IMPACT OF CLIMATE CHANGE ON YIELDS AND OUTPUT SUPPLY RESPONSES OF SELECTED CEREAL CROPS IN ETHIOPIA

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DEDICATION

This study is dedicated to my late mother Dinke Warri, who consistently encouraged and supported me to develop my knowledge and professional career.

DECLARATION

I, **ABERA GAYESA TIRFI**, declare that this thesis ‘‘*Impact of climate change on yields and output supply responses of selectedcereal crops in Ethiopia*’’, which I hereby submit for the degree of **Doctor of Philosophy in Agriculture** at the University of South Africa, is my own work and has not been previously submitted by me for a degree at this or any other institution.

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MARCH 10, 2022 Revised Submission

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(Mr.) ABERA GAYESA TIRFI

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ABERA GAYESA TIRFI,
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ABSTRACT

Climate change affects agricultural production and productivity in sub-Saharan Africa, including Ethiopia, where it poses some threats to sustainable economic growth and agricultural development. As studies conducted on the impact of climate change on crop production are limited, this study analyzed the impacts of the changes in climate on yields and output supply responses of teff, wheat and maize crops in Ethiopia.

The study employed time series secondary data on selected variables over the period of 1981 to 2018. The data were collected from various reputable sources such as the Ethiopian CSA, NMA, and FAO data set (FAOSTAT). The study adopted Cobb-Douglas Production Function and Autoregressive Distributed Lag (ARDL) modeling approaches. The impacts of climate change on crop yields and output was estimated using key climate parameters (minimum and maximum temperature and short- and long- season rainfalls).

The results of Production Function analysis on the impact of climate variables on yield of cereal crops revealed that *long-season rainfall* have negative (-0.352, -0.498, and -0.429) and significant (at 1% and 5% levels) impact on yields of teff, wheat and maize crops, respectively. Maximum temperature also had negative (-2.810 & -3.681) and significant (at 10% level) impact on the yields of wheat and maize crops while it had positive (0.372) and significant (at 10% level) impact on teff yield.

Equally, the impact of climatic variables on crop output supply responses was estimated based on crop season temperature and short- and long-season rainfalls. The results indicated that changes in *short*- and *long-season rainfalls* had negative (-0.453 and -0.077) and significant (at 1% level) impact on wheat and maize outputs in their first lag order. The results also demonstrated that crop growing period mean temperature had negative (-2.88 and -10.70) and significant (at 1% and 5% levels) impacts on wheat and maize outputs in their first lag orders. Although temperature and long-season rainfall parameters showed negative impact on teff output, their impacts were minimal as they were statistically insignificant. Conversely, carbon dioxide (CO_2) showed positive (4.76 and 2.256) and significant (at 5% and 1% level) impact on teff and wheat outputs in their first lag orders. This signified that teff and wheat outputs were positively responsive to an increase in CO_2 concentration.

Forecasted future changes in temperature and rainfall variables showed increasing trend in mean temperature (rise from -4.85^{0}C to 0.195^{0}C by 2080) in teff growing belt while future changes in rainfall (both short- and long-season rainfalls) showed a decreasing trend in teff (from -0.06mm to -1.58mm), wheat (from -0.11mm to -1.3mm), and maize (from -0.01mm to -0.17mm) growing belts by 2080. However, the projected future changes in the yields of wheat, maize and teff are positive over the selected scenarios. By

2080, yield of wheat would increase by 237% while those teff and maize would increase by48% and 10% respectively.

In conclusion, rainfall and temperature parameters were found to increase yield level and variability for wheat crop. However, rainfall and temperature parameters were individually found to have adverse effects on yield of teff and maize crops. Unless some abatement measures are taken on increasing CO_2 emission, the rise in temperature and the decrease in seasonal rainfall will continue and this will negatively affect cereal crop yields. It is therefore recommended that there is the need to design and implement adaptation strategies that reverse and mitigate the risks of changing climate. Development of early maturing and stress tolerant crop varieties as well as supporting research and extension tasks becomes imperative.

Keywords: Climate Change, Cereal Crops, Yield and Output Supply Response, Ethiopia

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ABBREVIATIONS

AEZ	Agro-ecological zones
AGDP	Agricultural Gross Domestic Product
AIC	Akaike Information Criteria
AGW	Anthropogenic Global Warming
AMO	North Atlantic Multidecadal Oscillation
AMS	American Meteorological Society
AR5	Fifth Assessment Report
ARCH	Autoregressive Conditional Heteroskedasticity
ARDL	Autoregressive Distributed Lag
ATHC	Atlantic Thermohaline Circulation
ADF	Augmented Dickey Fuller
CCD	Convention to Combat Desertification
CBD	UN Convention on Biological Diversity
CDM	Clean Development mechanisms
CGIAR	Consultative Group for International Agricultural Research
CH4	Methane
CO_2	Carbon Dioxide
CO_3	Carbonate

CGSRF	Crop Growing Season Rainfall
CRGE	Climate Resilient Green Economy
CRV	Central Rift Valley
CSA	Central Statistical Authority
CV	Coefficient of Variation
DSSAT	Decision Support System for Agro-Technology
ECLAC	Economic Commission for Latin America and the Caribbean
ECM	Error Correction Model
EEA	European Environment Agency
EGTE	Ethiopian Grain Trade Enterprise
EPACC	Ethiopian Program of Adaptation to Climate Change
ENSO	El Niño Southern Oscillation
ESSP	Ethiopian Strategy Support Program
FAO	Food and Agriculture Organization of the United Nations
FGLS	Feasible Generalized Least Square
FMAM	February, March, April and May
F-M	February to May
F-S	February to September
GDD	Growing Degree Days
GDP	Gross Domestic Product
GHG	Green House Gas
GoE	Government of Ethiopia

GTP	Growth and Transformation Plan
Ha	Hectare
HAC	Heteroskedasticity and Autocorrelation
HQIC	Hannan-Quinn Information Criterion
IFRCRCS	International Federation of Red Cross and Red Crescent Societies
IPCC	Intergovernmental Panel on Climate Change
ITCZ	Inter Tropical Convergence Zone
IV	Instrumental Variables
JJAS	June, July, August and September
LM	Breush-Godfrey Lagrange Multiplier
MC	Marginal Cost
MJO	Madden-Julian Oscillation
MOC	Meridional Overturning Circulation
MoFEC	Ministry of Finance and Economic Cooperation
MPP	Marginal Physical Product
MR	Marginal Revenue
MU	Marginal Utility
NAMAs	Nationally Appropriate Mitigation Actions
NAO	North Atlantic Oscillation
NAP	National Action Plan
NAPA	National Adaptation Program for Action

NASc	National Academy of Science
NBE	National Bank of Ethiopia
NBSAP	National Biodiversity Strategy and Action Plan
NMA	National Meteorology Agency
NMSA	National Meteorological Service Agency
N_2O	Nitrous Oxide
NOAA	National Oceanic and Atmospheric Administration
OECD	Organization of Economic Cooperation and Development
OLS	Ordinary Least Square
OLR	Ordinary Linear Regression
PDC	Planning and Development Commission
PDO	Pacific Decadal Oscillation
PP	Phillip Pherron
RSCZ	Red Sea Convergence Zone
SNNP	Sothern Nations, Nationalities and Peoples Region
SAS	Surrounding Antarctica Subsidence
SPSS	Statistical Package for Service Solution
SSA	Sub-Saharan African
SST	Sea-Surface Temperature
STJ	Sub Tropical Jet
TC	Total Cost
TEJ	Tropical Easterly Jet

