ADDIS ABABA UNIVERSITY

COLLEGE OF BUSINESS AND ECONOMICS

DEPARTMENT OF ECONOMICS

CLIMATE CHANGE AND AGRICULTURAL PRODUCTIVITY IN ETHIOPIA: A TIME SERIES ANALYSIS

By: Samson Haile Demisse

October, 2020

Addis Ababa, Ethiopia

CLIMATE CHANGE AND AGRICULTURAL PRODUCTIVITY IN ETHIOPIA: A TIMESERIES ANALYSIS

Samson Haile Demisse

A Thesis Submitted to the Department of Economics Presented in Partial Fulfillment of the Requirements for the Degree of Master of Science in Economics

Addis Ababa University

College of Business and Economics

Addis Ababa, Ethiopia

October, 2020

ADDIS ABABA UNIVERSITY

COLLEGE OF BUSINESS AND ECONOMICS

SCHOOL OF GRADUATE STUDIES

This is to certify that the thesis prepared by Samson Haile Demisse, entitled: "***CLIMATE CHANGE AND AGRICULTURAL PRODUCTIVITY IN ETHIOPIA: A TIME SERIES ANALYSIS***" and submitted in partial fulfillment of the requirements for the Degree of Master of Science in Economics complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

Signed by the Examining Committee:

Advisor__________Dr. Kefyalew Endale_______Signature____________Date_________________

InternalExaminerDr. Helen Berga_____________Signature____________Date_________________

ExternalExaminerDr. MisganawAsmelash______Signature____________Date_________________

____

Chair of Department or Graduate Program Coordinator

ACKNOWLEDGMENT

I would like to thank my sincere advisor Dr. Kefyalew Endale for his immeasurable guidance and support throughout we have been working the thesis. He has significantly impacted the papers progress by adding multidimensionalviews.

I also want to thank Dr. Bosede Ngozi Adeleye, creator and tutor of *CrunchEconometrix* and lecturer, researcher at Covenant University in Nigeria. Her videos had helped me to crunch model related issues and statistical softwareapplications.

Finally,IwanttothankemployeesfromCentralStatisticalAgencyfortheirsupportwhileIwas collecting relevant data for thisstudy.

Table of Contents

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

ACRONYMS

ADF	Augmented Dickey Fuller unit root test
AIC	Akaike‘s Information Criteria
ARDL	Auto Regressive Distributed Lag
CGE	Computable General Equilibrium
CSA	Central Statistical Agency
CV	Coefficient of Variation
DF	Dickey Fuller
DW	Durbin Watson
FAO	World Food and Agricultural Organization
GDP	Gross Domestic Product
IPPC	Intergovernmental Panel for Climate Change
MoA	Ministry of Agriculture
NAPA	National Adaptation Plans of Action
NBE	National Bank of Ethiopia
NDGAI	Notre Dame Global Adaptation Initiative
NEPAD	New Partnership for Africa’s Development
NSSA	Non Sub Saharan Africa
PP	Phillips Perron unit root test
SBC	Schwartz-Bayesian Criteria
SSA	Sub Saharan Africa
UNDP	United Nations Development Program
WB	World Bank
WMO	World Meter Organization

ABSTRACT

The aim of this paper is to assess the impact of climate change on agricultural productivity of Ethiopia. In this study we use annual average temperature and precipitation variations as indicators of climate variation. The data for the analysis are obtained from World Development Indicators and Central Statistical Authority. Descriptive and econometric methods are employed to investigate the impacts. Since there is sufficient time series data, an ARDL model is used to estimate the long run and short run effects of climate change on agricultural productivity.

Estimates of the ARDL model indicates both temperature and precipitation variation have significant negative impacts on agricultural productivity in the short run and a non-negative significant impact in the long run. On the other hand, the speed of adjustment (i.e. 0.369026) is found to be negative which shows past errors can be corrected in the current periods. Hence, from the study result climate change adaptation programs should be introduced to alleviate short run impacts of climate change; like provision of detailed forecast of weather for every region of the country and building infrastructure to hinder sudden damages of climate change on agricultural productivity ofEthiopia.

Keywords: Agricultural productivity, Climate change, ARDL, Ethiopia

1. INTRODUCTION

1.1. Background of thestudy

Climate change has been a challenging phenomenon in the world. Warming's of the climate system is unequivocal, and since the 1950s, many of the observed changes are unprecedented over the decades to millennia (IPCC, 2014). Science tells us that, even if we are successful in limiting warming to 1.5 °C, we will face significantly increased risks to natural and human systems. Yet, the data in this report show that 2019 was already 1.1 °C warmer than the pre-industrial era. The consequences are already apparent. More severe and frequent floods, droughts and tropical storms, dangerous heat waves and rising sea levels are already severely threatening lives and livelihoods across the planet (WMO, 2019).

Agriculture is the economic sector that is most vulnerable to climate change (Nastis et al., 2012). According to Barrios et al. (2010), Agriculture has traditionally had a higher share in GDP in Africa than in Non-sub Saharan (NSSA) countries – nearly 40% in 1960. Although this share has since decreased, it still represents almost one-third of total GDP compared to 14.1% in the rest of thedeveloping.

Consequently, in Ethiopia where agriculture is the main source of the economy and where crop production contributes more than 65% of the agricultural GDP of the country (Abeje and Alemayehu, 2019). Climate change is very likely to affect food security at the global, regional, and local levels. Climate change can disrupt food availability, reduce access to food, and affect food quality (USDA, 2015). On the other hand, the population is growing at a geometric progression. This makes the impact to double fold and agricultural productivity becomes a central issue to reduce the impact of climate change on the sector and increasing demand for food.

According to the fourth IPCC Assessment Report, it is anticipated that the impacts of climate change will vary greatly with the degree of temperature rise and the latitudinal locations. Therefore, studying the impact of climate change in every region and country is necessary to adapt or mitigate its consequences.

This paper aims to assess the impact of climate change on the agricultural productivity of Ethiopia. The paper indicates the sign and magnitude including how much the country should be prepared to minimize the impact of future changes in climate.

1.2. Statement of theproblem

The main characteristics of climate change are increases in average global temperature (global warming); changes in cloud cover and precipitation particularly over land; melting of ice caps and glaciers and reduced snow cover; and increases in ocean temperatures and ocean acidity – due to seawater absorbing heat and carbon dioxide from the atmosphere (UNFCCC, 2007).

Although climate change is expected to have many impacts on various sectors, agriculture is highly vulnerable. If future climate change leads to a widespread reduction in the food supply, there could be massive problems with hunger and starvation (Rosenzweig and Parry, 1994; Reilly, 1996). Rainfall could potentially have a wide array of economic implications anywhere in the developing world. This particular sensitivity to rainfall seems at least in part to rest on features specific to Africa (Barrios et al., 2010). Nearly all Ethiopian agriculture is dependent on rainfall, particularly the amount and seasonal occurrence. Future climate change predictions agree that changes in rainfall, temperature, and seasonality will impact Ethiopia with dramatic consequences (Evangelista et al.,2013).

About 45% of GDP comes from rain-feed agriculture and about 99% of electrical energy in the country on which the industrial and service sector dependence is generated by hydroelectric power which in turn depends on the volume of a rainfall (Ali, 2012). On the other hand, population growth further affects the shortage of food higher. Ethiopia's current population is estimated to be about 95 million, at least 80 percent of whom live in rural areas. With an annual population growth rate of 2.3 percent (2017), Ethiopia's population is expected to reach 150 million by 2035 (UNDP, 2018). The population will continue to exert serious pressure on the environment, basic services provision, infrastructure facilities, and agriculture. Rapid population growth, declining landholding size, soil erosion, deforestation, poor technical know-how, and rainfall-dependent agriculture are some of the root causes of poverty and destitution in Ethiopia (UNDP, 2018).

Hence, to catch up on the gap created by the current status quo of the economy what the impacts of climate change and population growth would impact the economy: Agricultural productivityis expected to be sensitive. Though, they are limited studies on the impact of climate change towards agricultural sector have been conducted (Deressa 2007; Deressa, Hassen, and Ringler 2008, Deressa et al. 2008; Deressa and Hassan 2009; Yesuf et al. 2008, Gebreegziabher et al. 2011, Gebreegziabher and Mekonnen 2015, Seid2012).

However, from the earlier studies conducted, I have deduced that most of the papers are organized at a regional or woreda basis and even to a specific crop types which literally cannot show the total effect of climate change on agricultural productivity at a national level, because, different places had exhibited different results from past researches. Second, some papers (Gebreegziabher et al. 2011, Gebreegziabher and Mekonnen 2015, Seid 2012) have utilized economy-wide models to assess the impact, models like CGE. Even though, they will visualize the impact by simulating over a long period, the baseline data used will have a significant impact on the process of simulation, since the baseline data maynot describe the overall climate change overtime. The use of social accounting metric (SAM) from a specific period for climate and socio economic variables will have a problem because climate is not a one period phenomenon rather it is a process or a chain ofevents.

Therefore, this research aims to fill the above mentioned literature gap using a viable interaction of output and inputs of agriculture to find out the impacts of climate change on agricultural productivity specially using productivity of land which is fixed (if it is not decreasing through urbanization and overutilization) input of the agricultural sector.

1.3. Researchquestion

The study answers the following questions:

1. Does climate change affect agricultural productivitynegatively?
2. What are the short-run and long run impacts of climate change on agricultural productivity inEthiopia?

1.4. The objective of thestudy

1.4.1. The general objective of thestudy

The main objective of the study is to assess the impact of climate change in Ethiopian agriculturalproductivity.

1.4.2. The specific objective of thestudy

The specific objectives of the study are:

1. To describe climate variables and socio economic variablesovertime.
2. To quantify the impact of climate change in agriculturalproductivity.
3. To reveal the short-run and long run impacts of climate change on Ethiopian agricultural productivity.

1.5. The hypothesis of thestudy

In analyzing the impact of climate change on agricultural productivity in the Ethiopian economy;

1. Climate change is expected to decrease agriculturalproductivity.

1.6. Significance of thestudy

The study contributes by finding the current impacts of climate change on Ethiopian agricultural productivity, hence, on the country's economy. The past climate phenomenon has indicated that the pattern of climate change's impact is diverse and unpredictable. Therefore, conducting researches continuously on the subject matter is required. The study also provides an insight into policy measures that could be taken by policymakers to adapt or mitigate the posed problem at hand. The study also plays its role to fill the gap of literature drought in our country on the subject matter.

1.7. Scope of thestudy

The study is conducted in the geographical area of Ethiopia. It assesses the impact of climate change on agricultural productivity of Ethiopia. A time-series data that span from 1991 – 2018 GC is used for the study.

1.8. Organization of thestudy

The study is organized in the following way. In chapter two, reviews theoretical and empirical literature. Then chapter three presents the methodology and data used. The fourth chapter analysis and interprets the econometric result. Finally, chapter five concludes the thesis with policy recommendations.

2. LITERATUREREVIEW

2.1. Theoretical LiteratureReview

2.1.1. Climate change and itsimpacts

Climate change is the variation in global or regional climates over time. It reflects changes in the variability or average state of the atmosphere over time scales ranging from decades to millions of years. These changes can be caused by processes internal to the Earth, external forces (e.g. variations in sunlight intensity) or, more recently, human activities. In recent usage, especially in the context of environmental policy, the term "climate change" often refers only to changes in modern climate, including the rise in average surface temperature known as global warming. In some cases, the term is also used with a presumption of human causation, as in the United Nations Framework Convention on Climate Change (UNFCCC, 1994).

Warming of the climate system is unequivocal, as is now evident from observations of increases in global average air and ocean temperatures, widespread melting of snow and ice and rising global average sea level. Rising sea level is consistent with warming. Global average sea level has risen since 1961 at an average rate of 1.8 [1.3 to 2.3] mm/yr and since 1993 at 3.1 [2.4 to3.8] mm/yr, with contributions from thermal expansion, melting glaciers and ice caps, and the polar ice sheets (IPCC,2007).

Anthropogenic green house gas emissions have increase since the pre-industrial era, driven largely by economic and population growth, and are now higher than ever. This has led to atmospheric concentration of carbon dioxide, methane and nitrous oxide that are unprecedented in at least the last 800,000 years. Their effects together with those of other drivers have been detected throughout the climate systems and are extremely likely to have been the dominant cause of the observed warming since the mid 20^{th} century (IPCC, 2014).

In recent decades, changes in climate have caused impacts on natural and human system on all continents and across the oceans. Impacts are due to observed climate change, irrespective of its cause, indicating the sensitivity of natural and human system to changing climate change (IPCC, 2014).

According to Adams et al (1998), Climate change is a real natural phenomenon on the Earth. It has been a big concern since it affects agriculture, water availability, market and natural resources on the Earth. Agriculture is a complex and sensitive sector, where climate, management factors, market and technology play an important role on the productivity and profitability of the field. Climate is the primary determinant of agriculturalproductivity.

The evidence from different researches shows that ignoring climate change will eventually damage economic growth. Our actions over the coming few decades could create risks of major disruption to economic and social activity, later in this century and in the next, on a scale similar to those associated with the great wars and the economic depression of the first half of the 20th century. And it will be difficult or impossible to reverse these changes. Tackling climate change is the pro-growth strategy for the longer term, and it can be done in a way that does not cap the aspirations for growth of rich or poor countries. The earlier effective action is taken, the less costly it will be (Stern review, 2008).

The globally averaged combined land and ocean surface temperature data as calculated by a linear trend show a warming of 0.85 [0.65 to 1.06] °C 2 over the period 1880 to 2012, when multiple independently produced datasets exist (IPCC, 2014).

Rainfall during a year occurs in different seasons. Unlike most of the tropics where two seasons are common (one wet season and one dry season), three seasons are known in Ethiopia, namely Bega (dry season) which extends from October-January, Belg (short rain season) which extends from (February-May), and Kiremt (long rain season) which extends from June-September (NAMA, 2007)

Temperatures are also very much modified by the varied altitude of the country. In general, the country experiences mild temperatures for its tropical latitude because of topography. Mean annual temperature distribution over the country varies from about 10°C over the highlands of northwest, central and southeast to about 35°C over north-eastern lowlands (NAMA, 2007).

Impacts of climate change on food security are global and local. Climate change will affect agricultural food systems in all countries, including exporters and importers as well as those at subsistence level. Changes in mean rainfall and temperate as well as the increase in extreme events will affect agriculture: livestock, forestry as well as fisheries. Many impacts, such as increased land degradation and soil erosion, changes in water availability, biodiversity loss, more frequent and more intense pest and disease outbreaks as well as disasters need to be addressed across sectors (FAO, 2008).

2.1.2. Climate change andAgriculture

Agriculture is the main source of economy in Africa. Likewise, Agriculture accounts for 46.3 percent of the nation's Gross domestic Product (GDP), 83.9 percent of exports, and 80% of the labor force (Wikipedia).

