTF_{t-1}	-0.561185			
	(0.21483)			
	[-2.61222]			
ΔTF_{t-2}	-0.443641			
	(0.22821)			
	[-1.94399]			
ΔWHT_{t-1}		0.008840		
		(0.37358)		
		[0.02366]		
ΔWHT_{t-2}		-0.371385		
		(0.23017)		
		[-1.61356]		
ΔRF_{t-1}	0.007525	0.026722	-1.028727	0.011000
	(0.00413)	(0.01127)	(0.26020)	(0.00052)

	[1.82106	[0.00222]	[-3.95359]	[0.21316]
ΔRF_{t-2}	0.006953	0.013961	-0.526659	-0.007710
	(0.00428)	(0.01168)	(0.26964)	(0.00054)
	[1.62369]	[1.19560]	[-1.95322]	[-0.33026]
$\Delta TEMP_{t-1}$	2.142984	-3.950972	248.4714	-0.317078
	(2.24559)	(6.12373)	(141.404)	(0.28165)
	[0.95431]	[-0.64519]	[1.75717]	[-1.12580]
$\Delta TEMP_{t-2}$	-2.617844	-11.66612	153.3682	-0.368344
	(2.29168)	(6.24939)	(144.306)	(0.28743)
	[-1.14233]	[-1.13704]	[-0.00281]	[-0.06871]
C	1.985096	2.319133	-0.132237	-0.006466
	(0.74794)	(2.03963)	(47.0973)	(0.09381)
	[2.65409]	[1.13704]	[-0.00281]	[-0.06871]
R-squared	0.667051	0.728479	0.632189	0.458443
Adj. R-squared	0.500577	0.592718	0.448283	0.187664
F-Statistic	4.006935	5.365912	3.437569	1.693054

Coefficient estimates of the VEC model are presented in Table 4.6 above. The long run equation is given as follows:

$TF_t = 85.46261 - 0.04754RF_t - 4.903566TEMP_t$

The value -0.04 suggests that a one unit decrease in total rainfall induces, on average, an increase of about 0.04 units in teff productivity. Similarly, one unit decrease in average temperature leads to an increase of about 4.90 units in teff productivity.

Table 4.6 also contains the coefficients of the error correction terms (cointEq1) for the co-integration vector. These coefficients are called the adjustment coefficients. This measures the short-run adjustments of the deviations of the endogenous variables from their long- run values. Using the error correction term as another independent variable in the unrestricted VAR model we can estimate the following Vector Error Correction Model.

The estimated model for teff productivity, wheat productivity, total rainfall and average temperature is respectively given by:

$$\Delta\hat{Y}_{1t} = \hat{C}_1 + \hat{\alpha}_1(Y_{1,t-1} + \hat{\beta}_1\ Y_{3,t-1} + \hat{\beta}_2\, Y_{4,t-1} + c) + \hat{B}_1\Delta Y_{1,t-1} + \hat{B}_2\Delta Y_{1,t-2} + \hat{B}_3\Delta Y_{3,t-1} + \hat{B}_4\Delta Y_{3,t-2} + \hat{B}_5\Delta Y_{4,t-1} + \hat{B}_6\Delta Y_{4,t-2}$$

$$\Delta\hat{Y}_{2t} = \hat{C}_2 + \hat{\alpha}_2(Y_{2,t-1} + \hat{\beta}_1\ Y_{3,t-1} + \hat{\beta}_2\, Y_{4,t-1} + c) + \hat{B}_7\Delta Y_{2,t-1} + \hat{B}_8\Delta Y_{2,t-2} + \hat{B}_9\Delta Y_{3,t-1} + \hat{B}_{10}\Delta Y_{3,t-2} + \hat{B}_{11}\Delta Y_{4,t-1} + \hat{B}_{12}\Delta Y_{4,t-2}$$

$$\Delta\hat{Y}_{3t} = \hat{C}_3 + \hat{\alpha}_3\left(\hat{\beta}_1\ Y_{3,t-1} + \hat{\beta}_2\, Y_{4,t-1} + c\right) + \hat{B}_{13}\Delta Y_{3,t-1} + \hat{B}_{14}\Delta Y_{3,t-2} + \hat{B}_{15}\Delta Y_{4,t-1} + \hat{B}_{16}\Delta Y_{4,t-2}$$

$$\Delta\hat{Y}_{4t} = \hat{C}_4 + \hat{\alpha}_4\left(\hat{\beta}_1\ Y_{3,t-1} + \hat{\beta}_2\, Y_{4,t-1} + c\right) + \hat{B}_{17}\Delta Y_{3,t-1} + \hat{B}_{18}\Delta Y_{3,t-2} + \hat{B}_{19}\Delta Y_{4,t-1} + \hat{B}_{20}\Delta Y_{4,t-2}$$