THC	Thermohaline Circulation
TR	Total Revenue
UNCBD	UN Convention on Biological Diversity
UNFCCC	United Nations Framework Convention on Climate Change
UNISA	University of South Africa
USA	United States of America
USAID	United States Agency for Development
VAR	Vector Auto Regression
VEC	Vector Error Correction
WB	The World Bank
WMO	World Meteorology Organization
WOFOST	World Food Studies

CHAPTER I

INTRODUCTION

1.1. Background to the study

Climate change is considered as one of the major environmental challenges of the 21st century that adversely affects the performance of the agricultural sector. Consecutive accounts of the Intergovernmental Panel on Climate Change (IPCC, 2007) evince that changes in climate variables would exert many-sided impacts on humankind. Equally, scientific evidence depicts that anthropogenic variables are mainly responsible for the predominant global changes in climate (Forster, *et al*., 2007).

Review of previous studies evidences that the last three decades have been consecutively warmer on the surface of the earth than any preceding decades since 1850 (WMO, 2020; NASc & Royal Society, 2020; IPCC, 2014). The World Meteorolgy Organization (WMO, 2020) reported that each successive decade has been warmer than any preceding decade since 1850 and 2010-2019 the warmest decade on record. The report further indicated that 2019 was ended with a global average temperature of 1.1°C above estimated pre-industrial levels, second only to the record set in 2016 when a very strong El Niño event contributed to an increased global mean temperature. The National Academy of Science and Royal Society (2020) explored that 1989 to 2019 was very likely the warmest 30-year period in more than 800 years; the most recent decade, 2010-2019, is the warmest decade in the instrumental record so far (since 1850).

Equally, the 2013 Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC, 2014) stated that “each of the last three decades has been successively warmer at the Earth’s surface than any preceding decade since 1850”. Data also shows that, globally, the last decade has been the warmest ever recorded. In fact, the globally averaged combined land and ocean surface temperature data as has been calculated by a linear trend influences authenticate a warming of 0.85°C for the period of 1880 to 2012 (IPCC, 2014). Besides, in many of the continents and regions of the world, consecutive global warming has resulted in melting of snow and ice that has led to changing precipitation and modification in the hydrological systems and impacted water resources, both in quantitative and qualitative terms.

Likewise, in recent times, changes in weather factors such as precipitation, temperature and CO_2 have caused great and most often irretrievable global influences on ecological and human beings. Basically, the effects are consequences of changes in the climate factors, regardless of its root cause, demonstrating the sensitivity of ecological and human being systems to changing climate. Assessments of various investigations encompassing a broad variety of district and crop varieties have proven that the depressing effects of changes in climate factors on yields of crops surpass the positive impacts (IPCC, 2014).

The National Geographic Society (2019) defines climate change as the long-term modification of temperature and typically weather patterns over an area. However, the definition postulated by IPCC (Rahman, 2013) adds that changes in climate factors include changes due to natural variability (increased incidence of climatic excessive events; the changed rainfall and transformative regimes; higher temperatures; elevated CO_2 concentration), alongside human activity (burning of fossil fuels; deforestation; overgrazing; improper crop field farming practices, and destruction of ecosystem).

That climate change poses significant risk to the agriculture and food supply in the 21st century cannot be disputed as authenticated by various researches, neither can it be refuted that African countries are more vulnerable to its impacts. The vulnerability can be attributed to the additional and inevitable temperature increases. The unabated increases are as a result of uncontrollable and natural warming of climatic factors, which subsequently affects their marginal water balance and in turn harms their agricultural sector. Following these facts, Chauvin *et al.* (2012) avows that African countries experience soaring levels of poverty, coupled with low levels of human and physical capital as well as meager expansion of infrastructure that made low capacity to abate their consequences. This is particularly noted in many Sub-Saharan African (SSA) nations which have low adaptive capacity (Shah *et al*., 2008). The implication is that suitable land areas for agriculture are bound to be negatively influenced by climatic change, in addition to the yield potentials of most high profile crops grown in semi-arid, arid and coastal areas (IPCC, 2014).

It is evident that smallholder farmers in developing countries have low capacity to take adaptation measure to tackle\ climatic and economic shocks. This stance corroborates Cairns *et al.*'s (2013) findings, that in as much as these farmers are obliged to continue in the farming business, then they cannot avoid the challenges that tailgate climate changes. They assessed smallholder farmers' adaptation capacity to climate change in SSA including Eastern Africa who dominantly produces cereal crops, particularly maize, sorghum and wheat crops under rain-fed conditions with low inputs that led to low crop yields. Their findings indicate that current and future climate change will severely test farmers' resourcefulness and adaptation capacity. Their findings further underscore the relevance of examining the response of selected cereal crops yield and output supply to changes in climate in Ethiopia. Available evidences also indicate that climate change undoubtedly poses negative effects on Africa's agriculture. It is not only impacting the health of land negatively, but also the marine-based ecosystems, including the health and food security of many of the region's most vulnerable people (IPCC, 2014).

Ethiopia, as one of the SSA countries is seriously affected by climate change which threatens sustainable economic growth and agricultural sector development. According to Deressa (2010), the Ethiopian agricultural sector is negatively influenced by climate-related calamity, while drought, landslide and flood constitute the major ones. These are regular phenomena and have mostly been caused by La Niña and El Niño, which brought direct impact on agriculture crop productivity and food availability. Following these observations, it is patent that extreme temperatures, low or extreme rainfall, and even rain variability will generally have adverse effect on crop yields and food security and accessibility in Ethiopia. Consequently, it can be rightly affirmed that the instability in the amount and irregular distribution of precipitation is among the major factors that determine fluctuation in yield of crops (Bewket, 2009). This fact is evidenced in the La Niña phenomenon in 2011 and El Niño induced droughts during 2015, for both impacted 4.5 million and 10.2 million people in the proceeded years, respectively in various regions of Ethiopia. As a matter of fact, the drought in 2015 has been described as one of the worst in several decades because it led to high food shortage as well as loss of lives of livestock in several parts of the country (IFRCRCS, 2016).

Given this, crop yields in Ethiopian agriculture could be reduced considerably due to changes in climate, eventuating into extreme consequences upon food production and availability. However, studies evidencing these situations in the country, particularly on aggregated national level are limited (Solomon, *et al*., 2021; Bayecha, 2013; and Yumbya *et al.*, 2011). Solomon, et al. (2021) studied the impacts of climate change in Ethiopia in general or its economy-wide impact in particular. However, their study was limited to impact of climate change at micro level as well as specific agro-ecologies which may generate insufficient insight into the impact of climate change. Bayecha, (2013) on his part studied the likely impacts climate variables change marginally on teff crop in Lume and Gimbich Districts. The study was, however, limited to the two districts and tried to assess farm level economic impacts on teff crop. Equally, the study by Yumbya *et al.* (2011) assessed the impact of climate change on teff production for three teff potential districts of Ethiopia in terms of expected future loss in current suitable area for teff through future projections. However, the study was limited in in-depth analysis of the economic impacts of climate change on teff production.