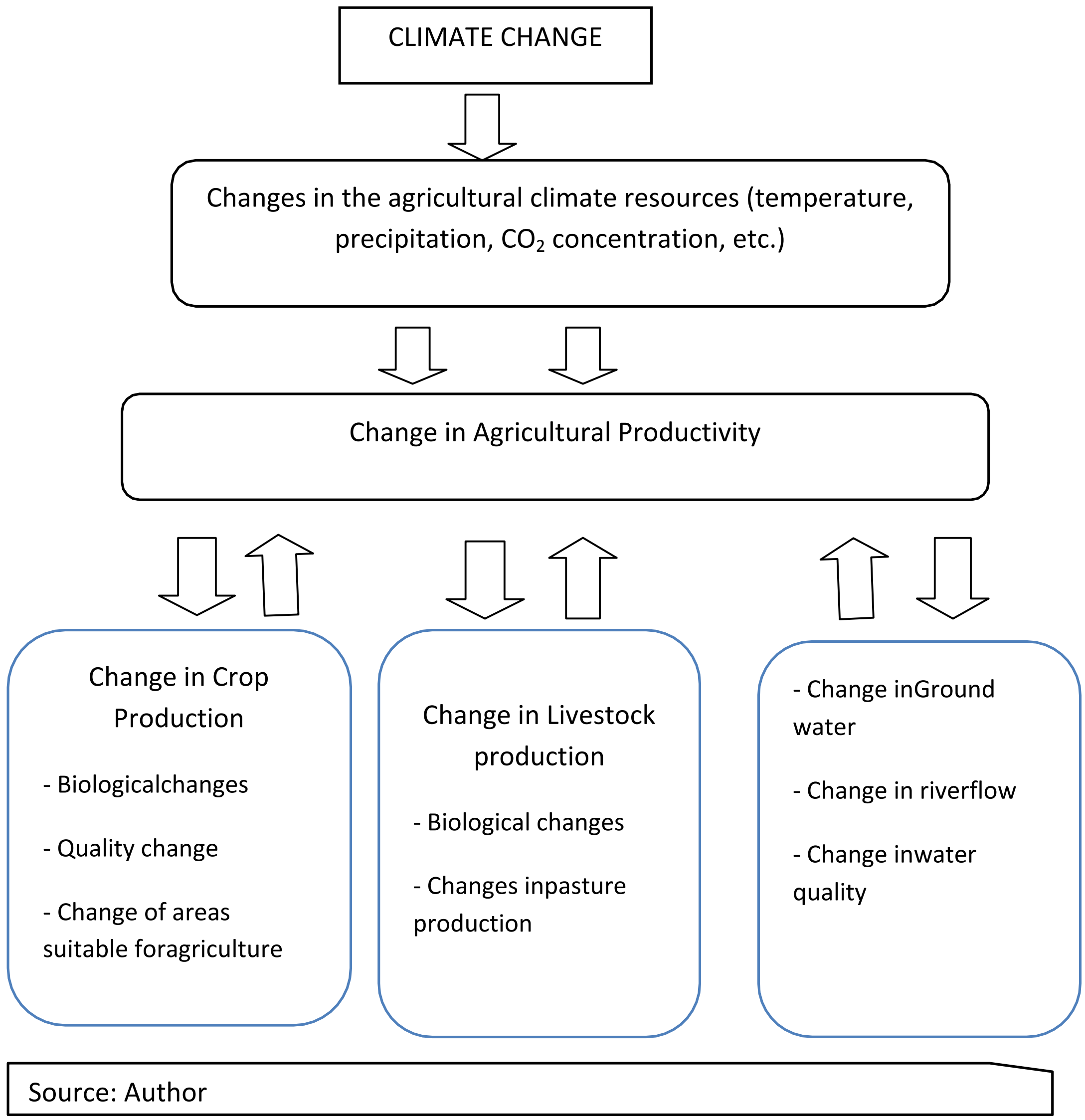
Agricultural production is carried out through the selection of crops and animals suitable for the climate of a specific region and application of proper farming methods. Therefore, agriculture is a climate dependent bio-industry with notable regional characteristics. Regional characteristics refer to the ecosystem characteristics determined by the climate of the region. Climate change disturbs the agricultural ecosystem, resulting in the change in agricultural climatic elements such as temperature, precipitation, and sunlight, while further influencing the arable, livestock, and hydrology sectors (Kim,2013).

Agriculture is arguably the most important sector of the economy that is highly dependent on climate. It is the main pass-through mechanism from climate change and environmental degradation to poverty. According to DFID (2005) and Rao et al. (2004), growth in agricultural production and productivity are considered essential to achieve sustainable growth and significant reduction in poverty in developing countries. This is primarily because the sector is the main source of employment and output in developing countries. There are also undeniable backward and forward linkages between agriculture and other pro-poor sectors of theeconomy.

Agriculture is not only a fundamental human activity at risk from climate change, it is a major driver of environmental and climate change itself. It has the largest human impact on land and water resources. About 1.4 billion ha of arable land (10 percent of total ice-free land) are used for crop cultivation and an additional 2.5 billion ha are used for pasture. Roughly four billion ha are forested land, five percent of which is used for plantation forestry (FAO,2012).

According to FAO report (2012), two billion tons of grains are produced yearly for food and feed, providing two-thirds of total protein intake by humans. About ten percent of total world cerealsupplyistradedinternationally.Inaddition,150milliontonsoffishandotheraquatic products are consumed annually. Aquatic products contribute 50 percent or more of total animal protein intake in some small islands and other developing countries.

Figure 2. 1: Conceptual framework of impact of climate change on agricultural productivity



As a result of these large-scale activities, agriculture is a significant contributor to land degradation and, in particular, a major emitter of greenhouse gases. It emits into the atmosphere 13-15 billion tons CO_2 e per year, about a third of the total from human activities. Overall, agriculture is responsible for 25 percent of carbon dioxide (largely from deforestation), 50 percent of methane (rice and enteric fermentation), and more than 75 percent of N_2O (largely from fertilizer application) emitted annually by human activities (FAO,2012).

Agriculture is the foundation of Ethiopia's economy where crop production contributes more than 65% of the agricultural GDP of the country. The impacts of climate change have been observed in Ethiopia over a long period of time which changes the environmental conditions that influence the livelihoods of the farmers and thus the national economy (Abeje and Alemayehu, 2019).

It is also the foundation of Ethiopian economy where crop production contributes more than 65% of the agricultural GDP of the country. According to IPCC's 2007 report, in Africa, by 2020 between 75 and 250 million people are projected to be exposed to increased water stress, and due to low adaptive capacity in the region, the agricultural sector will be severely affected by climate change, where some crop yield from rain-fed agriculture could be reduced by up to 50%; and this would further cause food insecurity and malnutrition.

2.1.3. Climate Change and Its impact inEthiopia

Climate change has become a reality, and is one of the greatest challenges the world is facing today. Climate change has led to increased frequency and intensity/ severity of extreme weather events (droughts, floods, heat waves, cold snaps, storms/hurricanes, etc.), melting of ice and glaciers, sea level rise, changes in global precipitation patterns, expansion of desertification, increased frequency and intensity of wildfires, loss of biodiversity, increased environmental pollution, decline in agricultural production and productivity, water scarcity, increased incidence of pests and diseases, and human migration and conflict (Stern, 2006; IPCC, 2007; Zegeye, 2013). The impacts of climate change are global in scope and unprecedented in scale. The environment and humanity have been threatened by the escalating impacts of climate change (Zegeye, 2013).

According to the UNDP climate change country profile, Ethiopia’s mean annual temperature has increased by 1.3°C between 1960 and 2006, an average rate of 0.28°C per decade. The increase in temperature in Ethiopia has been most rapid in July, August and September at a rate of 0.32°C per decade. Daily temperature observations show significantly increasing trends in the frequency of hot days, and much larger increasing trends in the frequency of hot nights. The average number of ‘hot’ days per year in Ethiopia has increased by 73 (an additional 20% of days) between 1960 and 2003 (UNDP,2016).

According to the UNDP country profile, strong inter-annual and inter-decadal variability in Ethiopia’s rainfall makes it difficult to detect long term trends. There is not a statistically significant trend in observed mean rainfall in any season in Ethiopia between 1960 and 2006.

The regional models for East Africa also state that over the past half century there has been substantial multi-decadal variability in rainfall. Parts of central Ethiopia were unusually wet in the 1970s and unusually dry in the 1980s and 1990s, while other parts of East Africa experienced the opposite pattern.

In Ethiopia, there is a strong link between climate change, food security and rural livelihoods. For many decades, agricultural production in the country has not kept pace with the rate of population growth. Especially in the drought prone and food insecure areas, food insecurity with high malnutrition has long remained a major problem where millions can quickly become dependent on relief aid during major droughts and in times of widespread livestock deaths, crop infestations and unseasonal floods. On the other hand, during prolonged drought years, increasing distances between water and pasture cause problems to the health of cattle and create local conflicts over resources in pastoral areas (NEPAD,2012).

Crop production in Ethiopia is affected by failure of rains or occurrence of successive dry spells during the growing season. Food shortages resulting from adverse weather conditions are not new in Ethiopia. However, food shortages have increased in severity, with frequent shortages in recent years. The degree of vulnerability varies between the different regions based on wealth, technology, availability of infrastructure and institutions, potential for irrigation, and literacy rates.Ingeneral,vulnerabilitytoclimatechangeinEthiopiaishighlyrelatedtopoverty.

Integrated rural development initiatives aimed at reducing poverty can play a role in increasing adaptive capacity to climate change (Irish aid, 2017).

The major effects of climate change on crop production include changes in regular crop planting times, length of growing season and shift in crop type or cultivars. Crop production in the country is highly correlated to the rainfall patterns. Rainfall variability and recurrent drought are leading to frequent crop failures, loss of life and property. Indigenous and improved technologies are used to reduce crop yield losses. Climate change exhibited through higher temperatures, rainfall variability, water scarcity, flooding, drought and displacement, negatively impacts agricultural production and causes breakdown in food systems (Irish aid,2017).

According the World Bank (2015), by 2050 climate change could reduce Ethiopian GDP by 8-10 percent and its impacts are likely to be felt most by the rural poor and particularly women. The poor in urban areas are also likely to be negatively impacted due to increasing food prices. Climate change will make the prospect of economic development harder for Ethiopia in at least two ways: first, by reducing agricultural production and output in sectors linked to agriculture, which is likely to reduce Ethiopia's GDP by about 10% from its benchmark level; and second, by raising the degree of income inequality which is likely to further decrease economic growth and fuel poverty (WB, 2015). In addition, extreme climatic events have historically been shown to be costly to individuals, reducing consumption or forcing the sale or destruction of assets; thereby re-enforcing poverty (Alebacheu, A. and Woldeamlak, B,2011).

Historically the Ethiopian economy has been vulnerable to climate fluctuations. The various climate projections show that climate variability will increase under all scenarios. Since agriculture (the economy's most climate sensitive sector) is likely to remain for some time one of Ethiopia's main engines of growth, climate-induced shocks will continue to be a threat to macroeconomic stability, because of the impacts on income, employment, fiscal revenues, capital formation, the drain on government expenditure, aid flows to support disaster relief, and so on (World Bank,2010).

Besides its geographical location and topography, the low adaptive capacity of the rural poor makes the country highly vulnerable to the adverse impacts of climate change. The Notre Dame

Global Adaptation Initiative (NDGAIN) Index ranks Ethiopia as the 36th most vulnerable and 40th least ready to adapt to climate change, of the countries it covered for 2015 (Irish Aid, 2017).

Causes for vulnerability of Ethiopia to climate variability and change include very high dependence on rain fed agriculture, under-development of water resources, low health service coverage, high population growth rate, low economic development level, low adaptive capacity, inadequate road infrastructure in drought prone areas, weak institutions, lack of awareness, etc (NAPA, 2007).

Vulnerability assessment based on existing information and rapid assessments carried out under NAPA has indicated that the most vulnerable sectors to climate variability and change are Agriculture, Water and Human health. In terms of livelihood approach smallholder rain-fed farmers and pastoralists are found to be the most vulnerable. The arid, semiarid and the dry sub-humid parts of the country are affected most by drought (NAPA, 2007).

Climate change impacts on agriculture are expected to be dominantly negative. While climate change is a global phenomenon, its negative impacts are more severely felt by poor people in under developed countries. Although agricultural producers, especially small scale poor farmers, are relatively small contributors of GHG emissions, proper agricultural technology and management systems are crucial to promote and sustain a low-carbon rural path (FAO, 2007).

The agricultural consequences of climate change are twofold. First, climate change may affect crop and livestock productivity. Second, ensuing economic responses may alter the regional distribution and intensity of farming. This means that, for some regions, the long-term productivity and competitiveness of agriculture may be at risk, farm communities could be disrupted, and conflicts over environmental impacts of agriculture on land and water resources could become increasingly contentious (Roy D. et al., 2011).

In the long run, climatic change could affect agriculture in several ways such as quantity and quality of crops in terms of productivity, growth rates, photosynthesis and transpiration rates, moisture availability etc. (Syed and Sazali, 2013). Climate change is likely to directly impact food production across the globe. Increase in the mean seasonal temperature can reduce the duration of many crops and hence reduce the yield. In areas where temperatures are already close to the physiological maxima for crops, warming will impact yields more immediately (IPCC, 2007).

Drivers of climate change through alterations in atmospheric composition can also influence agricultural production directly through its impacts on plant physiology. The consequences of agriculture's contribution to climate change, and of climate change's negative impact on agriculture, are severe which is projected to have a great impact on agricultural production and hence, require special agricultural measures to combat with (Anupama Mahato, 2014).

Agriculture and climate are directly related exerting mutual effects. Among the different economic sectors, climate change affects the agricultural sector most significantly because of its worldwide distribution and the strong linkage and dependence of the climate and environmental factors. Thus the effects of climate change on agricultural production impact the socio-economical dimension at both the macro and micro scales (Quasem, 2011).

The basic climatic elements directly influence the spatial distribution of crop types and agricultural systems, because different crops require different amounts of rainfall, humidity, warmth and sunshine. In rain-fed agriculture, climate is the main factor determining crop types and yields. Beyond certain climatic limits, it becomes impossible or disadvantageous to cultivate certain types of crops. The different climate conditions that exist at different altitudes affect agriculture production differently (Molua, 2006).

Impacts of climate variability and change on the agricultural sector are projected to steadily manifest directly from changes in land and water regimes, the likely primary conduits of change. Changes in the occurrence and intensity of droughts, flooding, and storm damage are also likely. Climate change is expected to result in long-term water and other resource shortages, worsening soil conditions, drought and desertification, disease and pest outbreaks on crops and livestock, sea-level rise, and so on. Vulnerable areas are expected to experience losses in agricultural productivity, primarily due to reductions in crop yields (Rosenzweig et al., 2002).

Climate change and variability affects countries' economies and households through a variety of channels. Rising temperatures and changes in rainfall patterns affect agricultural yields of both rain-fed and irrigated crops. Increasing temperatures will result in enhanced evapo-transpiration, leading to a reduction of the water availability. An increase in the magnitudes of the storms will result in an increase in the frequency of floods and flood damage which in turn will increase salt intrusion causing less amount of water available to use in the agriculture. A rise in the air and water temperatures will reduce plant efficiency and leading to major economic costs (Stern2006; World Bank,2007).

Depending on countries' natural conditions and economic structure, climate change affects countries differently. For example, Sub Saharan Africa is more vulnerable to an increase in climate variability, with projected large losses in their national output (Thurlow, 2009). Countries with large delta regions, such as Vietnam, are projected to be hit hard by rising sea levels, with strong implications for food security and the rural poor (Yu et al., 2010). Countries that are already experiencing water stress, especially those in the Middle East and North Africa, are likely to experience additional declines in agricultural yields, resulting in negative effects on rural incomes and food security (Breisinger et al.,2010).

Quasem (2011) stated in a study that climate change could reduce crop yield and areas vulnerable to drought could become marginal for cultivation thus posing a threat to national food security and exports earnings. Geographic distribution limits and crop yield could be modified due to changes in precipitation, temperature, cloud cover and soil moisture as well as increases in CO_2 concentrations. High temperatures and diminished rainfall reduce soil moisture, reducing the water available for irrigation and impairing crop growth in non-irrigated regions. The risk of losses due to weeds, insects and diseases could increase. Physical damage, loss of crop harvest, drop in productivity, and others related to crop potentials are examples of direct and indirect effects of the extreme climate change (Quasem,2011).

In contrast, interestingly enough, climate change is also expected to result in some beneficial effects, particularly in temperate regions (Mendelsohn et al., 2000). The initial benefits arise partly because more carbon dioxide in the atmosphere reduces "water stress" in plants and may make them grow faster (Long et al., 2006). The lengthening of growing seasons, carbon fertilization effects, and improved conditions for crop growth are forecast to stimulate gains in agricultural productivity in high-latitude regions, such as in northern China and many parts of northern America and Europe. Besides, Climate change may increase the amount of arable land in high-latitude region by reduction of the amount of frozen lands (IPCC, 2007).

Climate affects the productivity of critical development resources, such as crops and livestock, forests, fisheries, water, tourisms, and mining and aggravates poverty by reducing market access to the world's poor. Climatic impacts on populations inadequately or inappropriately prepared for climate change can have knock-on effects on all forms of development. Results from various impact assessments of climate change, show that Sub-Saharan Africa is one of the regions likely to emerge as the most vulnerable, with likely losses between 2 and 7% of GDP (Mendelsohn, et al.,2000).