Model of teff productivity:

ΔTFt = -0.66*(TF*t-1- 0.05*RFt-1- 4.90*TEMPt-1 - 85.46*) - 0.56*ΔTFt-1
- 0.44*ΔTFt-2 + 0.01*ΔRFt-1+ 0.01*ΔRFt-2 + 2.14*ΔTEMPt-1
-2.62*ΔTEMPt-2 + 1.99

Model of wheat productivity:

ΔWHTt= 0.26*(WHT*t-1-0.05*RFt-1- 4.90*TEMPt-1 - 85.46*)+0.01*ΔWHTt-1
-0.37*ΔWHTt-2 + 0.03*ΔRFt-1+ 0.01*ΔRFt-2-3.95*ΔTEMPt-1
-11.67*ΔTEMPt-2 + 2.32

Model of total rainfall:

ΔRFt= -5.49*(*-0.05*RFt-1- 4.90*TEMPt-1 - 85.46*)-1.03* ΔRFt-1
- 0.53* ΔRFt-2 +248.47* ΔTEMPt-1-+153.37* ΔTEMPt-2 -0.13

Model of average temperature:

ΔTEMPt= 0.43*(- *0.05*RFt-1- 4.90*TEMPt-1 - 85.46*)+ 0.01* ΔRFt-1

- 0.01* ΔRFt-2 – 0.32* ΔTEMPt-1-0.37* ΔTEMPt-2 -0.01

where: „*Δ*" stands for first difference (D), the value in the bracket is the error correction term and the coefficients of error correction term are called adjustment coefficients.

4.5. Model checking

In order to ascertain whether the model provides an adequate fit to the data or not, a test for misspecification should be performed.

4.5.1. Test of residual autocorrelation

Here we utilize VAR residual Portmanteau tests for autocorrelation and VAR residual serial correlation LM tests. The results of the two tests are illustrated in the following table. The test results show that the null hypothesis of no serial correlation in the residuals cannot be rejected since p-value exceeds level of significance (i.e. 0.9006 > 0.05 and 0.3464 > 0.05).

Table 4.7: Test of residual autocorrelation

Lags	Q-Stat		Adj Q-Stat		LM-Stat	
	value	Prob.	value	Prob.	value	Prob.
1	5.352516	NA*	5.543677	NA*	9.298346	0.9006
2	15.36458	NA*	16.29738	NA*	17.62309	0.3464
*The test is valid only for lags larger than the VAR lag order.						

4.5.2. Testing Normality

Multivariate version of the Jarque Bera tests is used to test the normality of the residuals. It compares the 3rd and 4th moments (skewness and kurtosis) to those from a normal distribution. The test has null hypothesis indicating that the error term in the model has skewness and kurtosis corresponding to a normal distribution. The results in Table below shows that p-value for the joint component is greater significance level (i.e. 0.07 > 0.05, 0.38 > 0.05 and 0.08 > 0.05). thus, the null hypothesis of multivariate normality of the residuals cannot be rejected for all tests considered at 5% level of significance.

Table 4.8. Normality test

Component	Skewness	X^2	Prob.	Kurtosis	X^2	Prob.	Jarque-Bera	Prob.
Joint		9.902128	0.0721		4.150316	0.3860	14.05244	0.0804

4.5.3. Lag exclusion test

To check whether the chosen lag is optimal or not, Wald lag exclusion test is used. The results are given in the following table. The values in the square brackets are probability values for the corresponding chi-square test statistics. The results show that jointly two lags of all endogenous variables are statistically significant. Therefore, restricted VAR (2) is found to be suitable for the data set, and hence, could be adopted.

Table 4.9: VAR lag Exclusion Wald Tests

	TFt	WHTt	RFt	TEMPt	Joint
Lag1	20.05579	9.616254	2.564203	4.654165	53.01852
	[0.000487]	[0.047413]	[0.633177]	[0.324657]	[0.00000749]
Lag2	9.636854	5.731990	2.843450	7.306673	47.78934
	[0.047010]	[0.220077]	[0.584356]	[0.120543]	[0.0000513]
Df	4	4	4	4	16
*denotes rejection at 5% significance level.					

4.6. Structural analysis

4.6.1. Granger causality test

Granger causality test is considered a useful technique for determining whether one time series is good for forecasting the other. The concept of granger causality test is explored when the coefficients of the lagged of the other variables is not zero. Table 4.10 presents results from the pair wise Granger-causality tests which were obtained with two lag for each variable.