Following the above justification, an in-depth research on the impact of changes in climate on yield of crops becomes important so as to explore the possibility of managing its consequential impact on the country. Aside the aftermaths of climate variability, non-climatic factors such as limited use of chemical fertilizers, inadequate availability and accessibility of improved crop seeds, inadequate access to irrigation facilities, to mention among others, also contribute to low level of crop yield in Ethiopia. Therefore, conducting researches on how changes in climate influence agricultural business and how agriculture responds to a change in climate as well as non-climatic factors becomes important because agriculture invariably influences the food supply and poverty reduction efforts of agrarian economies.

1.2. Problem Statement

Evidences indicate that climate change (climate extremes and fluctuations) substancially affected agriculture and food security in the 21st century. Previous studies showed that climate change has altered the frequency, intensity, spatial extent and duration of climate extreme events in many regions, especially in Sub-Saharan Africa (Shah *et al*., 2008; IPCC, 2014), where adaptation capacity is low. High vulnerability of seasonal rainfall over East Africa including Ethiopia has made it less predictable (Deresa, 2010 and Nicholson, 2014) as since majority of the population in these countries depend on subsistence rain-fed agriculture. The studies indicate that an increasing temperature and a decrease in rainfall would significantly reduce income obtainable from agriculture affecting food security. IPCC reports indicate that food production, including access to food, in many African countries is projected to be severely compromised by climate variability and change, since suitable land areas for agriculture would be negatively affected by climatic change along with the yield potentials of many high profile crops that are being grown in semi-arid, arid and coastal areas of the continent (IPCC, 2014).

Evidences indicate that average annual minimum temperature has increased by about 0.25^{0}C every ten years while average annual maximum temperature has increased by about 0.1^{0}C in Ethiopia (Lemma et al. 2013). Moreover, the National Meteorological Agency (NMA, 2007) further showed that there was high variability of rainfall over the past 50 years, increasing its frequency and spatial coverage over the past few decades. These trends of increasing temperature, decreasing rainfall and increasing frequency of droughts and floods are predicted to continue in the future in the tropics of Africa, where Ethiopia is also located (Deresa. 2010). Previous studies on the impact of climate change on crop production and productivity in Ethiopia revealed higher temperatures, declining rainfall pattern, and an increasing frequency of extreme climate events (such as droughts, floods, etc). Deressa (2007) in his study on the impact of climate change on agriculture reported that the Ethiopian agricultural sector is negatively affected by climate-related disasters with drought and flood being the major ones. These are frequent phenomena and have mostly been caused by La Niña and El Niño, which brought direct impact on crop productivity and food availability. Extreme temperatures, low or extreme rainfall and even rain variability have adversely affected crop yields, food security and accessibility in Ethiopia. The La Niña phenomenon over 2011 and El Niño induced droughts during 2015 impacted 4.5 million and 10.2 million people in the proceeded years, respectively in various regions of Ethiopia. The 2015 drought described as one of the worst in decades resulted in high food insecurity and death of livestock in several parts of the country (International Federation of Red Cross and Red Crescent Societies, 2016).

The agriculture sector in the country is dominated by small-scale mixed crop-livestock production with very low productivity drived by climate factors (such as droughts and floods) coupled with technical and socio-economic factors. These factors reduce the adaptive capacity or increase the vulnerability of smallholder farmers to future changes in climate and negatively affect the performance of the already weak agricultural production system. The effects of these factors would exert on crop production and productivity needs to be studied, quantified and analyzed in-depth to provide information necessary to design future adaptation strategies, which is the theme of this study.

Previous studies on the association among variability in climatic parameters and agricultural productivity at national levelin Ethiopia are scarce (Deressa, 2007; Mideksa, 2010). In this context, available studies are limited to some regions and local areas, while aggregated research at the national level on the impacts of climate change remains limited. For instance, Kassie (2014) measured the influences of changes in weather factors on crop production and productivity in the Central Rift and Kobo Valleys of Ethiopia, while Bocher (2016) analysed the influence of variations in rainfall on the yield of crops using crop yield model in Southern Ethiopia. Tesso, *et al (*2012) investigated the influences of changes in weather factors on crop production and productivity in the North Shewa Zone of Ethiopia. Bewket (2009) also carried out an assessment on variability in precipitation both on annual and seasonal bases. The study examined magnitude of the association prevailing among rainfall variable and crop production in Amhara region. Equally, Skambraks (2014) focused on how farmers in Zenzelima area of Amhara region are responding to changes in climate as well as their ability to adapt to future changes in climate. In contrast, Weldegerima *et al.* (2018) analysed the spatio-temporal trends in precipitation in the Basin of Lake Tana as well as their relationship to the global changes in sea-surface temperature (SST). Thus, it is apparent that none of these researches have examined the impact of climate change on cereal crops in Ethiopia at a national level.

Furthermore, Benti and Abera (2019) analyzed a time series trend of seasonal and annual weather variables (temperature and rainfall), in addition to examining the association among the two prominent climatic factors and commutative global CO_2 emission in Shaka zone (Masha area) of Southern Ethiopia. Wagesho (2016) also explored the annual and seasonal rainfall variability and farmers' perception towards such variability over the past twenty years in five contiguous areas of Hadiya, Halaba, Kembata-Tembaro, Silte, and Gurage zones in Southern Ethiopia between 1983 and 2012. Matewos (2019) assessed rural farmers' exposure to climate-induced impacts in selected Districts of Sidama, Southern Ethiopia. Again, it is evident that their focuses were not as expansive as the present study, which focuses on the country as a whole – Ethiopia.

Yibrah, Korecha, and Dandesa (2018) examined past weather variability (precipitation and temperature) as well as their impacts on cereal crops (such as wheat and barley) production in Enderta district of Tigray. They utilized daily and decadal weather variables (precipitation and temperature) data covering the period of 1984-2014. Still, their examination is limited to Tigray region of Ethiopia.

Tembo (2018) and Bayecha (2013) studied the influences of changes in weather variables on teff (*Eragrostis tef*) crop production in Endamehoni and *Raya Azebo* weredas of Tigray and Lume and Gimbichu districts of central Ethiopia, respectively. Araya *et al*. (2015) on the other hand assessed the impact of climate change on maize yield under high and moderate RCP scenarios for south-western Ethiopia. Fufa and Hassan (2003) equally investigated the effects of agricultural and weather inputs on the mean levels of yield of maize crop in Dadar woreda of Eastern Ethiopia. Abera *et al*. (2018) conducted an assessment on the manner weather variables such as temperature and precipitation are likely to change as well as affect the production of maize in Bako, Melkassa and Hawassa areas of Ethiopia.