World agriculture faces a serious decline within this century due to climate change. Overall, agricultural productivity for the entire world is projected to decline between 3 and 16% by 2080. Developing countries, many of which have average temperatures that are already near or above crop tolerance levels, are predicted to suffer an average 10 to 25% decline in agricultural productivity by 2080. Rich countries, which have typically lower average temperatures, will experience a much milder or even positive average effect, ranging from an 8% increase in productivity to a 6% decline (Anupama Mahato, 2014).

2.1.5. Economic impact assessment models

Various climate change impacts on agriculture used six different approaches to find out the consequences of climate change on agriculture. They can be mainly categorized as economy-wide analysis and partial equilibrium analysis. The partial equilibrium analysis contains five of the approaches; crop simulation models, Economic management models, Empirical yield models, Intertemporal net revenue models, Ricardian (Cross-Section) models. Hereunder, their way of analysis, pros, and cons are discussed based on the document released by World Bank, which was written by Mendelsohn and Dinar in(2009).

Crop Simulation Models: one of the most popular methods for estimating the impact of climate change on agriculture relies on crop simulation models. The models use functions that capture the interaction between growth and climate, soils, and management practices. The crop simulation models are calibrated to selected locations. Different climate change scenarios are run for each location for selected crops given a particular managementpractice.

Crop simulation models are attractive because they are developed based on a deep understanding of agronomic science. They can be carefully linked with hydrologic conditions. They can be integrated into the effects of carbon dioxide fertilization then are calibrated to local conditions.

However, crop simulation methods have important limitations on the most significant of these concerns to adaptation. First, the model doesn't capture the behavior of the farmer, the management practice of the farmer is assumed to be exogenous or fixed. Second, CSM is modeled one crop at a time. The CSM has not been used to predict how farmers would react as one crop becomes less suitable and another crop becomes more suitable. They do not predict crop switching. Third, a limited number of crops have been studied. Researchers have targeted the major grains tend to be grown in cool or temperate climates. Finally, CSM has been calibrated only in a limited number of places. If their locations are not a representation of all farms they can provide misleading predictions (Mendelsohn and Dinar,2009).

Production Function Models: the other way to measure the sensitivity of yield to climate change is to measure how actual yield varies under different climate conditions. For example, one can conduct cross-sectional studies of actual yields across different climate zones. By applying an empirical production function model, the production function links to water, soil, climate, and economic inputs to crop yield to specific crops.

This model can also be used to empirically measure the sensitivity of yields to examine the effect of weather on yields over some time. In this case, the changes in climate can be captured through variation of time. The estimated changes in yield caused by changes in environmental variables are aggregated to reflect the overall national impact (Olson, 2000) or incorporated into an economic model to simulate the welfare impacts of yield changes under various climate change scenarios (Adams, 1989; Kumar & Parikh, 1998; Chang, 2002).

The limitations of this model include; Farmers are often assumed to continue growing the same crop, with the same technology regardless of the change in the climate. The full set of adaptations available to farmers isunderestimated.

Economic Management Models: To capture farm behavior, it is important to model the farm and the farming sector, not just the plants. Farm simulation models assume that farmers wish to maximize their profits. One can then determine what farm behavior would lead to profit maximization. One can also determine which farm adaptations would maximize the profits in response to climate change. Farmers can alter planting times, crop varieties harvest dates, tillage and irrigation methods, the researcher would then be able to determine which activity would maximize profit and then could trace out actual yields and net revenues for different climates (Mendelsohn and Dinar, 2009).

In practice, the farm simulation models do not yet fully capture the full range of adaptation that farmers can practice. FSM can measure the behavior of a single farm (Kaiser et al., 1993; Mount and Li, 1994) or all farmers in a country (Adams et al., 1990, 1993, 1999). The single farm model can describe in detail the choices a farmer might make to maximize profit at a specific location. To perform the simulations, mathematical programming methods are employed to determine profit maximization choices of crops by farmers across thecountry.

Inter Temporal Net Revenue Approach: Instead of measuring how yields change over time, one can instead focus on measuring on the changes in net revenue using panel data, one can estimate the effect of change in weather on farm net revenue (Deschenes and Greenstone, 2007). By using fixed effects to control for the difference between one county and another this approach controls all the paramount differences between countries, including climate as well as other differences that are hard tomeasure.

However, at the same time, fixed effects also control for adaptations that farmers have made to adjust to the climate. The analysis focuses only on the inter-temporal differences between countries or regions which reflect year to year variations in weather. This approach in principle is an ideal method to measure short term responses to sudden changes in weather. However, it suffers from all the limitations of the yield studies in that it does not reflect adaptation (Deschenes and Greenstone, 2007).

Ricardian (Cross-Section) Model: A Ricardian technique estimates the net productivity of farmland as a function of climate, soils, and other control variables. The technique relies on a cross-sectional sample of farms that span a range of climates, to measure the sensitivity of land value or farm net revenue per hectare to climate. With a Ricardian technique, land value or net revenue is regressed on a set of climate variables (for example rainfall and temperature measured either in annual or seasonal values), other environmental characteristics, for example, soil and altitude); exogenous market factors, and other control variables.

By controlling properly for unwanted correlation, the regression can measure the impact of the climatic variables. Note that farm choices, such as labor, capital, and crop choices are not included in the Ricardian regression become they are endogenous. As with all empirical methods, the more accurate the measurement of the variables, the better-uncontrolled variables are accounted for, the more variation in the deserved variables (i.e. climate change) the larger the sample the more accurate the results are. The method was first applied to the study of land values in the USA (Mendeshohn et al.,1994),

The drawbacks of the model can be described as: the technique does not fully control for the impact of important variables that could also explain the variation in farm incomes, especially irrigation. Further, the model assumes that prices are constant when prices may in fact change (Cline, 1996). The assumption leads to a small bias that causes the method to overestimate damages and benefits (Mendelsohn and Nordhons, 1999b). Next, the Ricardian method does not measure the adjustment costs from one equilibrium to another. The Ricardian method is a comparative steady-state analysis of long-term climate impacts and not a dynamic analysis of short-term weather effects. Finally, if land within observed locations is heterogeneous, migration may cause bias (Timmins,2006).

The other group of analysis approaches used to assess the impact of climate change on agriculture is the economy-wide approach. Computable General Equilibrium (CGE) model is includedhere.

Computable General Equilibrium (CGE) Model: It incorporates efficient adaptation by farmers to climate change. The changes are large enough, they may affect the entire economy and change both input and output prices. An economy-wide approach may be needed to capture there broader changes. CGE models are used to capture economy-wide and globalchanges.

CGE models can predict how large shifts in supply and demand can alter prices and thus capture changes that the partial equilibrium models miss. Although the partial equilibrium models might capture shifts within the sector such as in crop prices, they invariably miss changes in interest rates or labor prices. The partial equilibrium models also tend to be country-specific so that they will miss trade effects as well.

The model depends on accurate measures of the underlying sensitivity of each sector to climate change. The models also need to have reliable estimates of how the different sectors of the economy interact. These inaccuracies are compounded with aggregation. It is very difficult for CGE modelers to predict how climate affects supply in large regions, much fewer regions that are poorly studied, such as developing countries. With the bulk of climate damages occurring in developing countries, one must treat CGE results withcaution.

Although CGE models can analyze the economy-wide impacts of climate change, there are some drawbacks to using them. Key limitations include difficulties with model selection, parameter specification and functional forms, data consistency or calibration problems, the absence of statistical tests for the model specification and the complexity of the CGE models, and the high skills needed to develop and use it (Gillig & McCarl, 2002).

To sum up, the above approaches have been developed in the literature and they all providesome needed insight. Although many assessment approaches can lead to different conclusions, they also can support and complement each other. One can also compare results across space. If every method suggests one specific region is more sensitive to climate, it is most likely that this result is true. Similarly, if all the results suggest another region is not sensitive to climate, then this increases confidence in that result aswell.

2.2. Empirical LiteratureReview

Hereunder I have tried to review current empirical findings related to climate change and economic impacts concerning agriculture more specifically. Nastis, Michalilidis, and Chatzitheodoridis (2012) have analyzed linkage climate change and agricultural productivity employing a time series analysis of over 30 years to find the costs of the economic impact of climate change on Greeks agricultural production. The study had used a carefully specified production function approach with a method of Newey-West standard. The OLS regression result has indicated, the average temperature has a negative sign with an elasticity of -0.77. That impliesthatahigheraveragetemperaturewillnegativelyaffecttheagriculturalproductivityof

Greece. On the other hand, the study had shown precipitation has a positive sign with an elasticity of 0.2 meaning the higher the average rainfall the higher the productivity ofagriculture.

According to Ali (2012), about 45% of GDP comes from rain-feed agriculture. Second, about 99% of electrical energy in the country on which the industry and service sector dependence is generated by hydroelectric power which in turn depends on the volume of rainfall. Using data from 1961 to 2008 he has tried to show the variability of rainfall in Ethiopia and its impact on the Ethiopian rain feed economy using a simple economic model. His findings suggest that there is an optimum amount of rainfall and if it deviates from that level then there will be a reduction in output. Variation in rainfall is important for growth but excessive variability in rainfall retards it. The study further revealed if there was no rainfall variation the Ethiopian economy would have been grown at a rate of 4.7% each year for the period 1965-2008 (Ali,2012).

This implies that mitigation and adaptation strategies of the developing countries towardsclimate change in the form of, for example, water harvesting, reducing the seasonal dependency of agricultural activities, and reducing the dependency of the economy on rainfall would put such countries on higher growth trajectories (Ali,2012).

A study in Nigeria on agricultural production and climate change was conducted and they have found that an impact which is significant and when rainfall increases agricultural production increases and vice versa. The estimation results revealed that a unit change in rainfall results in a 0.24 unit change in agricultural production. Considering the results, the researchers have implied, the current changes in climatic factors can be minimally controlled if the government gears their policy towards mitigation procedures and also if the private sector focus increasingly the output of agricultural production by developing technologies which will not contribute to changes in climate, but will increase agricultural production (Ajewole et al.,2010)

A study conducted by Ajewole et al. (2011), using a time series data spanning from 1980-2005 found temperature and rainfall have of course an impact on agricultural productivity in Nigeria. The study has shown high temperature harms the productivity of agriculture by depleting soil nutrients and making livestock and agricultural production very hard. The paper estimated an increase of past year rainfall by a 20% unit will decrease agricultural productivity by a unit.

As per the research by Barrios, Bertinelli, and Strob (2010), Agriculture has traditionally had a higher share in GDP in Africa than in Non-Sub Saharan (NSSA) countries – nearly 40% in 1960. Although these shares have since decreased, it still represents almost one-third of total GDP, compared to 14.1% in the rest of the developing world. In their study using cross-country data set, they have provided evidence of trends in rainfall that have affected economic growth rates in sub-Saharan African countries but the same has not seen in other developing countries. Additionally, they have identified that decline in rainfall that has been observed in Africa has had adverse effects on its growth rates. On the other hand, the simulation they performed revealed if rainfall had remained at previous levels, the current gap between GDP per capita relative to other developing countries could have been around 15% to 40% lower.

An estimation result, on his working paper titled climate change, growth, and poverty in Ethiopia of Aragie (2013), indicates that factors incorporated in the model are statistically important in determining agricultural output with expected signs indicating the validity of the model adopted for the case of Ethiopia. The adjusted R-squared of the estimated equation reveals that approximately 92% of the variation in agricultural output is explained by the variables included in the model. A close examination of the contribution of the variable of interest, mean rainfall, shows that elasticity of agricultural output to a unit increase in average rainfall in Ethiopia is close to 0.38. This result is higher than the elasticity level of 0.23 observed for the entire SSA by Barrios et al. (2004).

A study conducted by Odusola and Abidoye (2015), for the relation between economic growth and climate change, depicts how economic growth is dependent on temperature. As per the research, A 1o Celsius increase in temperature has slow down the economy by 41% for smaller samples while the same A 1o Celsius increase in temperature for a larger sample indicated a 27% decrease in GDP growth from a pooled estimate of data from 34 African countries from 1961-2009.

Research had carried out by Rosenberg et al. (2015) for an assessment of impacts of climate change on agricultural productivity and of water for irrigation using baseline time-series data from 1961-1990. They tried to investigate the impact using the simulation of three different scenarios, the status quo and two 10 year different times over using over 204 representative farms. The result of the simulation revealed yield increases for the great lakes. Most regions of the country and crop irrigation combinations were sensitive to the simulated climatic changes and CO2 fertilization effects. Evaporation in dry land is expected to increase in response to the warming projected by Had CM2 for both future periods. Accordingly, corn is predicted to decrease by 2-4 Kg/mm under climatechange.

Further, the balance of water supply and demand for corn irrigation could be affected by the geographical differences in temperature and precipitation changes predicted for tow future periods. In general, in absence of a CO2 fertilization effect, the water balance in 2030 derived from the Had CM2 projections improves in the east deteriorates throughout the Great Plains while it remains stable or even improves in the west (Rosenberg et al., 2015).

Gebreegziabher et al. (2011) have analyzed the economic impacts of climate change on Ethiopian agriculture using a countrywide CGE, Ricardian model. The model was used to evaluate current and future agricultural production. They have assessed it as a function of temperature and precipitation letter variables being climate change indicators. Their simulation results depicted that over 50 years; the projected reduction in agricultural productivity may lead to a 30% less average income when compared within the absence of climatechange.

The aim of a paper by Kumar and Gautam (2014) was to analyze the impact of climate change on agricultural productivity of India. They have found that average temperature change is predicted to be 2.33o Celsius - 4.78o Celsius with a doubling in CO2 concentration. These heat waves will lead to increased variability in summer monsoon precipitation, which will result in drastic effects on the agricultural sector in India. Using descriptive analysis, they have concluded that the effect of climate change poses many threats: out of the important consequences is bringing about changes in the quality and quantity of water resources and crop productivity.

According to Berhane (2018) study on climate change impacts on crop productivity, crop productivity is projected to increase slightly at mid to high latitude for local mean temperature increase 1o Celsius - 3o Celsius. However, in low tropical and dry areas crop productivity is projected to decrease with an increase in temperature 1^{o} Celsius - 2^{o} Celsius.

Crop production in Ethiopia is mainly dependent on rainfall as a source of moisture for growthof crops with irrigation contributing 1.1% of the total cultivated land in the country where the amount and temporal rainfall distribution are prominent for crop production (Berhane,2018).

Water productivity is the ration of the net benefits from the crop, foresting, fishing livestock, and mixed agricultural systems to the amount of water required to produce those benefits. Water productivity is a concept which can be defined as the amount of harvestable yield per unit of water consumed (Berhane, 2018).

Deressa (2007) analyzed the impact of climate change using a Ricardian approach, to describe farmer adaptation to varying environmental factors. The regression result revealed that most of the climatic, household, and soil variables have significant impacts on the net revenue per hectare. While the coefficients of spring and summer temperatures are both negative those of winter and fall are positive. On the other hand, the coefficients of winter and fall precipitation are negative whereas for spring and summer they are positive. Further, the study has also depicted the education level of the head of household and the livestock ownership is positively related to the net revenue per hectare. The distance to the input market place is negative as farmers incur more costs in terms of money and time as the market place becomes further from their farmplot.

A study presented an empirical analysis of the effect of global warming on Nigerian agriculture and estimation of the determinants of adaptation to climate change. Results have shown that hunger – released deaths could increase if grain production does not keep pace with population growth in the unfavorable climatic environment. However, climate change adaptations have a significant impact on farm productivity (Apata, 2018).

3. METHODOLOGY OF THESTUDY

3.1. Type and Source ofdata

The study has used secondary data to investigate the impact of climate change on Ethiopian agricultural productivity. Hence, the datasets has been collected from Ethiopian National Metrology agency (NMA), Central Statistical Agency (CSA) of Ethiopia, World Food and Agricultural Organization (FAO) and World Bank Group (WB). A yearly time series data on net agricultural output, land input available for agriculture, employment in agriculture, animal stock, weight of fertilizer used, pesticides imported, annual average temperature, annualized average precipitation are gathered from the above indicated sources. The time span of the study covers from 1981 to 2018 as per the Gregorian calendar. The data that has been collected relied on the availability of the dataset and the relevance of the variables to the study.