Table 4.10: Pair-wise Granger causality Wald tests

Null Hypothesis:	Obs	F-statistic	Prob.
RF does not Granger Cause TF	29	9.69186	0.05104
TEMP does not Granger Cause TF	29	7.62589	0.02177
RF does not Granger Cause WHT	29	8.50099	0.01031
TEMP does not Granger Cause WHT	29	0.62522	0.5436
TEMP does not Granger Cause RF	29	0.47861	0.6254
RF does not Granger Cause TEMP	29	1.33882	0.2810

The result show that total RF granger cause teff productivity, while the converse is not true at 10% level of significance. This indicates that the change in total rainfall precedes the change in teff productivity, and that the last information on total rainfall provides important information to forecast future value of teff productivity. In addition, the average temperature granger cause teff productivity while the converse is not true at 5% level of significance. Furthermore total rainfall ganger cause wheat productivity at 5% level of significance. The result is almost consistent with the studies of Naveed Mehmood and Samina Khalil (2013) using Vector Autoregressive model in Pakistan.

4.6.2. Impulse-Response Functions

Impulse responses trace out the responsiveness of the dependent variables in the VAR to shocks to each of the variables. So, for each variable from each equation separately, a unit shock is applied to the error, and the effects upon the VAR system over time are noted. Thus, if there are g variables in a system, a total of g^2 impulse responses could be generated. A standard Cholesky decomposition is used in order to identify the short run effects of shocks on the levels of the endogenous variables in the VECM.

Figure A1 (i) (Appendix) shows the response of teff productivity to Cholesky one standard deviation innovations in teff productivity, total rainfall and average temperature. Figure A1 (ii) (Appendix) shows the response of wheat productivity to Cholesky one standard deviation innovations in wheat productivity, total rainfall and average temperature. On the x-axis we have the time horizon or the duration of the shock while the y-axis gives the direction and intensity of the impulse. From Figure A1 (i) we can see that teff productivity innovations have a negative impact on teff productivity. Total rainfall innovations have a negative impact on teff productivity. From Figure A1 (ii) we can see that wheat productivity innovations have a negative impact on wheat productivity. Total rainfall and average temperature innovations have a negative impact on wheat productivity. The result is consistent with study of Naveed Mehmood and Samina Khalil (2013) using Vector Autoregressive model in Pakistan.

4.6.3. Discussion of major results

The results showed that the annual temperature and rainfall had both negative and positive impact on teff and wheat productivity. This result is consistent with the of Ben Zaied (2013) using the dynamic panel method and fully modified ordinary least squares (FMOLS) in Tunisia.

From Pair-wise Granger causality Wald tests results, total rainfall granger cause teff productivity at 10% level of significance. This indicates that the change in total rainfall precedes the change in the teff productivity and that the last information on total rainfall provides important information to forecast future value of teff productivity. In addition, the average temperature granger cause teff productivity at 5% level of significance. Furthermore, total rainfall ganger cause wheat productivity at 5% level of significance. The result is consistent with the studies of Naveed Mehmood and Samina Khalil (2013) using Vector Autoregressive model in Pakistan.

From the impulse response function of the total rainfall and teff productivity, total rainfall innovations have a negative impact on teff productivity. Total rainfall and average temperature innovations have a negative impact on wheat productivity. The result is consistent with study of Naveed Mehmood and Samina Khalil (2013) using Vector Autoregressive model in Pakistan.

CHAPTER 5

5. CONCLUSION AND RECOMMENDATION

5.1. Conclusion

The aim of this study was to examine climate variability and its effects on crop productivity for the last three decades in Ada'a district of East Showa Zone of Oromia Regional State using Vector Autoregressive (VAR) and Vector Error Correction models.

The period covered in the study spanned from 1985 to 2015. A stationarity test was carried out using the Augmented Dickey-Fuller (ADF) and Phillip-Perron (PP) tests. The null hypothesis of a unit root was rejected for all series except for teff productivity implying that wheat productivity, total rainfall and average temperature are all stationary in level. Consequently, the first differenced series for all variables were considered for further analysis as the corresponding unit root tests indicated the absence of unit roots. The estimated long run model shows that there exists a strong inverse long-run relationship between climate variability and crop productivity of the study area. A further effort was made to check the causality relationships that exist between the variables by employing the VAR-Granger causality test. According to the results, a unidirectional causality was seen running from climate variability to crop productivity.