Thus, it is apparent from the preceding assessments of literatures that most of the studies have been conducted at regional, zonal and even at local areas. Besides that, majority of these studies rely solely on climatic data from few meteorological stations, which make them spatially relevant (Alemu and Bawoke, 2019). There exist limited studies at the national and regional levels that examined the impact of changes in climate on the production of crops using different crop yield models, including predictions (Admasu *et al*., 2013; Thomas, Dorosh and Robertson, 2019; Gebreegziabher *et al*., 2011; Yalew *et al*., 2018; and Deressa and Hassan, 2009). Admasu *et al*. (2013) in their study used crop models such as ‘‘decision support system for agrotechnology transfer (DSSAT)’’, MIROC, and CSIRO to determine the direct effect of climate change on crop yield and project climate effects on key crops in Ethiopia between 2000 and 2050. Even though Admasu *et al*. (2013)’s study extended beyond Ethiopia to cover East African countries, it failed to consider the responses of output supply, which this present research regards as crucial in ascertaining the impact of climate change on cereal crops. Thomas, Dorosh and Robertson (2019) also conducted a study on the potential effects of projected changes in climate scenarios for cereal crop yields in Ethiopia by 2035, 2055, and 2085 using crop yields models that is similar to that of Admassu *et al.* (2013), but different because of its utilization of agro-ecological zones that corresponded more closely to cropping patterns in Ethiopia, in addition to drawing on the results of a wider array of climate models. They utilized estimated coefficients from regressions of simulated crop yields from a crop simulation model, the DSSAT crop systems model, with climate variables as explanatory variables. Differently, Gebreegziabher *et al.* (2011), Yalew, *et al.* (2018) and Deressa and Hassan (2009) examined economy-wide and regional impacts of shocks in Ethiopia’s agricultural production systems due to changes in weather variables (rainfall and temperature) using a country-wide computable general equilibrium (CGE) model.

The foregoing assessments of literature indicate that Admasu *et al.* (2013) and Thomas *et al.* (2019) employed DSSAT as analytical tool, but Thomas *et al.* (2019) differs because the study specifically used agro-ecological zones more closely to the cropping pattern. Gebreegiabher *et al.* (2011) and Yalew *et al.* (2018) examined country-wide as well as economy-wide effects of changes in climate and shocks on agricultural production system respectively, the former employed CGE and Ricardian models disaggregated by agroecological zones. Gebreegziabher *et al.* (2011), and Deressa and Hassan (2009) also used similar model, the Ricardian approach and agroecological zones. Although these analytical models (CGE, Ricardian, Agroecological models) can investigate the effects of weather variations (rainfall and temperature) on the crop-, economy- or country-wide analysis, there exist some disadvantages in using them. These disadvantages may include difficulties with selection of the model, parameter specification and functional forms of the models, consistency of data or calibration problems, among others (Gillig and McCarl, 2002). Likewise, other existing researches in the area focusing on the national investigations, such as Deressa (2007), who used surveys, but survey-based data on the changes in climate may bring about valuation problems and requires respondents' knowledge.

Conversely, *agro-ecological zoning (AEZ) approach* has been used by many researchers for the prediction of the effect of changing weather variables on the potential agricultural outcomes and cropping patterns. The disadvantage of the AEZ approach lies in the fact that it is difficult to predict the final outcomes without modelling all the relevant constituents overtly, apart from the elimination of one most important variable would significantly influence the model's predictions validity (Mendelsohn and Tiwari, 2000).

The Ricardian model, on the other hand, interprets a cross section of farming data under different weather conditions and investigates the association among the value of land or net revenue variables and the agro-climatic factors (Kumar and Parikh, 2001). However, the disadvantage of the model is that it is not based on controlled experiments across farms; neither does it consider price and carbon fertilization effects (Cline, 1996) as well as criticized since it presupposes suitable independent adaption and modification in farming decisions and executions (Yalew, 2016).

Thus, it is obvious from the foregoing analysis that there is a significant gap that needs to be filled in the study of agriculture in terms methodological approach as well as area coverage. This is particularly emphasized through the study approach and models used by extant studies, as well as the spatial coverage of most of the researches. Ipso facto, to address the noted deficiencies, the current study adapts 'major crop growing belts' for each crop rather than agro-ecological zonation. Then, for each major crop growing belt of selected crop, 12 – 13 representative meteorological stations were selected and meteorological time series data covering 38 years as recorded in NMA were used in this study. Regarding crops and related data, nationally aggregated total cultivated area, production, and inputs data for each of the selected crop have been included in the analysis. In terms of methodology and models, an augmented Cobb-Douglas production functional model has been used in this study to examine the impact of climate variables on yield of selected cereal crops (teff, wheat and maize). In addition, an autoregressive distributive lag (ARDL) model was used in this study to analyze the aggregated output supply response of each selected crop to changes in climate and socio-economic variables.

The Cobb–Douglas functional model associates inter-annual changes in yield of crops (y_t) to climate (x_{jt}) and other economic variables (x_{kt}). The parameter values of the Cobb–Douglas functional model are specifically comparable across crops and spatial sites as relative yield effects by a relative increase of the exogenous variables (Wooldridge, 2013). It has also been assessed that many of the researchers have used Cobb–Douglas functional model to examine the impact of climate change on yield of crops and have proven that the model can be applied in both economic (You *et al*., 2009) and agronomic practices (Lee et al., 2013).

In the ARDL model, the dependent variable is articulated by the lag and current values of independent variables and their own lag values. ARDL model is one of the most general dynamic unrestricted models, more robust and performs better for small sized data which is suitable for research. In practice, the ARDL approach to cointegration enables to achieve consistency in the supply response model estimates, with the amalgam of regressor endogeneity, in addition to allowing for explicit assessment of both long-run and short-run elasticities when external variables have different characterization. ARDL bounds testing method is a cointegration test that has been developed by a modelist called Pesaran *et al.* (2001) to test the evidence of the long-run association among factors that were included in the model. The ARDL bounds test approach is postulated based on the supposition that the variables included in the model are of mixed order of integration, I(0) or I(1). The ARDL approach constitutes both short and long run dynamics. Additionally, empirical results validate its utility, as superior, besides aiding consistency in results of small sample size.

In summary, conducting systematic study on the effect of changes in weather variability (rainfall and temperature) on agricultural production, particularly on yield of crops and food crop output supply aggregately at national level becomes extremely important, which is the theme of this study. Quantifying the likely impact of variability in weather variables (rainfall and temperature) and providing indicative result to policy makers would enable to design on how to abate the adverse impacts of the changes in climatic factors on the yield crops as well as crop output supply (Wang *et al.*, 2011).

1.3. Research Questions

Several factors may have prevented Ethiopia from reducing the contribution of agriculture to overall output of the economy. These may include unpredictable weather conditions, traditional nature of agricultural activities, and less use of improved farm inputs.

Consequent upon that, this current research seeks to measure the impact changes and variability in weather variables (rainfall and temperature) on the yields of selected crops and changes in socio-economic factors influencing cereal crop production and supply. Exclusively, the current study seeks to addresses the following key questions:

- What are the trends or patterns of rainfall and temperature over a long period of time in Ethiopia?
- What is the response of yields of some selected crops (*teff*, wheat and maize) to climate change in Ethiopia?
- To what extent has the variability in climate and agro-economic variables influenced supply responses of some selected crops (*teff*, wheat and maize) in Ethiopia?