3.2. Econometric ModelSpecification

The study has employed autoregressive distributed lag (ARDL) model of order p and q, ARDL (p, q) where the dependent variable regresses on p of its own lags and on q lags of one or more additional repressors. As time series analysis had always has a problem of unit root problem of the variables in consideration during the time period of investigation.

Using ARDL model is beneficial since it allows the researcher to use I(0) and I(1) order variables to be incorporated simultaneously. The model also allows investigating the impact of the subject matter at hand from both long run and short run perspective. Further, the adjustment coefficient reveals the divergence or convergence of the co-integratedvariables.

In a literature, there are two main ways of addressing the impact of climate change on the whole economy or specifically on sectionals of the economy. Namely, the approaches are economy wide models (i.e. CGE models) and partial equilibriummethods.

The economy wide model or general equilibrium model tries to asses by incorporating all economy actors and depict the impact on specific sector from the general results found. While, the partial economy model assess the impact based on only part of the overall economy or subset markets (Sadoulet and De Janvry, 1995).

Computable general equilibrium (CGE) models can insight micro-level impacts from the interaction of producers and consumers interaction created from their small economy simulation capable of capturing complex economy wide effects (Oladosu et al., 1999; Mabugu, 2002).

On the other hand, the literature found on partial equilibrium mainly concentrated on crop productivity and ricardian approaches (Mendelsohn et al., 1994). Though, both category methods of ways of analyzing the impact of environmental externalities on the economies have its own advantages and disadvantages. Starting from the budget requirements allotted in developing countries is very small for research and development, the availability of data and implementation problems has convinced by production function way of tackling the research problem.

The production function was first mentioned by Charles Cobb and Paul Douglas in 1927 (Cobb-Douglas, 1928). Agricultural output is a function of its input factor to produce the required output. The relation between climate change indicators and other input factors can solely be integrated to measure or analyze their impacts directly (Adams, 1989; Kaiser et al., 1993; olsa et al., 2000).

Following the literature (particularly Nastis, Michailidis and chatzitheodoridis, 2012) Agricultural output net of its input cost is assumed to depend on area of land available, employment of labor in agriculture, capital, animal stock, fertilizer used, and pesticides used for every period t.

$$Y_t=f(L_t,K_t,A_t,F_t,S_t,P_t) \qquad (1)$$

Where:

- L_t is labor employed in agriculture sector per time period t
- K_t is capital employed in agriculture sector per time period
- t A_t is total area of cultivated land per time period t
- F_t is the amount of fertilizer used per time period t
- S_t is livestock units available per time period t
- P_t is the amount of pesticides used per time period t

Having the above specification, since significant amount of our agricultural production is produced by non capital intensive production method and because of availability of data on capital employed in agriculture the researcher has been convinced to drop capital from specification and be expressed as part of the residual term and maintain the remaining variables.

The main research question paused is to find the impact of climate change in agricultural productivity. Agricultural productivity can be measured either single input factor productivity or total factor productivity. I have used a single input productivity measure because of data availability and mainly because agricultural productivity of land in Ethiopia is very crucial having fixed amount of land, level of adaptability to technology and the growing number of population overtime.

Hence, dividing equation (1) by area of land in agriculture (A_t)

$$Y_t/A_t=f(L_t/A_t,F_t/A_t,S_t/A_t,P_t/A_t) \text{......} (2)$$

Or using small letter for the proportion ofLand

$$y=f(l, f, s,p)$$

Now, incorporating climate change indicator variables, coefficient or variation of average temperature and coefficient of variation of average precipitation; we can capture the effect of climate on agricultural productivity. Because, these variables are out of control of the farmer they are notincluded.

Hence, after inclusion of the climate indicators the functional form can be:

$$y=f(l, f, s, p, temp, perc) \text{......} (3)$$

Where: perc and temp are coefficient of variation of precipitation and temperaturerespectively.

Thegeneralized ARDL model canb especified as:

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \Delta Y_{t-i} + \sum_{i=0}^{q} \delta_i \Delta X_{t-i} + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \varepsilon_t \quad \varepsilon_t \sim iid\ (0, \sigma^2) \text{ ----(4)}$$

Deducing from the above equation the model employed in this study can be written as follows:

$$\Delta \ln(LAP_t) = \alpha_0 + \sum_{i=1}^{p} \alpha_{1i} \Delta \ln(LAP_{t-i}) + \sum_{i=1}^{q} \alpha_{2i} \Delta CVT_{t-i} + \sum_{i=1}^{q} \alpha_{3i} \Delta CVP_{t-i} + \sum_{i=1}^{q} \alpha_{4i} \Delta \ln(LPPL_{t-i})$$
$$+ \sum_{i=1}^{q} \alpha_{5i} \Delta \ln(FPL_{t-i}) + \sum_{i=1}^{q} \alpha_{6i} \Delta \ln(ASPL_{t-i})$$
$$+ \sum_{i=1}^{q} \alpha_{7i} \Delta \ln(PPL_{t-i}) + \beta_1 \ln(LAP_{t-1}) + \beta_2 CVT_{t-1} + \beta_3 CVP_{t-1} + \beta_4 \ln(LPPL_{t-1})$$
$$+ \beta_5 \ln(FPL_{t-1}) + \beta_6 \ln(ASPL_{t-1}) + \beta_7 \ln(PPL_{t-1}) + \varepsilon_t - - - - - - - - - - - - (5)$$

Where:

- LAP_t is agricultural productivity of land;
- CVT_t is the coefficient of variation of mean monthly annual temperature;
- CVP_t is the coefficient of variation of mean annual precipitation;
- $LPPL_t$ is agricultural labor per area of
- land; FPL_t is fertilizer used per area of
- land; $ASPL_t$ is animal stock per area of
- land; PPL_t is pesticides used per area of
- land;
- U_t a white noise error term.
- β's are the long run coefficients and

  α's are the short run coefficients of the ARDL model.

3.3. Description of the variablesincluded

3.3.1. DependentVariable

i) Land productivity ofAgriculture

The dependent variable of the study is land productivity of agriculture. The variable is created by the ratio of net agricultural value added to area of land available for agricultural production. According to Abeje and Alemayehu (2019), Agriculture has been the foundation of Ethiopian economy. On the other hand, the country's population growth has been fast. Hence, agricultural productivity have to increase better than the year before in order to meet the demand forfood.

3.3.2. IndependentVariables

ii) Employment on agricultural sector

Vast research findings have indicated how much share of the countries employment of the agricultural sector has employed. Labor has been a main source of input factor for the countries agriculture production. Nevertheless, the researcher expected that labor has negative impact for agricultural productivity because there is a fixed amount of land available and through population increment and land fragmentation the higher the availability of agricultural labor force per area of land has negative impact to land productivity ofagriculture.

iii) Fertilizerused

Fertilizer is one of the input factors of the sector. Given the scarce hard currency resource the country has to buy the required amount of fertilizer. The researcher expected the more amount of fertilizer used per area of land the better the agricultural productivity will be. Unfortunately, the available data for this variable was limited to years from 2002 to 2018. The remaining datasets were generated using stata's built in interpolation method. The researcher has expected fertilizer used to have positive impact on land productivity ofagriculture.

iv) Animal Stock

Animal stock helps the productivity of the sector in two ways. One, their output can be counted as output of agriculture. Second, their wastes can also be used as a fertilizer substitute in some instances. The proportion of the animal stock to area of land should be optimal. If livestock unit of animal per area of land are excess of the land available or economically speaking if it is not optimal, then there will be shortage of grazing and plough land and vice versa.

The researcher has collected the data from FAO database and during the data management process the units of the animal stock has been different. For the purpose of the analysis the different units has been converted to standard livestock unit (LSU) as per specification of FAO (1987).

v) Pesticide

For agricultural production pesticides are also vital input factors. The study has used all imported amounts of pesticide are assumed to be used in agricultural production efficiently. The researcher has expected positive relation between the value of pesticides used and agricultural productivity ofland.

vi) Coefficient of variation of temperature

As per the report of IPCC (2007), one of the main indicators of climate change is the rise in global warming. Hence, including such variable as an indicator is a requirement in order to capture the impact of climate change on agricultural productivity. The researcher used coefficient of variation (CV) as an independent indicator variable of climate change because many studies have found different results on variation in temperature on a different geographical locations.

So rather than using the average temperature value itself calculating its CV of yearly temperature will indicate how temperature variability can affect or impact the agricultural productivity of Ethiopia. Hence, the researcher expected negative impact of temperature departure from its trend mean on agriculturalproductivity.

vii) Coefficient of variation of precipitation

The other climate change indicator variable used is precipitation. According to Ali (2012), rainfall is the heart of agriculture and consequently the whole economy as a whole. Therefore, finding the impact of rainfall or precipitation variability on agricultural productivity will be a profound question in order to have an insight about our intervention: weather it is an adaptation or mitigation.

A yearly coefficient of variation data from 1981 to 2018 was used for this analysis. Form the result the researcher has strongly expected that rainfall variability will affect agricultural productivity. In Ethiopia, both higher and lower precipitation has a negative impact on agricultural production. Hence, rather than using the level dataset, using their coefficient of variation helps figure out how departure from trend mean will impact agricultural productivity.

3.4. Unit roottest

A unit root test is one of the main sources of non-stationary. A non stationary process can emanate from trend stationary where the trend is predictable from past process. A non stationary process can also be difference stationary if it is not predictable from past process.

Hence, many time series variables are stationary only after differencing using differenced variables poses loss of long term properties or information of equilibrium relationships between the variables under consideration. The presence of unit root can be tested using durbin-watson

(DW) test, dicky-fuller (DF) test (1979), augmented dicky-fuller (ADF) test (1981), philip-perron (PP) test (1988). But, these are not a complete list of available tests that can be performed to test the presence of unit root test.

Durbin-Watson statstics: as per Granger-Newbold (1974), reveals it the value of durbin-watson statstics is less than the coefficient of determination (R-squared), it indicates that the series is not stationary.

Dicky-Fuller (DF) test: as per specification of dicky and fuller on their article Distribution of the estimators for auto regressive time series with a unit root they have indicated how to test for the presence of unit root in an autoregressivemodel.

Augmented Dicky Fuller (ADF) test: the difference between the DF and ADF tests of stationarity lies over the nature of the error term; If the error term is uncorrelated, then we can use Dicky Fuller (DF) test; but if it is correlated, then we have to use Augmented Dicky Fuller (ADF) test. In the case of ADF test we add the lagged values of the dependentvariable.

Phillips Perron (PP) test: It makes use of the nonparametric statistical methods to address the problem of serial correlation in the error terms with adding the lagged difference terms. This is because of the fact that the asymptotic distribution of the PP test is the same as the ADF test statistic (Gujarati, 2004, p. 841). We may use the following two regression equations to undertake the PP test (Sreelata & Anup,2014);

3.5. Lag Length SelectionCriterion

The ARDL method estimates (p+1)k number of regressions in order to obtain optimal lag length for each variable, where p is the maximum number of lag to be used and k is the number of variables in the equation. The model can be selected using the model selection criteria like Schwartz-Bayesian Criteria (SBC) and Akaike‟s Information Criteria (AIC). SBC is known as the parsimonious model: selecting the smallest possible lag length, whereas AIC is known for selecting the maximum relevant lag length. To apply these criteria calculate the following statistics for the system for each lag length. Select the model with the lowest AIC or SBC value.

3.6. Test for Cointegration (BoundsTest)

The idea of cointegration was first formalized by granger (1981) and Engle & Granger (1987) which provide tests and estimation procedure inorder to evaluate the existence of long run relationship between the variables within a dynamic specification framework.

Cointegration engages a certain stationary variables linear association which are individually non stationary but integrated to an order, I(d). Cointegration is an economic concept that mimics if there is long run equilibrium among the underlying economic timeseries that converges overtime. Hence, testing for the presence of cointegration is a necessary step to follow to find out if a model empirically exhibits meaningful long runrelationship.

Pesaran and Shin (1995) and Pesaran et al. (1996) which proposes Autoregressive Distributed Lag (ARDL) approach to cointegration or bound procedure for a long-run relationship, irrespective of whether the underlying variables are I(0), I(1) or a combination of both. In such situation, the application of ARDL approach to cointegration will give realistic and efficient estimates. Autoregressive Distributed Lag (ARDL) approach to cointegration helps in identifying the cointegrating vector(s). That is, each of the underlying variables stands as a single long run relationshipequation.

The ARDL bound test is based on the Wald-test (F-statistic). The asymptotic distribution of the Wald-test is non-standard under the null hypothesis of no cointegration among the variables. Unlike other tests two critical values are given by Pesaran et al. (2001) for the cointegration test.

The lower critical bound assumes all the variables are I (0) meaning that there is no cointegration relationship between the examined variables. The upper bound assumes that all the variables are I (1) meaning that there is cointegration among the variables. When the computed F-statistic is greater than the upper bound critical value, the variables are cointegrated). If the F-statistic is below the lower bound critical value there is no cointegration among the variables). When the computed F-statistics falls between the lower and upper bound, then the results are inconclusive here in this case we have to check the error term for stationarity (Pesaran et al., 2001). Based on the results of the ARDL bounds test either the error correction model (ECM) in case of existence of long run relationship or short run ARDL model in case of no cointegration isspecified.

3.6.1. Long Run Representation of the ARDL Model/ Error Correctionmodel

Here below is the long run representation of the ARDL model or the Error Correction model (ECM). This long run model will be estimated by OLS if the F-statistic exceeds the upper bound critical value and the existence oflongr un relationship is confirmed.

$$\Delta\ln(LAP_t) = \alpha + \sum_{i=1}^{p} \alpha_{1i}\,\Delta\ln(LAP_{t-i}) + \sum_{i=1}^{q} \alpha_{2i}\Delta CVT_{t-i} + \sum_{i=1}^{q} \alpha_{3i}\Delta CVP_{t-i} + \sum_{i=1}^{q} \alpha_{4i}\Delta\ln(LPPL_{t-i})$$
$$+ \sum_{i=1}^{q} \alpha_{5i}\,\Delta\ln(FPL_{t-i}) + \sum_{i=1}^{q} \alpha_{6i}\,\Delta\ln(ASPL_{t-i})$$
$$+ \sum_{i=1}^{q} \alpha_{7i}\Delta\ln(PPL_{t-i}) + \delta ecm_{t-1} + \varepsilon_t ----------(6)$$

Where; δ is speed of adjustment parameter with a negative sign which shows convergence overtime.

3.6.2 Short Run Representation of the ARDL Model

Theshortrun dynamics of the ARDL model specifiedas follows:

$$\ln(LAP_t) = \beta_0 + \sum_{i=1}^{q} \beta_1\,\Delta\ln(CVTt-i) + \sum_{i=1}^{q} \beta_2\,\Delta\ln(CVPt-i) + \sum_{i=1}^{q} \beta_3\,\Delta ln(LPPLt-i)$$
$$+ \sum_{i=1}^{q} \beta_4\Delta\ln(FPLt-i) + \sum_{i=1}^{q} \beta_5\Delta\ln(ASPLt-i) + \sum_{i=1}^{q} \beta_6\,\Delta ln(PPLt-i)$$
$$+ \varepsilon_t ------------------------------(\mathbf{7})$$

3.7. Post Estimation Tests

Testing robustness of the model is performed using the diagnostic test. After estimation is done, it is must to check whether the model has achieved the desired properties. In this study, various diagnostic checks i.e. Serial correlation, Functional form test, Normality test and Hetroscedasticity are carried out. The dynamic model which incorporates both the long run and short run model simultaneously is tested with the diagnostic tests of Serial Autocorrelation, Hetroscedasticity and any modelmisspecifications.

In testing for the serial correlation both the Durbin Watson test and Breusch-Godfrey LM test for autocorrelation will be used. The Breusch-Godfrey LM test for autocorrelation is based on a null hypothesis of no serial correlation indicating that there is no serialdependency among the errors.

Ramsey RESET test for functional form is conducted to test for functional form specification and any model misspecification. The Ramsey RESET test is based on the null hypothesis that the model is specified correctly. Furthermore, failing to reject the null in Ramsey reset test also further confirms that our model did not suffer from omitted variable bias.