Climatic variables, temperature and rainfall, are useful to crop productivity but turning out to be negative beyond a certain limit. The estimated results obtained from analysis indicated that there is significant effect of climate variability on the magnitude and fluctuation of crop productivity.

The statistical analyses have provided essential numerical evidences for the existence of variability in total rainfall and crop productivity in the study area. The long-term annual rainfall and crop productivity showed high variability from year to year.

Results from impulse response function measures show that the response of a variable for a one standard deviation of its innovations has a significant impact on its own for all variables included in the analysis. For a one SD change in total rainfall, average temperature has an opposite response while crop productivity has direct response to rainfall. Rainfall and crop productivity showed a negative response for a one SD change in average temperature.

5.2. Recommendation

The following are recommendations drawn from this study to reduce the effects of climate variability on crop productivity for the study area.

I. The temperature may shorten the growth periods; hence the cultivation should be adjusted accordingly. The government has to take initiative to introduce the high temperature resistant crops as the increase in temperature in future will affect crop productivity.
II. Climate change also alters the rainfall pattern across the country; therefore it is necessary for researchers to introduce the drought resistant crops.
III. As the farmers across the country are mostly illiterate, they need to know that changes in climate will lead to reduction in the output so need to have in time knowledge as in the long run these changes will affect the farmers throughout the country.

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7. APPENDICES

Figure A1(i): Response of TF, RF and TEMP to Cholesky One S.D. innovations

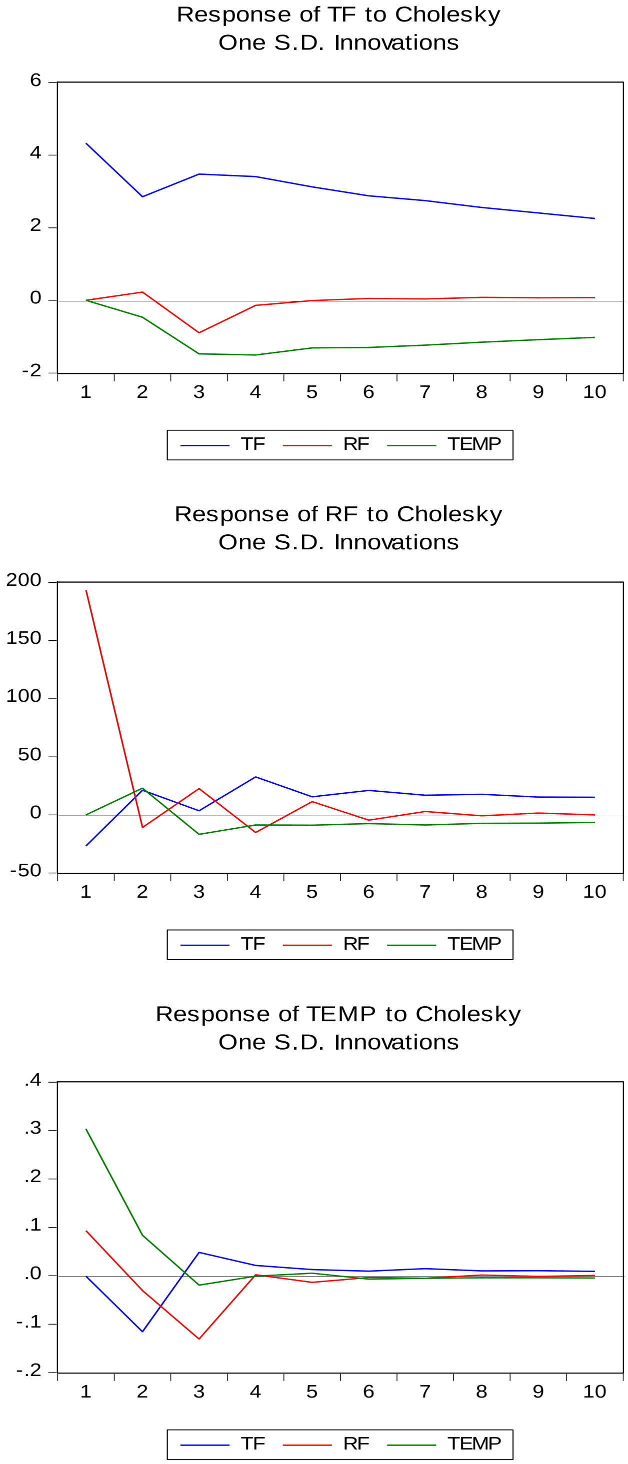

Figure A1(ii): Response of WHT, RF and TEMP to Cholesky One S.D. innovations