1.4. Objectives of the study

The overall aim of this study is to analyze the impact of climate change on the yields of selected cereal crops in Ethiopia, while the specific objectives are:

(i) To characterize rainfall (annual and seasonal) and temperature (minimum and maximum) trends in Ethiopia and review the causes of the changes using time series secondary climate data for 38 years from 1981 to 2018;

(ii) To determine the impact of weather variability on yields of selected cereal crops, viz. *teff.* wheat, and maize;

(iii) To examine the supply responses of selected cereal crops to the changes in the economic variables (price, fertilize, seeds, land area, irrigation, etc) and some weather variables.

1.5. Analyses of Objectives and Research Hypothesis

Considering the above specified research questions and objectives, this study seeks to test the following hypotheses as presented in Table 1.1.

Table 1.1 Analyses of objectives, model for analysis and hypothesis to be tested

Objective	Data requirements	Model for analysis	Hypothesis to be tested
To characterize rainfall and temperature trends	Long-term data on rainfall and temperature	Standardized anomaly (rainfall & temperature); Linear trend model (rainfall & temperature)	Rainfall and temperature variables have no significant declining or rising trend over long-run;
To determine the impact of weather variability on the yields of selected cereal crops, (*teff.* wheat, and maize).	Time series data on crop yields and outputs, cropped area under selected crops, prices of crops, inputs used, weather variables	Crop yield model (Cobb-Douglas Production Function model)	Temperature and rainfall patterns have no significant influence on the selected cereal crops
To analyze supply responses of selected cereal to changes in prices, inputs used and weather variables	Time series data on crop output, producer prices of selected crops, annual and seasonal rainfall and temperature	Output supply response model(Autoregressive Distributed Lag–ARDL Model)	Climate variability and change does not significantly influence supply responses of selected cereal crops

The terms ‘‘climate change’’ and ‘‘climate variability’’ were introduced in hypothesis 3 above. The difference beteewn the two terms, i.e. climate variability and climate change needs to be explained for clarity and understanding. The American Meteorological Society (AMS, (.)) defines climate variability as a change in the average state of the climate on all spatial and temporal scales separate from singular weather events. Variability may be due to natural internal processes within the climate system or to variations in anthropogenic (caused by human) external forcing. In other words, climate variations occur with or without human actions. It is critical to assess precisely which human actions affect climate and those that do not. The Michigan Sea Grant (2011) adds that climate variability is year-to-year variation (AMS, (.); Michigan Sea Grant, 2011).

On the other hand, climate change is a change in the state of the climate system, mostly identified by changes in the average conditions and the variability of its properties, which persists for an extended period, typically decades or longer, due to natural and/or anthropogenic processes and forcings (AMS, (.)). In other words, climate change is a long-term continuous change (increase or decrease) to the average weather conditions (e.g. average temperature) OR the range of weather (e.g. more frequent and severe extreme storms) (The Michigan Sea Grant, 2011).

1.6. Significance of the study

This study is significant because it aims to analyze the change and variability in weather variables and their effects on productivity and output supply of selected cereal crops which have not been adequately considered by earlier researchers. Following this, this current research is anticipated to narrow the notable gaps on the effects of the changes in climate variables (rainfall and temperature) on agricultural production and productivity by proposing new and improved knowledge needed to enhance farmers' cereal crops productivity and supply. As such, this current study would have triple contributions. First, it will contribute to existing knowledge on climate change (rainfall and temperature in particular); and will function as a totalizing background knowledge and reference for subsequent studies on the effect of changes in weather variables on agricultural crops production business.

Secondly, while most of the reviewed studies have utilized the modified Cobb-Douglas Production Function as a methodological model to ascertain the impacts of climate and socio-economic variables on yield and output of crops, the present study deviates from the overused model. Rather this study builds on the methodological and the empirical foundations for measuring the influence of changes in climate factors on production of teff, wheat and maize crops in Ethiopia. It should be noted that while the modified Cobb-Douglas Production Functional model with time series data has been used extensively in Asia and Europe to assess the efficiency of resource use in agriculture including climate factors, the utilization of such analytical models to examine the impact of climate and related factors on crop production in Ethiopia is however limited. Accordingly, this study will build on these analytical mthodologies employed to examine the impact of changes and variability in climate variables on selected cereal crops under the Ethiopian situation which can be further adopted by succeeding researchers in the future.

Thirdly, the study will provide informative information that help policy makers in Ethiopia and other developing countries in designing policies and mitigation strategies that can significantly abate the negative effects of changes in climate variables on yield of crops. Additionally, the current study results can also be used as a policy proposition for relevant policy makers in examining the impacts of climate change on agriculture and food security. Thus, the underscored significances make this current research extremely necessitous.

1.7. Structure of the thesis

This thesis is structured under seven chapters. Chapter one of the thesis provides the background of the study which has been discussed; Chapter two presents an overview of agro-climatic, agriculture and climate variability in Ethiopia. Chapter three expatiates on the review of theoretical, methodological and empirical literature; while Chapter four details the data, its collection and methodological approaches employed in this study. Chapter five describes characterization of weather variables (rainfall, temperature, etc.), and Chapter six elucidates the results of the empirical econometric modelling and analysis of the relationship between climate variables and yield of cereal crops under study. Finally, Chapter seven comprises summary, conclusion, and policy implications.

CHAPTER II

AGROCLIMATIC ZONES, CEREAL PRODUCTION AND CLIMATE VARIABILITY IN ETHIOPIA

2.1 Introduction

This chapter presents the brief description of the location of the country as well as its agro-climatic zones and the variability of the main climatic factors. It also presents a brief assessment of the cereal crop sector and description of the crops selected for this current study.

2.2 Ethiopia's location and agro climatic zones

Ethiopia is situated in east Africa, particularly in the Horn of Africa. It is located between $3^0$34' and $14^0$53' north and $32^0$42' and $48^0$12' east. In the east, it is bordered by Djibouti and Republic of Somalia; in the west it shares a borderline with the Sudan and South Sudan; in the north it is bordered by Eritrea; and in the south it is bordered by the Republic of Kenya.

Topographically, the physical features of the country show that the Great Rift Valley, which runs from northeast to almost south west, separates the landscape of the country into two branches setting up the western and eastern highland plateaus of the country. The country is diversely jagged with mountains, hills, plateaus, plains, valleys and gorges. The topography also encompasses the lowlands and highlands surrounding these mountains in every direction (MoA, 2005).

Further, the diverse landscape characteristics of the country also represent the diversified altitudes and gradients with lowest end at the Danakil depression in the Afar region with about 126m below sea level (m.a.s.l) and the highest peak on Ras Dashen Mountain in the Amhara region with a height of about 4,620m.a.s.l. However, the diverse topographic and atmospheric systems affect climate of the country, which in turn resulted in changing weather conditions across the country.

Likewise, climatic system of Ethiopia is classified in many ways. In congruent with that, the most popular classification systems used in practice is the traditional agro-climatic zonation of the country. Agro-climatic zonation of the country can be defined as a spatial categorization of the scenery into specific area entities with “comparable” farming and environmental distinctiveness.