White’s test is carried out to test for the existence of autoregressive conditional hetroscedasticity in the residual at 5% level of significance. TheWhite’s test is based on the null hypothesis that the model is homoscedastic. The failer toreject the null hypothesis shows that there is no hetroscedasticity and indicates the existence of constantvariance.

The stability of the model and the coefficients are checked through the CUSUM test, in which the CUSUM examine the stability of the long run and short run parameters, while the graphical presentation of the recursive coefficients is used to judge the stability of thecoefficients.

4. RESULT ANDDISCUSSION

4.1. Description of thedataset

An observation that runs from 1981 to 2018 is used for the analysis. As indicated in table 4.1 there are 38 observations for each variable.

Table 4. 1: Summary Statistics of the variables

Variable	Mean	Std.Dev.	Min.	Max.	Skewness
Agriculture gross output per km2 of land	24,185.40	21,434.00	6,698.89	76,178.55	1.282
Fertilizer used per km2 land	352.91	362.80	4.40	1,294.52	0.865
Animal Stock per km2 land	130.49	50.40	60.91	215.40	-0.003
Agriculture labor per km2 land	6,003.58	2,636.26	1,921.92	9,458.40	-0.478
Pesticides used per km2 land	84.06	103.55	5.31	403.43	1.840
Annual average temperature	23.02	0.395	22.28	23.84	0.257
Annual average precipitation	66.79	6.28	51.57	80.35	-0.128

Sources: The results are calculated by the author using STATA 15.1 software

The above table shows that the average level of gross agricultural output per input land is found to be \$24,185.40 while its standard deviation, minimum and maximum values exhibited \$21,434.00, \$6,698.00 and \$76,178.55 per kilometer square, respectively. This values reveal that there is a huge variation over time in respect of agricultural output per land since the value of standard deviation is greater than its mean. It also implies that the variable is positively skewed which is clearly indicated by a value of1.282.

The studies main variables which are used as indicators of climate change, annual average temperature and precipitation, has shown a mean value of 23.02 degree celsius and 66.79 mm, respectively. Further, the maximum annual average temprature value was registered in 2015 to be 23.85 degree celsius while the minimum value during the period 1981-2018 has been found to be 22.28 degree celsius which was registered in1989.

The mean amount of fertilizer used per area of land has found to be 321.91 kg per square kilometer which also exhibited a slightly higher level of standard deviation 362.80 kg per square kilometer. During the study period the minimum and maximum values are 4.40 kg and 1,294.52 kg per square kilometer, respectively.

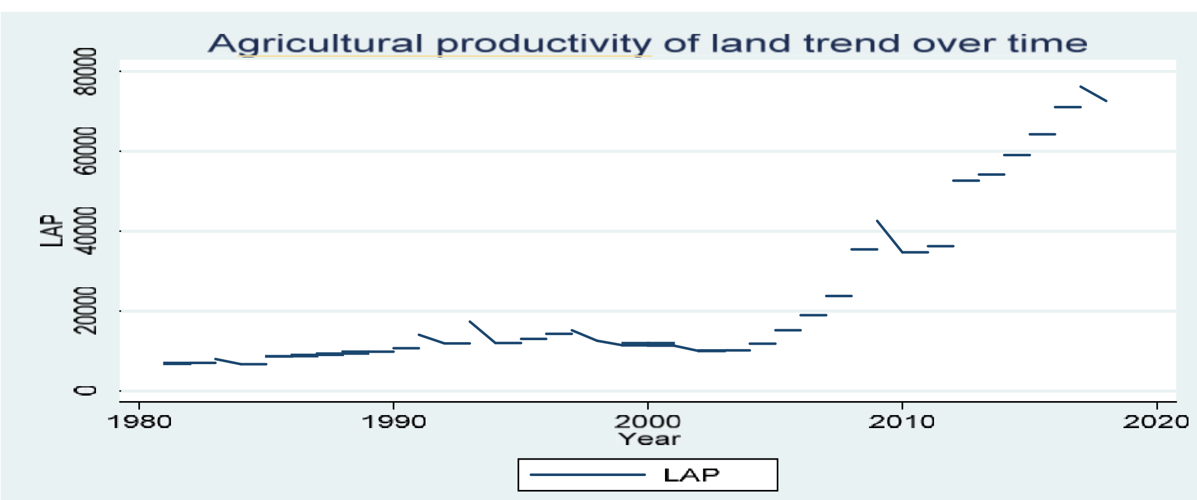
One of the main inputs for our agricultural production in Ethiopia, animal stock, has registered a mean value of 130.49 livestock unit per square kilometer with a skewness of almost zero which alo implies the variable is nearly perfectly skewed.

Equivalently, the other main input for the agricultural sector in Ethiopia, agricultural labor, has found to employ 6004 employees per square kilometer. Other things being equal, this implies that how our farming lands are over populated in average and need special attention. Further, the minimum and the maximum values are 1,922 and 9459 number of employees per square kilometer,respecitively.

4.2. Trends ofVariables

i) **Agricultural productivity of land:** The trend of agricultrual productivity of land indicates that it is growing overtime especially from the period around after 2002 it is increasing faster. (see Fig4.1).

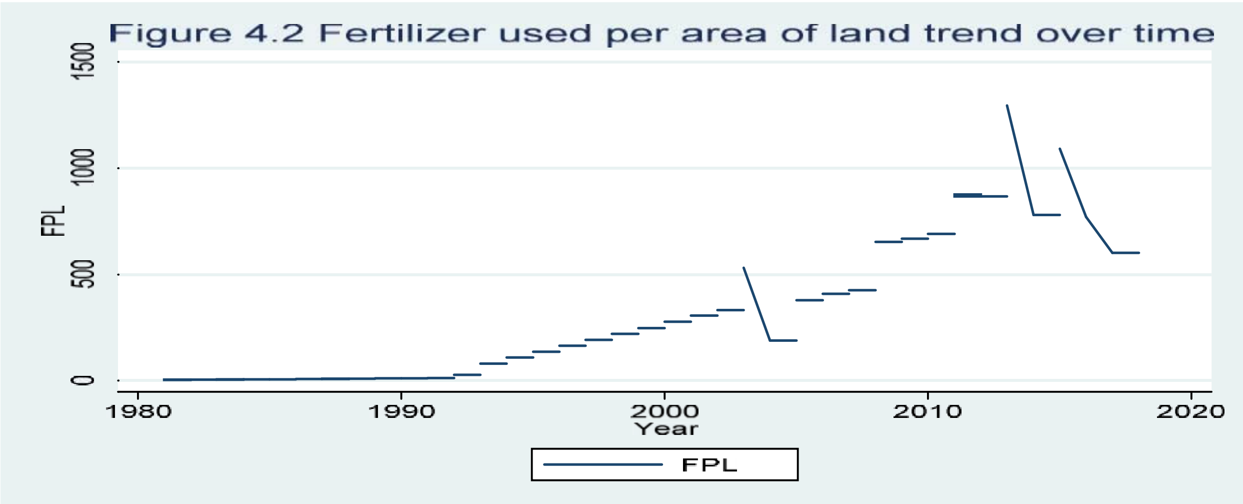
Figure 4. 1: Agricultural productivity of land trend



Sources: Author using STATA 15.1 software

ii) **Fertilizer used per area of land:** Relatively the trend of this variable is constant for the period of 2002 and above. The curve gets sharper and sharper when we go further to the previous year before 2002. (See Fig4.2).

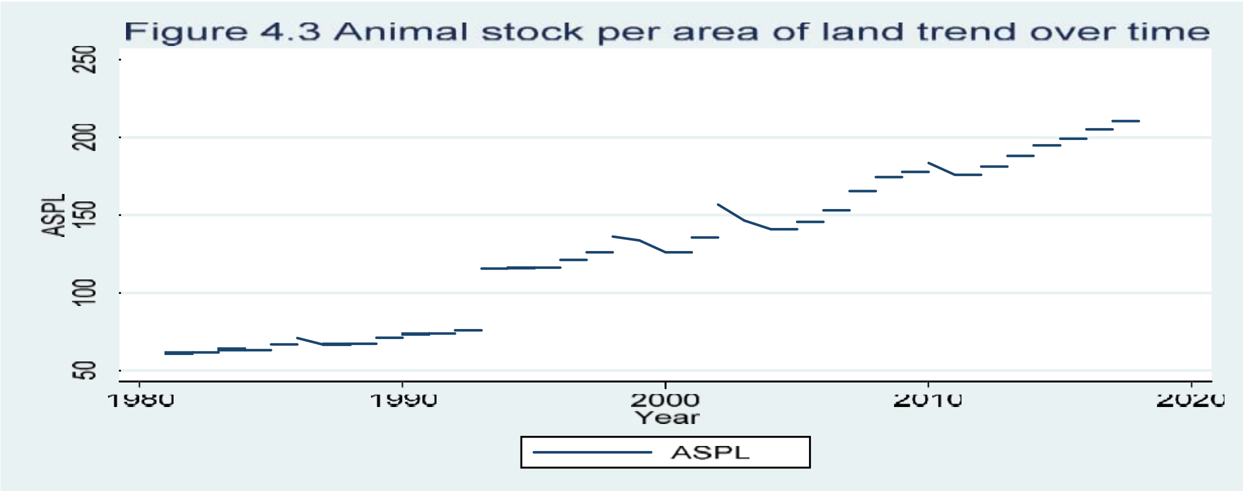
Figure 4. 2: Fertilizer user per land trend



Sources: Author using STATA 15.1 software

iii) **Animal stock per area of land:** like agricultural productivity and fertilizer used animal stock per area of land has similar trend of growing over time. (See Fig4.3).

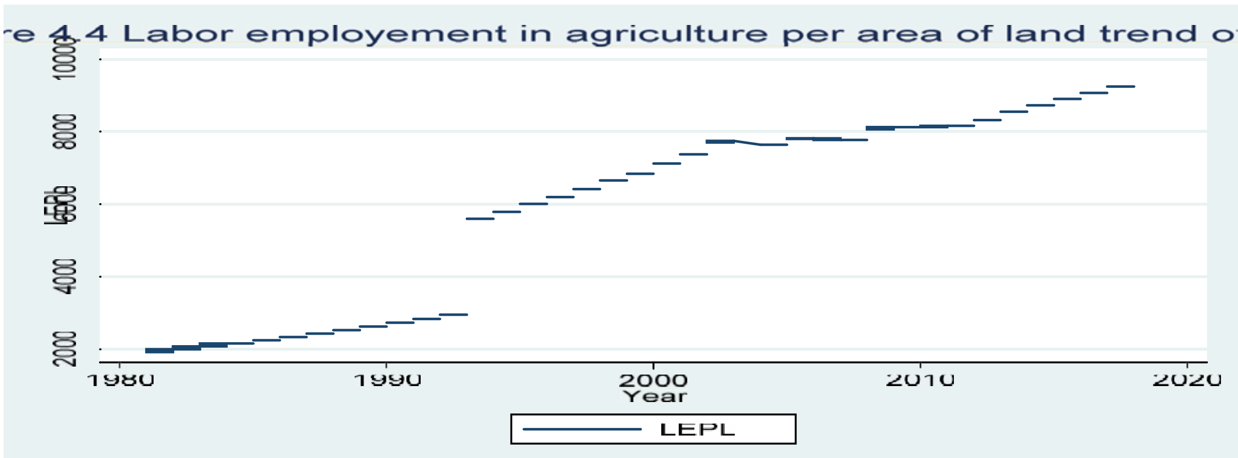
Figure 4. 3: Animal stock per land trend



Sources: Author using STATA 15.1 software

iv) **Labor employment per area of land:** even though, there is a change in trend after 1992 the growth is flatter than the other variables. (See Fig4.4).

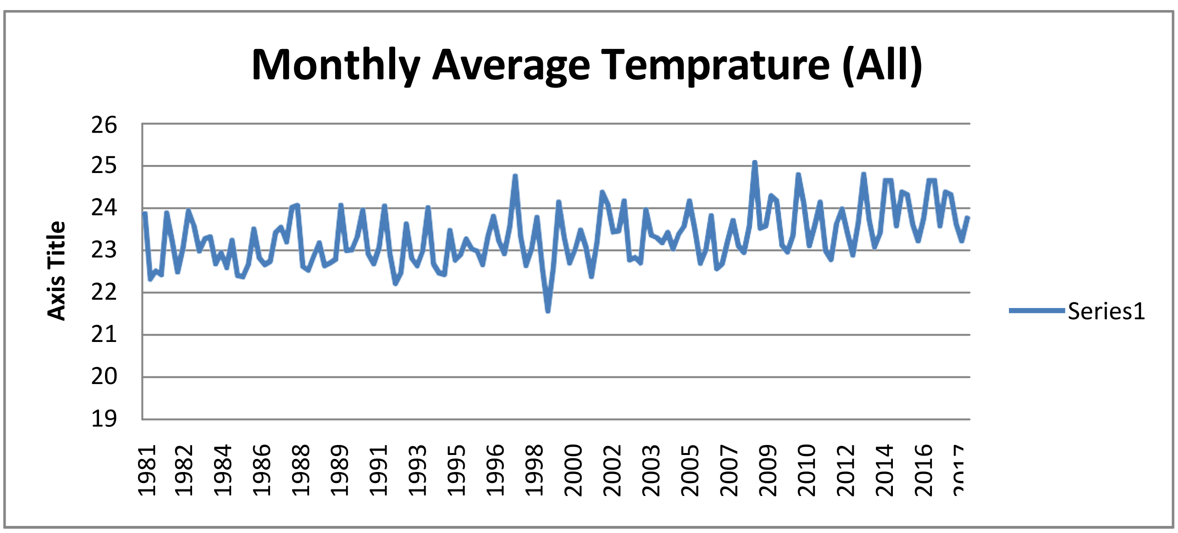
Figure 4. 4: Agricultural employment per land trend



Sources: Author using STATA 15.1 software

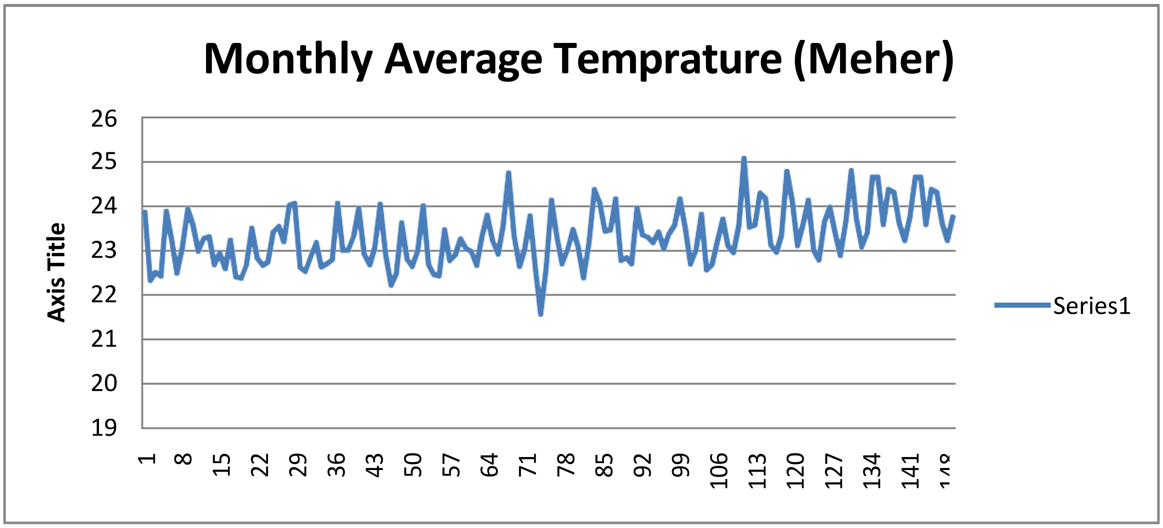
v) **Temperature:** unlike the above variables discussed this independent variable has a fluctuation in variable. It provide any evidence of trend dependent movement. It oscillates around the value range of 22 to 25 degree Celsius. (See Fig4.5).