According to traditional agro-climatic zonation, the country is classified into five climatic zones; viz. Wurch, Dega, Weynedega, Kola, and Berha (MoA, 2005) (see Table 2.1 for details).

Table 2.2: Traditional climatic zones and physical characteristics of Ethiopia

Zone	**Altitude (meters)**	**Rainfall (mm/year)**	**Average annual temperature (^{0}c)**
Wurch (upper highlands)	>3,200	900 – 2,200	>11.5
Dega (highlands)	2,300 – 3,200	900 – 1,200	17.5/16 – 11.5
Weynedega (mid-lands)	1,500 – 2,300	800 – 1,200	20.0 – 17.5/16
Kola (lowlands)	500 – 1,500	200 - 800	27.5 – 20.0
Berha (desert)	<500	<200	>27.5

Source: Deressa et al. (2010) cited in Kelbore (2012)

In terms of agricultural suitability, the different traditional agro-climatic zones mentioned above are suitable for various types of agricultural crops. Accordingly, the *Wurch zone* is characterized as a zone where no rainfed crop is expected to be grown due to the fact that frost, which limit growth of plants, is more frequent in this zone. In this climatic zone, afroalpine grasslands are the dominant vegetation and land use type.

The *Dega zone* is characterized as a zone where crops such as barley, wheat, and pulses are grown. However, teff and maize would not be expected to grow in this belt. The Dega zone is further differentiated into High Dega and Lower Dega. In *High Dega*, only barley and potatoes are grown, while in *Lower Dega*, wheat and pulses are grown.

The *Weyna Dega Zone* is characterized as the most dominant agricultural belt of the country; the zone is known for its suitability to grow almost all the major rainfed crops, particularly the teff and maize crops. This zone is the agro-climatic zone where both agroclimatic as well as ecological conditions are highly suitable for rainfed farming. The lower part of the *Weyna Dega* is also suitable for cash crops such as coffee and tea, or for inset, another major staple crop of southwestern and southern Ethiopia. This zone usually has sufficient amount of rainfall, allowing at least one cropping season each year.

The *Kolla Zone* is normally the belt where moisture limitations prevail for growing crops such as maize, potatoes, wheat and pulses. However, sorghum crop is a dominant crop in the Kolla belt. Teff and maize will also be grown in this zone if rainfall permits. This zone is a belt where temperatures are much warmer, higher rainfall variability, and recurring drought conditions are prevailing.

The *Berha Zone* is the belt where no rainfed cultivation is normally possible. These belts cover large areas in the lowlands of the country. Very hot temperatures and persistent drought render the area unsuitable for rainfed agriculture, although large-scale irrigation systems along major rivers have been developed in some areas, particularly along the Awash River. See Figure 2.1 for detailed presentation on map.

However, the agro-climatic zonal classification that utilizes water balance conception and length of crop growing season becomes the most practical classification for agricultural business purposes of the country (NMA, 1996). This classification affords identification of three distinct zones; area without a significant growing period (N), areas with a single growing period (S) and areas with a double growing period (D). The zones are captured in Fig 2.2.

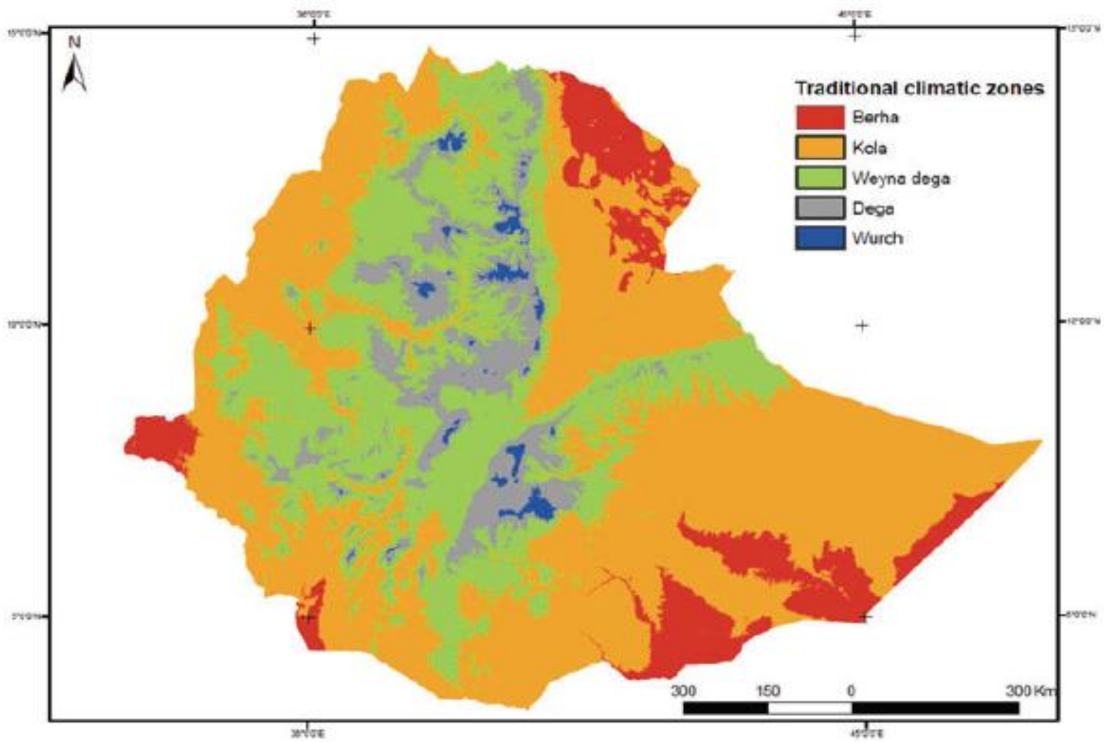


Figure 2.1: Traditional Climatic Zones of Ethiopia

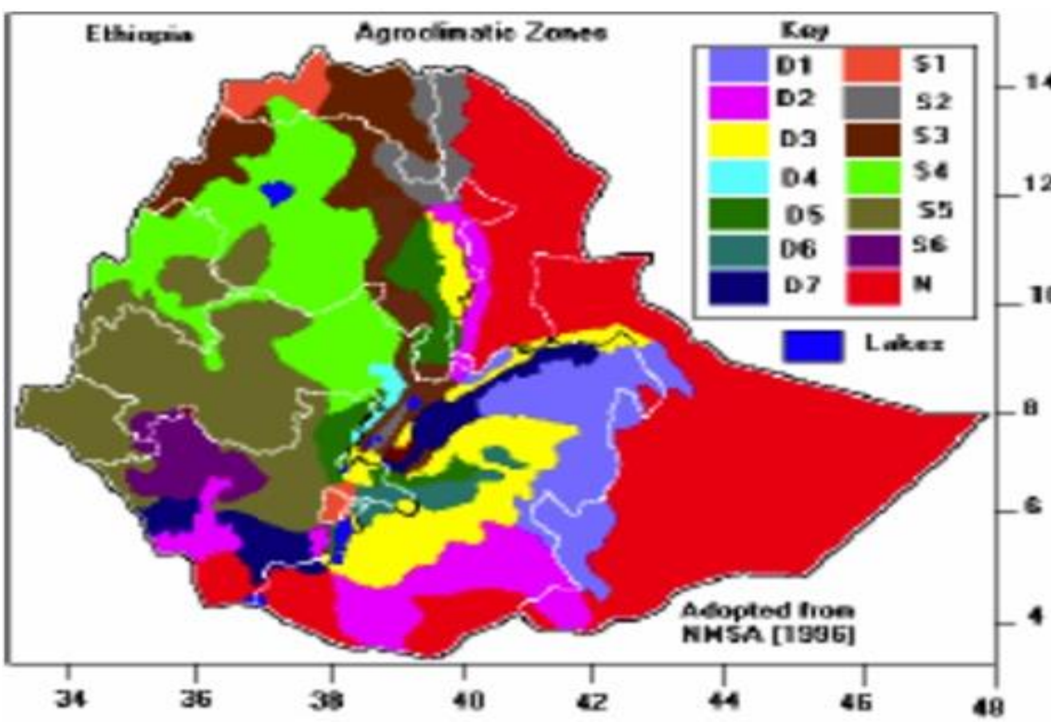


Figure 2.2: Agro-climatic zones of Ethiopia (NMSA, 1996).

In addition, the three major crop growing periods are classified into fourteen (14) broad zones as shown in Fig 2.2 above. Thus, the agroclimatic zoning described above provides a condensed inventory of the agro-climatic potential and the constraints as they have been determined by temperature and moisture regimes in a given area (NMA, 1996).

2.3 Agriculture Sector Performance in Ethiopia

This sub-section exhibits brief review of the agriculture sector that mainly focus on cereal crops production in general, and cereal crops selected for this specific research: viz. teff, wheat and maize, in particular.

2.3.1 Contribution of agriculture sector to the national economy

It cannot be gainsaid that the agriculture sector is the main source of livelihood in every nation of the world, besides being a major contributor to the national economy, Ethiopia inclusive. For instance, the National Planning Commission (NPC, 2018) asserts that the agricultural sector contributes about 35% to the national GDP during 2017/18. Still with-in the agricultural sector, the crop sub-sector is a recognized major contributor to the na-tional GDP, for it contributes about 65% from total agriculture sector's contribution, while just 35% is contributed by livestock, fishery and forest sub-sectors.

Correspondingly, the five major cereals contributing to Ethiopia's agriculture and food economy, and accounts for 81% of the area cultivated ubder crops and 87% of the total grain crops production during the period of 2017 and 2018 are teff, wheat, maize, sor-ghum, and barley (CSA, 2018).

2.3.2 Cereal crops production in Ethiopia

Table 2.2 displays area cultivated and production levels of the main crops grown in the country between 2017 and 2018. The examination of the data reveals that cereal crops dominate the Ethiopian crop production business. The reason for the dominance can be attributed to the fact that cereal crops accounted for 80.7 percent of the total area cultivated under grain crops, thus allowing for 87.5 percent of the total grain production during 2017/18. Correspondingly, the information captured in Table 2.2 evinces that about 12.68 million hectares of land was cultivated and covered with grain crops during the aforesaid periods, out of which cereals covered 10.23 million (80.7 percent) hectares in the same year. Additionally, from these cultivated areas, a total of 306.1 million quintals of grain crops were produced, out of which 267.8 million quintals (87.5 percent) were contributed by cereals. While teff accounted for 23.8 percent of total grain cropped area, the aggregated position occupied by wheat and maize were 13.4 and 16.8 percents, respectively. Equally, the production of maize with respect to total annual cereal production during the same period was a ratio of 27, and teff and wheat contributed 17.3 and 15.2 percent, respectively.

Meantime, the rationale behind the selection of teff, wheat and maize, which are the three major cereal crops for the current study, was not only because of the area they occupy, but also their production volume, including the number of holders engaged in the business and their contributions to food security of the country. Besides, water requirement and length of crop growing period of each crop has also been considered in this current study. Moreover, in terms of area coverage, teff, maize and wheat crops occupy about 54 percent of the total area covered by all grain crops, and subsequently representing 60 percent of the total grain production of the country during 2017 and 2018. In contrast, other cereals such as sorghum, barley, millet, oats, and rice occupied only 26.7 percent of the total area covered by grains, contributing just 27.6 percent to the volume of total grain production. Moreover, many smallhoder farmers engaged in maize, teff and wheat production business to support their livelihoods. In point of fact, according to CSA (2018) the number of smallholder farmers dealing in maize, teff and wheat farming were 10.57, 6.77 and 4.21 million respectively. These respective numbers consequently indicated that these crops form major staple food of the smallholder farmers. Contrastingly, just a meagre number of about 0.16 – 5.4 million only were producers of sorghum, millet, oats and rice amongst the smallholder farmers.

Table 2.2: Number of holders, total area, and production of grain crops for main season by smallholder farmers during 2017/18

Crop category	Number of Holders (millions)	Total area cultivated		Total Production		Yield (Tons/Ha)
		Area (Ha)	% share	Quantity (Quintals)	% share	
Cereals		10,232,582.23	80.71	267,789,764.02	87.48	-
Teff	15.05	3,023,283.50	23.85	52,834,011.56	17.26	1.748
Barley	6.77	951,993.15	7.51	20,529,963.72	6.71	2.157
Wheat	3.50	1,696,907.05	13.38	46,429,657.12	15.17	2.736
Maize	4.21	46,429,657.12	16.79	83,958,872.44	27.43	3.944
Sorghum	10.57	1,896,389.29	14.96	51,692,525.40	16.89	2.726
F. millet	1.76	456,057.32	3.6	10,308,231.53	3.37	2.260
Oats	0.21	25,896.22	0.20	526,318.93	0.17	2.032
Rice	0.16	53,106.79	0.42	1,510,183.30	0.49	2.844
Pulses	0.21	1,598,806.51	12.61	29,785,880.89	9.73	-
Oilseeds	0.16	846,493.53	6.68	8,550,738.16	2.79	-
Grain crops	8.32	12,677,882.27	100.00	306,126,383.06	100.00	

Source: CSA, 2018

Aside from the popularity of the three selected cereals for the present study in cereal production, the period of growth needed for each crop is shorter than the ones that are not selected. For instance, teff requires a shorter growing period of 80 – 85 days, while wheat requires a medium growing period of 120-150 days, maturity and harvesting periods inclusive. On the other hand, maize requires relatively longer period, between 125 and 180 days (FAO, 2020). Although barley and oats have similar growing period with wheat, but their area coverage, volume of production, productivity and number of farmer holders are relatively lower than that of wheat. Equally, finger millet and sorghum shares almost similar growing periods, from 105 to 140 days and 120 to130 days respectively, but the number of grower farmers, area coverage and productivity of finger millet is relatively low (see Table 2.3 for details).

Even though FAO (2020) states that the water requirement of cereal crops depends on the climate and length of growing season, withal, teff's water requirement has not been studied in detail. Rather it is commonly assumed by local agronomists that teff's water requirement is like that of wheat and barley (Araya, et al., 2010) which ranges between 450 and 650 mm. For instance, maize is a long period crop that ranges between 500 and 800 mm, and as a result it requires comparatively high rainfall amount for its production. Likewise, even though millet, sorghum and rice require almost the same amount of rainfall as maize, but the range is between 450 and 600 mm. These are represented in Table 2.3.