Figure 4. 5: Monthly Average temperature (All)



Sources: Author using MICROSOFT EXCEL 2007 software

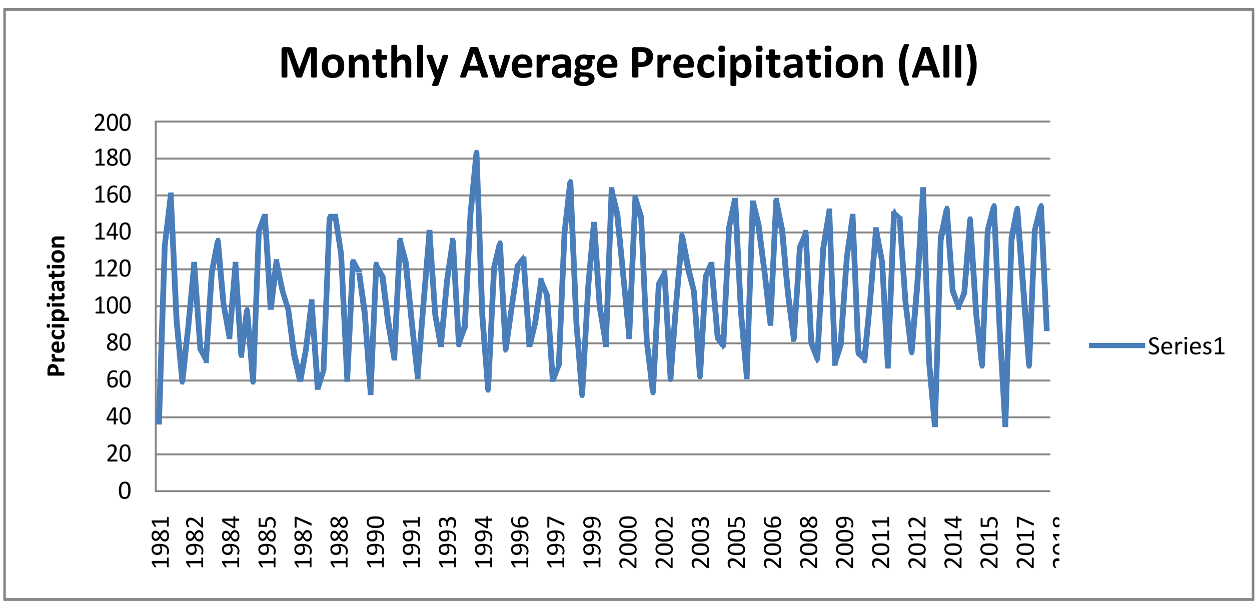
Figure 4. 6: Monthly Average temperature (Meher)



Sources: Author using MICROSOFT EXCEL 2007 software

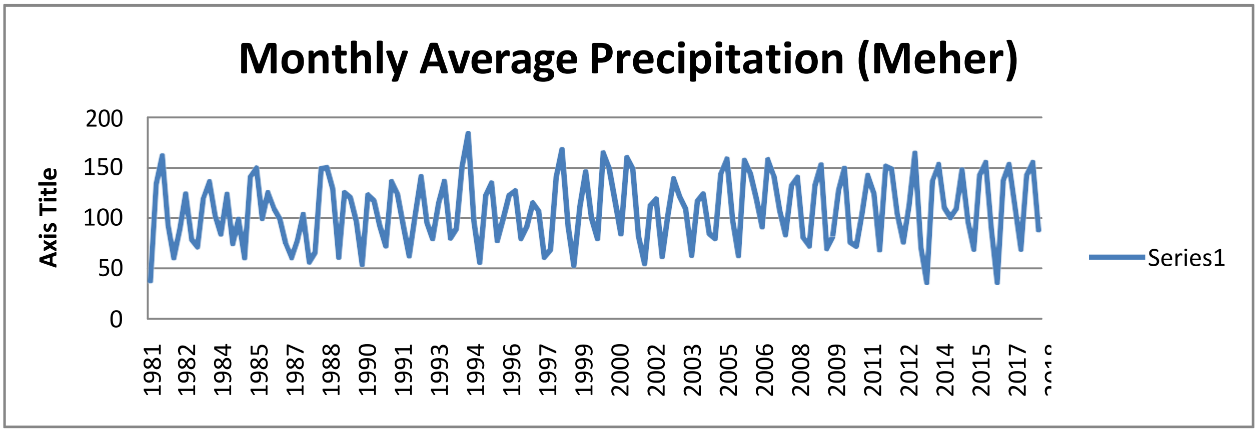
vi) **Precipitation:** similar to temperature this independent variable also does not have a trend related movement rather it swings around the value of 60 to 180 mmrainfall.

Figure 4. 7: Monthly Average Precipitation (All)



Sources: Author using MICROSOFT EXCEL 2007 software

Figure 4. 8: Monthly Average Precipitation (Meher)



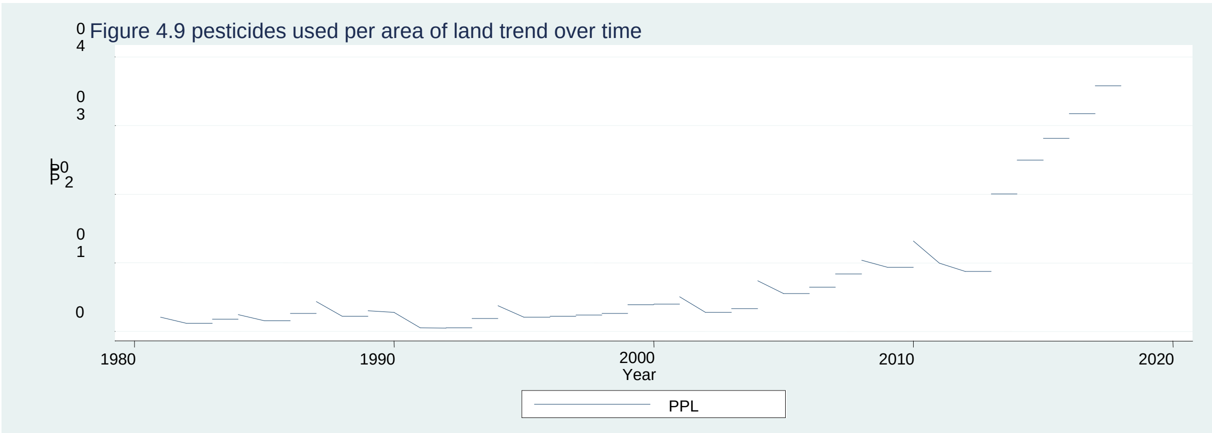
Sources: Author using MICROSOFT EXCEL 2007 software

Figure 4.8 shows the trend of average monthly rainfall for the month of June to September which is the main season of rainfall in the country. As we can depict from the graph although the trend is similar with around 100mm average precipitation over the years. There were times it has increased above 180mm bar and also decreased below the 40mm bar.

The above figure in conjunction with figure 4.7 reveals how much the countries rainfall is correlated with the period of famines occurred in Ethiopia. Monthly average rain falls below average consequently limit the agricultural production and as a result famine will happen. If we look at the graphs closely the two major periods happened in Ethiopia with in the period of this studies coverage has registered low average monthly precipitation.

vii) **Pesticides used per area of land:** even though, it exhibited to have some fluctuations at the first decade of the study on the other two consecutive decades the value of this variable has been increasing with the value of time. (See Fig4.9).

Figure 4. 9: Consumption of pesticides per area of land



Sources: Author using STATA 15.1 software

4.3. Unit roottest

Before regression of the model is executed both dependent and independent variables has been checked for the presence of unit root. The stationary test is performed using augmented dickey fuller and Phillips-Perron testes. One of the requirements of these tests is to find the optimal length of the lagged variables. Hence, hereunder the optimal lag length shown according to the information criteria of AIC, the HQIC, and SBIC.

Table 4. 2: Optimal lag level selection

Variables	F-Statistics	Cointegration	Lag Optimal
LN_LAP	-0.603913 [1]	-0.573294 [1]	-0.514127 [1]
LN_FPL	0.79984 [1]	0.830459 [1]	0.889626 [1]
LN_ASPL	-2.15182 [1]	-2.1212 [1]	-2.06203 [1]
LN_LEPL	-1.658 [1]	-1.62738 [1]	1.56821 [1]
LN_CVT	-1.23657 [0]	-1.22126 [0]	-1.19168 [0]
LN_CVP	-1.81414 [0]	-1.79883 [0]	-1.76925 [0]
LN_PPL	1.41152 [3]	1.47276 [3]	1.59109 [3]
ALL	-11.6367 [3]	-9.27897 [3]	-5.74198 [1]

Sources: The results are calculated by the author using STATA 15.1 software

The above table reveals that all lag selection information criterions has shown similar optimallag length except for the all variables at the same time. Using this result further the variables has been diagnosed for the presence of unit root test based on the Augmented Dickey-Fuller and Phillips-Perron testes. Both methods try to asses if the variables and their lagged values have serial correlation. In this test our objective is to reject our null hypothesis that states there is a unit root test which implies that variable is not stationary. If the variable has found non stationary (i.e. if we fail to reject our null hypothesis) at level then their first difference is checked using the sameprocedure.

Results from table to of ADF unit root test imply that two of the variables the researcher considering has found to be stationary at level. The variables are climate indicators coefficient of variation of temperature and precipitation. The calculated t-value [-6.001 and -5.355] or CV of temperature and precipitation respectively is less than the 1% critical value [-3.750]. Hence, we have sufficient evidence to reject our null hypothesis stating there is a unit root. The same result has been exhibited by the intercept and trend modelalso.

Then, for those variables a unit root is observed an ADF has been run on their first difference both using the intercept term only and intercept & trend term models. As shown in table 2 all variables have found to be stationary after a first difference.

Phillips-Perron test has confirmed the results I have mentioned above. At 1% level of significance we are confident that log of coefficient of variation of temperature and precipitation are stationary at level and the remaining variables are found to be stationary after first difference with the same level oferror.

Hence, the ADF and Phillips-Perron unit root tests have indicated that the series of our variables in consideration are of order zero and order one. From the results of above mentioned tables, target variables log of coefficient of temperature and precipitation have a series of order zero (i.e. I (0)) while log of agricultural productivity of land (LN_LAP), log of fertilizer used per area land (LN_FPL), log of pesticides used per area of land (LN_PPL), log of animal stock per area of land (LN_ASPL) and log of employment of agriculture per area of land (LN_LEPL) are found to have a series of order one (i.e.I(1)).

Table 4. 3: Augmented Dickey-Fuller unit root test

Variable	Level				First Difference				I(d)
	Intercept		Intercept & Trend		Intercept		Intercept & Trend		
	t-value	p-value	t-value	p-value	t-value	p-value	t-value	p-value	
LN_LAP	0.242	.9745	-1.260	.8975	-3.800***	.0029	-3.898**	.0122	I(1)
LN_FPL	-1.558	.5046	-0.783	.9671	-3.874***	.0022	-4.135***	.0056	I(1)
LN_ASPL	-0.920	.7812	-2.121	.5345	-5.410***	.0000	-5.377***	.0000	I(1)
LN_LEPL	-1.619	.4731	-4.279	.9223	-3.883***	.0022	-4.128***	.0057	I(1)
LN_CVT	-6.001***	.0000	-6.282***	.0000	-	-	-	-	I(0)
LN_CVP	-5.355***	.0000	-5.286***	.0001	-	-	-	-	I(0)
LN_PPL	0.081	.9647	-2.117	.5367	-4.391***	.0003	-4.707 ***	.0007	I(1)

Makinnon Critical Values					
		Intercept		Intercept & Trend	Significance
Makinnon Critical Values	1%	-3.750		-4.380	***
	5%	-3.000		-3.600	**
	10%	-2.630		-3.240	*

Sources: The results are calculated by the author using STATA 15.1 software

Since, both tests have indicated there is no series of order two I (2) and all the variables considered in this study has either have a series of order one or order two. This paves the way to use an ARDL model since it requires the dependent and independent variables to be stationary at level of after a first difference.

4.4. Bound test forco-integration

Bound test is one way of checking for the presence of co-integration among the variables considered in the model. The test works when the variables are either integrated of order zero I(0) or integrated of order oneI(1).

F-statistic of the model is used to compare with the critical values of Narayan. The values are shown for both I(0) and I(1) integrated series. Our null hypothesis indicates that there is no cointegration among variables. While the alternative hypothesis indicates there is a cointegration.

Hence, if the F-Statistic is greater than the critical values indicated for I(1) bounds then we can reject our null hypothesis and settle for the presence of cointegration among variables. On the other hand, if the F-statistic is less than the critical values indicated for I(0) bound, then we have no sufficient evidence to reject our Ho and we settle for no cointegration among variables. But if the F-statistic fall between the critical values of I(0) and I(1) then it is inconclusive to decide whether the variables are cointegrated or not.

Table 4. 4: Co-integration Bound test result

Variables	F-Statistics	Co-integration	Lag Optimal
	16.166	Co-integration	1,2,0,1,1,3,3
F(LN_LAP, LN_FPL,	Critical Value	Lower Bound I(0)	Upper Bound I(1)
LN_ASPL, LN_LEPL,	1%	2.12	3.23
LN_CVT, LN_CVP,	5%	2.45	3.61
LN_PPL)	10%	3.15	3.99

Sources: The results are calculated by the author using STATA 15.1 software

From the above table, the F-Statistic falls above the Narayan critical values bounds. It is 16.166 while the critical values of 1% level of significance I(1) bound is 4.43. Hence, at 1% level of significance, we have sufficient evidence to reject the null hypothesis that states there is no cointegration and we can settle for the presence of cointegration and further an error correction model can be triggered in order to find out the long-run relationship factor.

4.5. Long run representation of the ARDLmodel

From the above sections discussion of bound test for cointegration test we have concluded that there is a long run relationship among the variables considered in the model, because we have rejected the null hypothesis that states there is no cointegration between the variables. The regression results long run estimates is shown in the table 5 below.

Table 4. 5: Long run estimation result

Dependent Variable: LN_LAP		
Variables	Coefficients	T-Ratio
LN (Fertilizer used per area of Land)	-0.517497 **	-2.19
LN (Animal Stock per area ofLand)	-1.020198	-0.98
LN (Agricultural Employment per area of Land)	2.448414**	2.48
LN (Coefficient of variation of temperature)	5.402263***	4.68
LN_(Coefficient of variation of Precipitation)	5.691062***	5.40
LN (Pesticides used per area of Land)	1.317655***	7.02

, **, *** imply the coefficients are significant at 10%, 5% and 1% level of significance

Sources: The results are calculated by the author using STATA 15.1 software

From Table 4.6 We can see that the independent variables log of coefficient of variation of temperature (LN_CVT), log of coefficient of variation of precipitation (LN_CVP) and log of pesticide user per area of land (LN_PPL) are statically significant at 1% level significance which implies that the coefficients of the regarding variables are statistically different from zero at 1% error percentage. While log of fertilizer used per area of land (LN_FPL) and log of labor employment in agricultural sector per area of land (LN_LEPL) are statistically significant at 5% level of significance meaning we can reject the null hypothesis that states the coefficients of the respective variables are equal to zero at 5% level of significance.

In the long run, log of labor employment in agriculture per area of land (LN_LEPL), log of coefficient of variation of temperature (LN_CVT), log of coefficient of variation of precipitation (LN_CVP) and log of pesticides used per area of land (LN_PPL) has a positive impact on agricultural productivity of land. While log of fertilizer used per area of land were found to have a negative impact in the long run which can imply that over use of fertilizer can deduct the productivity of the land overtime.

According to the result on table 5, other things being equal, in the long run a percentage increase in a coefficient of variation of temperature will increase agricultural productivity of land by about 5.40%. On the same fashion, a percentage increase in a coefficient of variation of precipitation will increase agricultural productivity of land by 5.69%, citrusparibus.

Table 4. 6: Short run estimation result

Dependent Variable: Δ LN_LAP		
Variables	Coefficients	T-Ratio
Δ LN (Fertilizer used per area of Land)	0.216016 **	2.72
Δ LN (Fertilizer used per area of Land) (-1)	0.099711	1.61
Δ LN (Agricultural Employment per area of Land)	0.983105 ***	4.10
Δ LN (Coefficient of variation of temperature)	-0.838541***	-5.39
Δ LN (Coefficient of variation of Precipitation)	-2.425429 ***	-6.54
Δ LN (Coefficient of variation of Precipitation) (-1)	-2.275673 ***	-7.59
Δ LN (Coefficient of variation of Precipitation) (-2)	-0.906630 ***	-5.12
Δ LN (Pesticides used per area of Land)	-0.485464 ***	7.74
Δ LN (Pesticides used per area of Land) (-1)	-0.368473 ***	-7.66
Δ LN(Pesticides used per area of Land) (-2)	-0.129500 **	2.73
Error Correction Model (-1)	-0.369026 ***	-5.43
Cons.	-28.72656 ***	-6.97
R-Squared	0.9215	
Adj. R-Squared	0.8430	
F-Statistics	16.166	

, **, *** imply the coefficients are significant at 10%, 5% and 1% level of significance

Sources: The results are calculated by the author using STATA 15.1 software

4.6. Short run representation of themodel

Here under, an error correction model has been estimated as shown in table 6, the results reveal that the short term coefficient and their significance level, the error correction term which is also known as the adjustment factor and the overall significance of the model which provides joint significance of the equation with the harmony of above long run results indicated.

From the table, all the independent variables with their lagged values coefficient are found to be statistically significant at 1% or 5% level of error term except for one year lag first difference of fertilizer usage per area of land which is found to be statistically insignificant.

In this analysis, the speed of adjustment entails that about 40% of errors at the past are corrected at the current period and the adjustment will lapse at current period. The result is in line with theoretical expectation of the adjustment factor. Therefore, the model is converging in the long run, and the model will be stable.

In the table, the climate change indicator variables: coefficient of variation of temperature and precipitation including their lagged values has both negative impacts on agricultural productivity of land. While fertilizer used per area of land and agricultural labor employment per area of land including their lagged values has a positive impact on the dependent variable. While pesticides used per area of land have negative impact on productivity of agriculture per area of land.

In the short run, citrus paribus, a percentage increase in coefficient of variation of precipitation in current year and last year will decrease agricultural productivity of land by around 2%. While a percentage increase coefficient of variation of precipitation of the year before last year decreases the current year agricultural productivity around a percent. Similarly, in the short run, citrus paribus, a percentage increase in coefficient of variation of temperature will decrease agricultural productivity of land by around 0.83%.

From the result, since, agricultural productivity is highly and significantly affected negatively by climate change in the short run. Hence, the government should prioritize climate change adaptation programs in order to tackle it. The government should provide efficient and detailed climate or weather forecast depending on the variation of the geographical approaches of the country. Introducing policies to build climate resilient infrastructure and preserving trees and stopping from cutting them will reduce erosion of soil and hence will reduce the short run negative impacts on agricultural productivity.

4.7. Post estimationdiagnostic

The model has also tested for post estimation diagnostics in order to be confident weather the model can be reliable for further interpretation and policy intervention indicator. The results are shown in table 7 below:

Table 4. 7: Post estimation tests

Diagnostic Statistical Checking		
	Test Statistics	Probability
Durbin-Watson Stat	2.271824	NA
Breusch-Godfrey serial correlation LM test	χ 2(3) = 3.848	[.2783]
Breusch-Pagan-Godfrey test for heteroskedasticity	χ 2(1) = 0.23	[.6339]
White's test for heteroskedasticity	χ 2 (34) = 35	[.4204]
Jacque-Bera normality test	χ 2 (2) = .3148	[.8544]
Ramesey RESET specification test	F(3,14) = 0.19	[.9039]
Cumulative sum test for parameter stability (structuralbreak)	χ 2 (2) = 0.3245	[.9479]

Sources: The results are calculated by the author using STATA 15.1 software

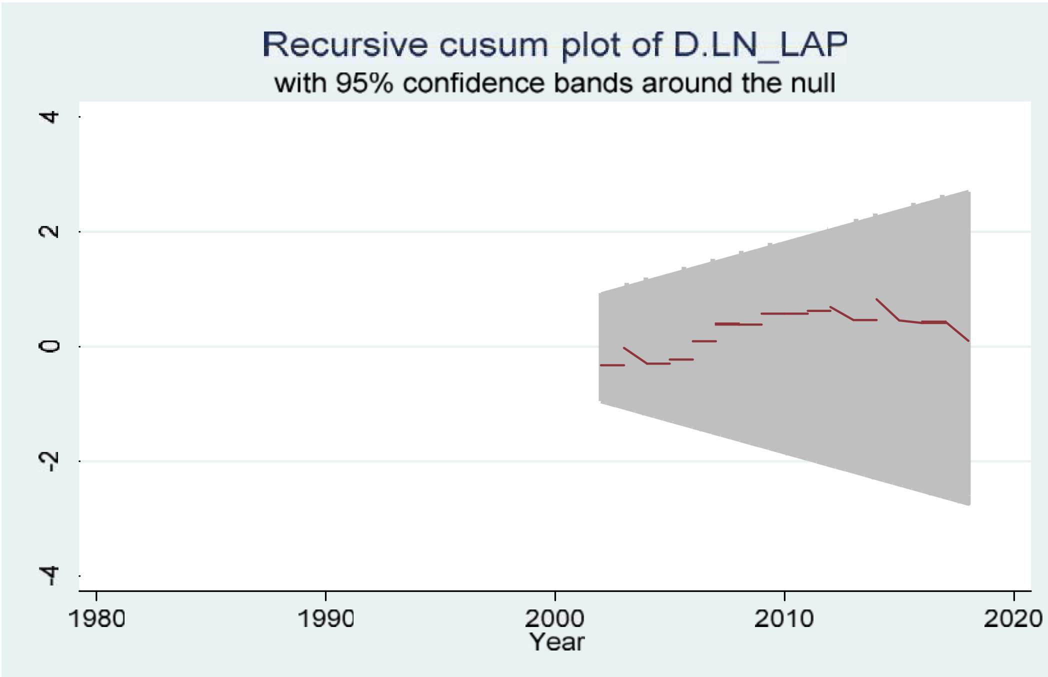
First, the model was checked for the presence of autocorrelation both using durbin-watson d-statistics and breusch-godfrey LM test. Both testes indicated that, there is no evidence even at 1% level of significance to reject our null hypothesis that states there is no serialcorrelation.

Next, to verify for the presence of hetroskedasticity, the researcher has employed White's test and IM test. The result reveals that at 1% level of error, there is no significant evidence to reject the null hypothesis ofhomoskedasticity.

Further, the model has been tested if there was structural breakdown over the course of the study period which is almost 40 Years. The test was conducted using cumulative test for parameter stability test. Once again, the model is found free from structural break down the fitted values graph lie inside the boundary. The p-value also indicates the null hypothesis remains un-rejected at 1% level of significance.

Finally, the researcher has checked the model if there is a significant variable which is omitted employing Ramsey RESET test. Our null hypothesis in this test "Model has no omitted variables" has been preserved since the p-value is found to be nearunity.

Figure 4. 10: Stability test of the model



5. CONCLUSION AND POLICYIMPLICATIONS

Climate change has been a global phenomenon especially after 1900s and its impacts have been seen at different places with a different level of catastrophes. Hence, this paper aims to show the impact of climate change on agricultural productivity using a time series data from 1981-2018 in Ethiopia. The paper has used an ARDL model to measure the impact of climate change on agricultural productivity (i.e. measured as agricultural value added per land) regressed on socio economic and climate variables.

The study used both ADF and PP unit root tests to check for the presence of non stationary variables. Consequently, the unit root tests indicated that the variables are stationary either I (0) or I (1). In addition, the results of ARDL model showed the long run association between agricultural output, temperature, precipitation, consumption of pesticide, agricultural employment and consumption of fertilizer at 1% and 5% level of significance. The coefficients of long run and short run model indicate that agricultural labor employment has positive impact on agricultural productivity. On the other hand temperature, consumption of pesticide and precipitation has positive impact in the long run while negatively affect in the shortrun.

Based on the finding and considering the countries agrarian economy, policies should prioritize on the short run impacts of agricultural productivity. Hence, policies those which allow adaptation of climate change should be implemented. The government should provide detailed awareness on the forecast of the whether at each level of geographical differences throughout the country. The natural resources that help to reduce the impact of climate change like tress should be preserved, atleast no more trees should not be cut since growing them takes time, and infrastructures should be built to combat the short run impacts of climate change.

Finally, the country’s population is growing fast and most of the employment is in agricultural sector which increases the demand for food. Hence, due emphasis should be given through technological advancement, and increase its productivity to meet its demand. If these happen, the country can adapt to the short term changes to climate change and surpass the impact with minimal negativeeffects.

REFERENCE

Abeje, A., & Alemayehu, M. (2019). Impacts of Climate Change on Crop Production and Its Adaptation and Mitigation Strategies in Ethiopia. Journal of Agriculture and Environmental Sciences, 4(2).

Abidoye, B. and A.F. Odusola. (2015). Climate change and economic growth in Africa: an econometric analysis. Journal of African Economics 24(2):277–301

Adams, R. M., Hurd, B. H., Lenhart, S., & Leary, N. (1998). Effects of global climate change on agriculture: an interpretative review. *Climate research*, *11*(1), 19-30.

Ahmed, H., C. Arndt, S. Robinson, D. Willenbockel. (2009). Ethiopia: A Country Study on the Economic Impact of Climate Change. World Bank Report No.46946-ET. World Bank, Washington, DC.

Ali, S. (2012). Climate Change and Economic Growth in a Rain-fed Economy: How Much Does Rainfall Variability Cost Ethiopia? Available at SSRN 2018233. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2018233.

Antle, J.M. and S.M. Capalbo. (2010). Adaptation of Agricultural and Food Systems to Climate Change: An Economic and Policy Perspective, Applied Economic Perspectives and Policy v32, pp386-416.

Ayinde, O. E., Ajewole, O. O., Ogunlade, I., & Adewumi, M. O. (2010). Empirical analysis of agricultural production and climate change: A case study of Nigeria. *Journal of Sustainable Development in Africa*, *12*(6), 275-283.

Barrios S., B. Ouattara, E. Strobl. (2008). The impact of climatic change on agricultural production: Is it different for Africa? Food Policy, 33, 287-298.

Barrios S., L. Bertinelli, E. Strobl. (2010). Trends in rainfall and economic growth in Africa: a neglected cause of the African growth tragedy. Review of Economics and Statistics 92, 350-366.

Bezu, A. (2020). Analyzing Impacts of Climate Variability and Changes in Ethiopia:A Review. *American Journal of Modern Energy*, *6*(3),65-76.

Breisinger, C., Van Rheenen, T., Ringler, C., Pratt, A. N., Minot, N., Aragon, C., ... & Zhu,T. (2010). Food security and economic development in the Middle East and North Africa. *International Food Policy Research Institute*,1-52.

Brown, R. L., J. Durbin, and J. M. Evans. (1975). Techniques for testing the constancy of regression relationships over time. Journal of the Royal Statistical Society, Series B 37: 149–192

Cabré, M. M. (2011). Issue-linkages to Climate Change Measured through NGO Participation in the UNFCCC. *Global environmental politics*, *11*(3), 10-22.

Cameron, A. C., and P. K. Trivedi. 1990. The information matrix test and its applied alternative hypotheses. Working Paper 372, University of California-Davis, Institute of Governmental Affairs.

Chen, I. C., Hill, J. K., Ohlemüller, R., Roy, D. B., & Thomas, C. D. (2011). Rapid range shifts of species associated with high levels of climate warming. *Science*, *333*(6045), 1024-1026.

Cheung, W.H., G.B. Senay and A. Singh. (2008). Trends and Spatial Distribution of Annual and Seasonal Rainfall in Ethiopia. International Journal of Climatology

Cheung, Y.-W. & Lai, K.S., 1995. Lag order and critical values of the augmented Dickey–Fuller test. Journal of Business & Economic Statistics, 13(3), pp.277–280

Deressa T., T. (2007). *Measuring the Economic Impact of Climate Change on Ethiopian Agriculture: Ricardian Approach* . The World Bank, Policy Research Working Paper 4342.

Deressa, T. H. (2008). *Measuring Ethiopian Farmers' Vulnerability to Climate Change Across Regional States* . International Food Policy Research Institute (IFPRI) Discussion Paper 00806.

Deressa, T.T., and R.M. Hassan (2009), 'Economic impact of climate change on cropproduction in Ethiopia: evidence from cross-section measures', Journal of African Economies 18(4): 529–554.

Deressa, T.T., R.M. Hassen, T. Alemu, M. Yesuf, and C. Ringler. 2008. Analyzing the Determinants of Farmers' Choice of Adaptation Methods and Perceptions of Climate Change in the Nile Basin of Ethiopia. IFPRI Discussion Paper 00798. Washington, DC: International Food Policy Research Institute.

Deschênes, O., & Greenstone, M. (2007). The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *American Economic Review*, *97*(1), 354-385.

Dinar, A., Mendelsohn, R., Evenson, R., Parikh, J., Sanghi, A., Kumar, K., ... & Lonergan, S. (1998). *Measuring the impact of climate change on Indian agriculture*. The WorldBank.

Evangelista, P., Young, N., & Burnett, J. (2013). How will climate change spatially affect agriculture production in Ethiopia? Case studies of important cereal crops. *Climatic change*, *119*(3-4), 855-873.

Fazal, S. A., & Wahab, S. A. (2013). Economic impact of climate change on agricultural sector: a review. *Journal of Transformative Entrepreneurship*, *1*(1), 39-49.

Gebreegziabher, Z. A. (2016). *Mapping Vulnerability to Climate Change of the Farming Sector in the Nile Basin of Ethiopia A Micro-level Perspective* . EfD Discussion Paper Series 19-16.

Gebreegziabher, Z., A. Mekonnen, R. Deribe, S. Abera, and M.M. Kassahun. (2012).Crop–livestock inter-linkages and climate change implications for Ethiopia's agriculture:a Ricardian approach. RFF Discussion Paper Series No. EfD 13-14, Resources for the Future(RFF).

Gebreegziabher, Z., Mekonnen, A., Deribe, R., Abera, S., & Kassahun, M. (2014). Climate change can have significant negative impacts on Ethiopia's agriculture. *Research Brief. Addis Ababa, Ethiopia. EDRI, EfD.*

Gillig, D., & McCarl, B. A. (2002). Introduction to Computable General Equilibrium Model (CGE). *Department of Agricultural Economics, Texas A and M University*.

IPCC. (2007). Climate change 2007: Fourth assessment report, Intergovernmental Panelon Climate Change,Geneva.

IPCC. (2013). Climate change 2013: The physical science basis, Intergovernmental Panelon Climate Change,Geneva.

IPCC. (2014). Climate change 2014: Impacts, Adaptations and Vulnerability, Volume I+II, Intergovernmental Panel on Climate Change, Geneva.

Kassie, M., Pender, J., Yesuf, M., Kohlin, G., Bluffstone, R., & Mulugeta, E. (2008). Estimating returns to soil conservation adoption in the northern Ethiopian highlands. *Agricultural economics*, *38*(2), 213-232.

Mabugu, R. (2002). Short-term effects of policy reform on tourism and the macroeconomy in Zimbabwe: Applied CGE analysis. *Development Southern Africa*, *19*(3), 419-430.

Mahato, A. (2014). Climate change and its impact on agriculture. *International Journal of Scientific and Research Publications*, *4*(4), 1-6.

Matouš, P., Todo, Y., & Mojo, D. (2013). Roles of extension and ethno-religious networks in acceptance of resource-conserving agriculture among Ethiopian farmers. *International Journal of Agricultural Sustainability*, *11*(4), 301-316.

Mendelsohn, R. (2009). The Impact of Climate Change on Agriculture in Developing Countries. Journal of Natural Resources Policy Research 1 (1): 5–19.

Mendelsohn, R. O., & Dinar, A. (2009). *Climate change and agriculture: an economic analysis of global impacts, adaptation and distributional effects*. Edward Elgar Publishing.

Mendelsohn, R., W.D. Nordhaus, and D. Shaw. (1994). The Impact of Global Warming on Agriculture: A Ricardian Analysis. The American Economic Review 84(4):753–771.

Molua, E. L. (2006). Climatic trends in Cameroon: implications for agricultural management. *Climate Research*, *30*(3), 255-262.

Nastis, S. A., Papanagiotou, E., & Zamanidis, S. (2012). Productive efficiency of subsidized organic alfalfa farms. *Journal of Agricultural and Resource Economics*, 280-288.

Quasem, M. A. (2011). Conversion of agricultural land to non-agricultural uses in Bangladesh: extent and determinants. *The Bangladesh Development Studies*, 59-85.

Ramsey JB (1969) Tests for specification errors in classical least-squares regression analysis, Journal of the Royal Statistical Society, Series B 31, 350-71

Rao, D. P. (2004). *Agricultural Productivity Growth, Employment, and Poverty in Developing Countries, 1970-2000. Employment Strategy Paper*. Center for Efficiency and Productivity Analysis (CEPA), School of Economics, University of Queensland.

Rosenzweig, C., & Tubiello, F. N. (2007). Adaptation and mitigation strategies in agriculture: an analysis of potential synergies. *Mitigation and adaptation strategies for global change*, *12*(5), 855-873.

Rosenzweig,C.,Tubiello,F.N.,Goldberg,R.,Mills,E.,&Bloomfield,J.(2002).Increasedcrop damage in the US from excess precipitation under climate change. *Global Environmental Change*, *12*(3),197-202.

Sadoulet, E., & De Janvry, A. (1995). *Quantitative development policy analysis* (Vol. 5). Baltimore: Johns Hopkins University Press.

Stern, N. (2006). What is the economics of climate change? World Economics. vol 7, no 2. Economic &Financial Publishing, London, UK, pp 1–10

Stern, N. (2007). The Economics of Climate Change: The Stern Review. Cambridge University Press, Cambridge

Thurlow, J., Zhu, T., & Diao, X. (2009). The impact of climate variability and change on economic growth and poverty in Zambia.

UNDP. (2007). Human Development Report 2007/08: Fighting Climate Change. UNDP: New York

United Nations Framework Convention on Climate Change. (1994). Climate Change. available at http://unfccc.int/essential_background/convention/background/items/1349.php

World Food program. (2016). *Ethiopia World Food Program* . Country brief. October 2016.

World Bank. (2008a). *Ethiopia: A Country Study on the Economic Impacts of Climate Change.* Development Prospects Group, Report Number 46946-ET.

World Bank. (2008a). Strategic Framework on Development and Climate Change. World Bank Environment Department: Washington, DC.

World Bank. (2008b). Making Development Climate Resilient for Sub-Saharan Africa. Sustainable Development Department, Africa Region. Washington, DC.

World Bank. (2010). The Cost to Developing Countries of Adapting to Climate Change: New Methods and Estimates. Washington, DC: World Bank.

WorldBank. (2010).EconomicsofAdaptationtoClimateChangeStudy (EACC). A SynthesisReport. Final Consultation Draft,August2010, WorldBank, WashingtonD.C. worldbank.org/.../EACC_Final Synthesis Report 0803

Zenebe, G., S. Jesper, M. Alemu,& A. Atlaw. (2011). Climate Change and the Ethiopian Economy a CGE Analysis. www.rff.org/files/sharepoint/WorkImages/Download/EfD-DP-11-09

APPENDICES

Appendix 1: Results of Lag selection

Selection-order criteria
Sample: 1985-2018 Number ofobs = 34

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-37.46				.56242	2.26235	2.27766	2.30725
1	12.2665	99.453*	1	0.000	.032012*	-.603913*	-.573294*	-.514127*
2	12.4796	.4262	1	0.514	.033539	-.557625	-.511695	-.422946
3	12.6642	.36923	1	0.543	.035209	-.509661	-.448422	-.330089
4	12.6862	.044	1	0.834	.037334	-.452132	-.375583	-.227667

Endogenous: LN_LAP
Exogenous: _cons

Selection-order criteria
Sample: 1985-2018 Number ofobs = 34

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-65.7336				2.96729	3.92551	3.94082	3.9704
1	-11.5973	108.27*	1	0.000	.130302*	.79984*	.830459*	.889626*
2	-10.6201	1.9544	1	0.162	.130519	.801182	.847111	.935861
3	-10.4985	.24313	1	0.622	.137528	.852854	.914093	1.03243
4	-9.88288	1.2313	1	0.267	.140821	.875464	.952013	1.09993

Endogenous: LN_FPL
Exogenous: _cons

Selection-order criteria
Sample: 1985-2018 Number ofobs = 34

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-15.2309				.152118	.954761	.970071	.999654
1	38.5809	107.62*	1	0.000	.006809*	-2.15182*	-2.1212*	-2.06203*
2	38.6259	.09017	1	0.764	.007204	-2.09564	-2.04971	-1.96096
3	39.9384	2.6249	1	0.105	.007078	-2.11402	-2.05278	-1.93445
4	39.9584	.04007	1	0.841	.007506	-2.05638	-1.97983	-1.83191

Endogenous: LN_ASPL
Exogenous: _cons

Selection-order criteria
Sample: 1985-2018 Number ofobs = 34

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-23.0603				.241098	1.41531	1.43062	1.4602
1	30.186	106.49*	1	0.000	.011156*	-1.658*	-1.62738*	-1.56821*
2	30.1868	.00174	1	0.967	.011836	-1.59923	-1.5533	-1.46455
3	30.1872	.00078	1	0.978	.01256	-1.54043	-1.47919	-1.36085
4	30.1885	.00251	1	0.960	.013334	-1.48168	-1.40513	-1.25721

Endogenous: LN_LEPL
Exogenous: _cons

Selection-order criteria
Sample: 1985-2018 Number ofobs = 34

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	22.0217				.017002*	-1.23657*	-1.22126*	-1.19168*
1	22.1006	.15788	1	0.691	.017951	-1.18239	-1.15177	-1.0926
2	22.1603	.1193	1	0.730	.018978	-1.12707	-1.08114	-.992395
3	24.2101	4.0997*	1	0.043	.017852	-1.18883	-1.12759	-1.00926
4	25.4822	2.5441	1	0.111	.017588	-1.20483	-1.12828	-.980369

Endogenous: LN_CVT
Exogenous: _cons

Selection-order criteria
Sample: 1985-2018 Number ofobs = 34

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	31.8404				.009542*	-1.81414*	-1.79883*	-1.76925*
1	32.6072	1.5335	1	0.216	.009675	-1.80042	-1.7698	-1.71063
2	32.7731	.33186	1	0.565	.010165	-1.75136	-1.70543	-1.61668
3	32.9763	.40637	1	0.524	.01066	-1.70449	-1.64325	-1.52491
4	32.9908	.02913	1	0.864	.011308	-1.64652	-1.56997	-1.42206

Endogenous: LN_CVP
Exogenous: _cons

Selection-order criteria
Sample: 1985-2018 Number ofobs = 34

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-50.7243				1.22722	3.04261	3.05792	3.0875
1	-24.8203	51.808	1	0.000	.283632	1.57766	1.60828	1.66745
2	-24.8108	.01897	1	0.890	.300747	1.63593	1.68186	1.77061
3	-19.9958	9.63*	1	0.002	.240445*	1.41152*	1.47276*	1.59109*
4	-19.8095	.37258	1	0.542	.252499	1.45938	1.53593	1.68385

Endogenous: LN_PPL
Exogenous: _cons

Selection-order criteria
Sample: 1985-2018 Number ofobs = 34

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	46.3815				2.3e-10	-2.31656	-2.20939	-2.00231
1	196.352	299.94	49	0.000	6.5e-13	-8.25599	-7.39864	-5.74198*
2	271.371	150.04	49	0.000	2.1e-13	-9.78652	-8.17899	-5.07276
3	351.823	160.91*	49	0.000	1.2e-13	-11.6367*	-9.27897*	-4.72316
4	.	.	49	.	-9.4e-45*	.	.	.

Endogenous: LN_LAP LN_FPL LN_ASPL LN_LEPL LN_CVT LN_CVPLN_PPL
Exogenous: _cons

Appendix 2: Results of Unit root tests

```
. dfuller LN_LAP, lags(1) //non stationary
```

Augmented Dickey-Fuller test forunitroot Numberof obs = 36

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	0.242	-3.675	-2.969	-2.617

MacKinnon approximate p-value for Z(t) = 0.9745

```
. dfuller LN_FPL, lags(1) //stationary

Augmented Dickey-Fuller test forunitroot           Numberof obs    =        36

                               ----------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -1.558            -3.675            -2.969            -2.617
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.5046

Augmented Dickey-Fuller test forunitroot           Numberof obs    =        36

                               ----------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -0.920            -3.675            -2.969            -2.617
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.7812


. dfuller LN_LEPL, lags(1) //non stationary

Augmented Dickey-Fuller test forunitroot           Numberof obs    =        36

                               ----------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -1.619            -3.675            -2.969            -2.617
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.4731
```

```
. dfuller LN_CVT, lags(0) //non stationary

Dickey-Fuller test forunitroot                      Numberof obs    =        37

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value            Value
------------------------------------------------------------------------------
 Z(t)             -6.001            -3.668            -2.966            -2.616
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000


. dfuller LN_CVP, lags(0) //non stationary

Dickey-Fuller test forunitroot                      Numberof obs    =        37

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value            Value
------------------------------------------------------------------------------
 Z(t)             -5.355            -3.668            -2.966            -2.616
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000


. dfuller LN_PPL, lags(3)

 Augmented Dickey-Fuller test for unit root         Number of obs   =        34

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value            Value
------------------------------------------------------------------------------
 Z(t)              0.081            -3.689            -2.975            -2.619
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.9647
```

```
. dfuller d.LN_LAP, lags(1) //non stationary

Augmented Dickey-Fuller test forunitroot          Numberof obs    =        35

                               ---------- Interpolated Dickey-Fuller ----------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -3.800            -3.682            -2.972            -2.618
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0029
```

```
. dfuller d.LN_FPL, lags(1) //stationary

Augmented Dickey-Fuller test forunitroot          Numberof obs    =        35

                               ---------- Interpolated Dickey-Fuller ----------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -3.874            -3.682            -2.972            -2.618
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0022
```

```
. dfuller d.LN_ASPL, lags(1) //stationary

Augmented Dickey-Fuller test for unit root         Number of obs   =        35

                               ---------- Interpolated Dickey-Fuller ----------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -5.410            -3.682            -2.972            -2.618
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000
```

```
. dfuller d.LN_LEPL, lags(1) //non stationary

Augmented Dickey-Fuller test for unit root         Number of obs   =        35

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -3.883            -3.682            -2.972            -2.618
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0022


. dfuller d.LN_CVT, lags(0) //non stationary

Dickey-Fuller test forunitroot                     Numberof obs    =        36

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)            -10.471            -3.675            -2.969            -2.617
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000


. dfuller d.LN_CVP, lags(0) //non stationary

Dickey-Fuller test forunitroot                     Numberof obs    =        36

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -8.921            -3.675            -2.969            -2.617
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000
```

```
. dfuller d.LN_PPL, lags(3)

Augmented Dickey-Fuller test for unit root         Number of obs   =        33

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -4.391            -3.696            -2.978            -2.620
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0003
```

Appendix 3: Result of ARDL Bounds Test of Cointegration

```
Pesaran/Shin/Smith (2001) ARDL Bounds Test
H0: nolevelsrelationship              F=   16.166
                                      t =-5.428

Critical Values (0.1-0.01), F-statistic, Case 3

      | [I_0]   [I_1] | [I_0]   [I_1] | [I_0]   [I_1] | [I_0]   [I_1]
      |    L_1     L_1|    L_05    L_05|   L_025   L_025|    L_01    L_01
------+---------------+---------------+---------------+---------------
  k_6 |   2.12    3.23|   2.45    3.61|   2.75    3.99|   3.15    4.43
accept if F < critical value for I(0) regressors
reject if F > critical value for I(1) regressors

Critical Values (0.1-0.01), t-statistic, Case 3

      | [I_0]   [I_1] | [I_0]   [I_1] | [I_0]   [I_1] | [I_0]   [I_1]
      |    L_1     L_1|    L_05    L_05|   L_025   L_025|    L_01    L_01
------+---------------+---------------+---------------+---------------
  k_6 |  -2.57   -4.04|  -2.86   -4.38|  -3.13   -4.66|  -3.43   -4.99
accept if t > critical value for I(0) regressors
reject if t < critical value for I(1) regressors

k: # of non-deterministic regressors in long-run relationship
Critical values from Pesaran/Shin/Smith (2001)
```

Appendix 4: ARDL ECM regression result

ARDL(1,2,0,1,1,3,3) regression

Sample:	1984 - 2018	Number of obs =	35
		R-squared =	0.9215
		Adj R-squared =	0.8430
Loglikelihood=	56.620458	Root MSE =	0.0689

D.LN_LAP	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ADJ						
LN_LAP						
L1.	-.3690258	.0679914	-5.43	0.000	-.5124752	-.2255765
LR						
LN_FPL	-.5174972	.236183	-2.19	0.043	-1.0158	-.0191946
LN_ASPL	-1.020198	1.037965	-0.98	0.339	-3.210112	1.169716
LN_LEPL	2.448414	.9855563	2.48	0.024	.369072	4.527756
LN_CVT	5.402263	1.154255	4.68	0.000	2.966999	7.837528
LN_CVP	5.691062	1.053884	5.40	0.000	3.46756	7.914564
LN_PPL	1.317655	.1876846	7.02	0.000	.9216751	1.713635
SR						
LN_FPL						
D1.	.2160157	.079286	2.72	0.014	.0487369	.3832945
LD.	.0997108	.0620902	1.61	0.127	-.0312881	.2307096
LN_LEPL						
D1.	.9831054	.2397998	4.10	0.001	.4771721	1.489039
LN_CVT						
D1.	-.8385413	.1556958	-5.39	0.000	-1.167031	-.5100519
LN_CVP						
D1.	-2.425429	.370708	-6.54	0.000	-3.207555	-1.643304
LD.	-2.275673	.2998901	-7.59	0.000	-2.908386	-1.64296
L2D.	-.9066299	.1772072	-5.12	0.000	-1.280504	-.5327554
LN_PPL						
D1.	-.4685643	.0605205	-7.74	0.000	-.5962513	-.3408773
LD.	-.3684762	.0480828	-7.66	0.000	-.469922	-.2670304
L2D.	-.1295499	.047485	-2.73	0.014	-.2297344	-.0293653
_cons	-28.72656	4.122494	-6.97	0.000	-37.42426	-20.02886

Appendix 5: Post estimation diagnostics

```
.estatdwatson    //(Durbin Watson statistics, at 1st orderautocorrelation).

Durbin-Watsond-statistic(18,      35)=   2.271824

. estat bgodfrey, lags(3) //(Breusch Godfrey LM test for higher order autocorrelation)

Breusch-Godfrey LM test for autocorrelation
```

lags(*p*)	chi2	df	Prob > chi2
3	3.848	3	0.2783

```
                        H0: no serial correlation

. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of D.LN_LAP

         chi2(1)      =     0.23
         Prob > chi2  =   0.6339

. estat imtest, white

White's test for Ho: homoskedasticity
         against Ha: unrestricted heteroskedasticity

         chi2(34)     =    35.00
         Prob>chi2    =   0.4204

Cameron & Trivedi's decomposition of IM-test
```

Source	chi2	df	p
Heteroskedasticity	35.00	34	0.4204
Skewness	9.99	17	0.9041
Kurtosis	0.27	1	0.6008
Total	45.26	52	0.7342

```
. estat sbcusum

Cumulative sum test for parameter stability

Sample:       1984-       2018                    Number ofobs=          35
Ho: No structural break
```

Statistic	TestStatistic	1%Critical Value	5%Critical Value	10% Critical Value
recursive	0.3245	1.1430	0.9479	0.850

```
. estat ovtest

Ramsey RESET test using powers of the fitted values ofD.LN_LAP
       Ho:  model has no omittedvariables
                  F(3, 14) =      0.19
                  Prob >F =       0.9039



. jb resid
Jarque-Beranormalitytest:    .3148Chi(2)   .8544
Jarque-Bera test for Ho: normality:
```

DECLARATION

I, the undersigned, declare that this thesis is my original work and it has never been presented for a degree or masters in any other university, and that all source of materials used for the thesis have been duly acknowledged.

The examiners' comments have been duly incorporated.

Declared by:

Name: SAMSON HAILE DEMISSE

Signature: ________________

Date: ____________________