Table 2.3: Growing period and water requirement of cereal crops

Cereal Crop	**Growing period (days)**	**Water needs (mm/ growing period)**	**Suitable agroecology**
Teff	80 – 85	450 - 550	Highland, midland and lowland
Maize	125 - 180	500 - 800	Midland and lowland
Wheat	120 - 150	450 - 650	Highland and midland
Barley	120 - 150	450 - 650	Highland and midland
Oats	120 - 150	450 - 650	Rainfed highland
Sorghum	105 - 140	450 - 650	Highland, midland, and lowland
Millet	105 - 140	450 - 650	Highland, midland, and lowland
Rice	90 -150	450 - 700	Highland, midland and lowland

Source: Crops water and soil requirements - FAO (2020) at: www.fao.org.

In conclusion, considering the number of smallholder farmers engaged in the production of teff, maize and wheat, coupled with the significant area of coverage of these cereals, as well as their notable contributions to staple food, and their growing periods, including their water requirements, then it becomes apropos to carry out an in depth study on the effect of the variability and changes in the weather variables and related factors on yields and output of cereal crops in order to augment their productivity and production volume. Nonetheless, this research still recommends that sorghum and barley should equally get priority in future studies in order to augment food security in the nation. The rationale for this suggestion is due to the fact that sorghum and barley covered about 1.83 million hectares (17.4 percent of area cultivated under cereals) and 0.95 million hectares (9 percent of area cultivated under cereals) and accounted for 5.3 million tons (17.7 percent of cereal production volume) and 2.4 million tons (8 percent of cereal of cereal production volume) of production, respectively during 2019/20 production period (CSA, 2020).

2.3.3 Teff production in Ethiopia

With respect to production and consumption, production and consumption of teff ranks the highest in all the cereal crops in Ethiopia; it is also cultivated as food grain in Eritrea (FAO, 2015). As (*Eragrostis Teff*) is a nutritious small grained cereal, teff can be likened to millet. It is believed that itcame into existence in Ethiopia and was subsequently adapted as a domestic staple food by Ethiopian farmers between 3 and 6 millennia ago (Samuel and Sharp, 2008).

Virtually, it is estimated that half of farming households grow teff, and even more in the highlands. Teff accounts for 23 percent of all cultivated land during 2017 and 2018. Though teff is primarily grown in mid-highlands (*Weyna Dega Zone*) and upper-lowlands of the country, it can also be cultivated under a wide-range of agro-climatic environments of the country. In terms of altitude, teff can be grown up to elevations ranging from 0 - 2,800 meters above sea level (masl), but under an equally extensive diversity of humidity, temperature, and soil situations. Besides, there exists a concurrence between its optimum growing conditions and its conventional production vicinities or belts: 1,800–2,100 masl, with mean annual precipitation of 750–1,000mm, and mean annual temperature of 10–27^{0}C. The two major regions of the country where teff is primarily grown are Amhara and Oromia regions, both places contributed to the total cultivated area and production of an aggregate of 85.4 and 87.5 percents between 2017 and 2018, respectively. In Ethiopia, East and West Gojam zones of Amhara and East and West Shoa zones of Oromia are specifically recognized as the highest teff growing production belts. The details are presented in Table 2.4.

Teff is primarily cultivated and grown by smallholder farmers in the central, eastern and northern highlands of the country on fragmented lands under rain-fed conditions in both, *Long-rainfall* and *Short-rainfall*, seasons (Engdawork, 2009). According to FAO (2015), teff is considered as a crop relatively resistant to many biotic and abiotic stresses. It can be grown under different agro-ecological conditions of the country, ranging from lowland to highland areas. Although teff crop is primarily grown during the long-rainy season, it also grows during short-rainy season, particularly in North, South West and East Shewa Zones of Oromia Region as well as North and South Wollo Zones of Amhara regions where short-rany season (*Belg*) normally prevails. These zones usually receive *bimodal* type of rainfall during *short*- and *long-rainy* seasons. According CSA and MoA (2001), short-rain season contributes about 10 percent of the total grain production while long-rain season contributes about 90 pecent of the total grain production in the country.

Table 2.4: Major teff producing regions in Ethiopia, 2017/18

Region	No of Holders (million)	Area Cultivated		Production		Yield (Qt/Ha)
		Hectare (million)	% share	Quintals (million)	% share	
Tigray	0.17	0.17	5.55	2.58	4.88	15.37
Amhara	2.54	1.14	37.65	20.39	38.61	17.92
Oromia	2.77	1.44	47.77	25.81	48.87	17.88
Benshangul-Gumuz	0.04	0.02	0.81	0.33	0.62	13.40
SNNP	0.97	0.25	8.21	3.70	7.01	14.93
Total	**6.49**	**3.0**	**100.0**	**52.81**	**100.0**	**15.9**

Source: CSA, 2018

Geographically, teff is primarily produced in the centeral and the northwest part of the country. Zone-wise, East Gojjam, East Shewa, West Shewa and North Shewa zones are the four most important teff producing zones; all being located in the Amhara and the Oromia regional states (Yihenew *et al.*, 2013). As indicated in the above table, relatively smaller quantities of teff is also cultivated and produced in Tigray, SNNP and Benshan-gul-Gumuz regions. Considering the volume of teff production and supply in the country, some regions are surplus producers and others are deficit suppliers of teff output (Engdawork, 2009). Among the key surplus producing regions and zones are: all Shewa zones of Oromia and all Gojjam zones of Amhara regions of the country. Oppositely, Wollo zones in Amhara, Tigray region, Harar region, and Dire Dawa City Adminstrative Council in the eastern parts of Ethiopia and most pastorals areas of the country are considered as deficit areas in teff production and supply. For further geographical details, the map of major teff producing regions is presented in Fig. 2.3.

Regarding the trend of teff production, a remarkable increase has been observed in the last decade and half. Figure 2.4 shows trend of teff production over the period of 1987/88 to 2017/18. It can be seen from the figure that teff showed a consistent increase of its production between 2003/04 and 2017/18, both in its production and yield per hectare. During these period teff production escalated from 14.2 million quintals in 2002/03 to 52.8 million quintals in 2017/18, which is nearly quadrupled. Thus, this evidenced that teff crop production registered 271.8 percent growth between 2002/03 and 2017/18 at a rate of 27.2 percent per annum. Additionally, besides the significant increase in the percentage growth of teff, the same trend is registered in its yield; hence teff's yield consistently increased from the level of 7.35 quintals/hectare in 2002/03 to 17.48 quintal /hectare during 2017/18. However, the increase in area cultivated under teff crop during the same period is minimal, implying that area expansion towards teff production is limited.

From the above evidences, one can concluded that the increase in volume teff production has been achieved due to improvement in its yield, as well as minimal expansion in area cultivated. The momentous increase in the yield of teff can also be attributed to use of improved fertilizers, improved seed varieties, pesticides, and better agronomic practices.

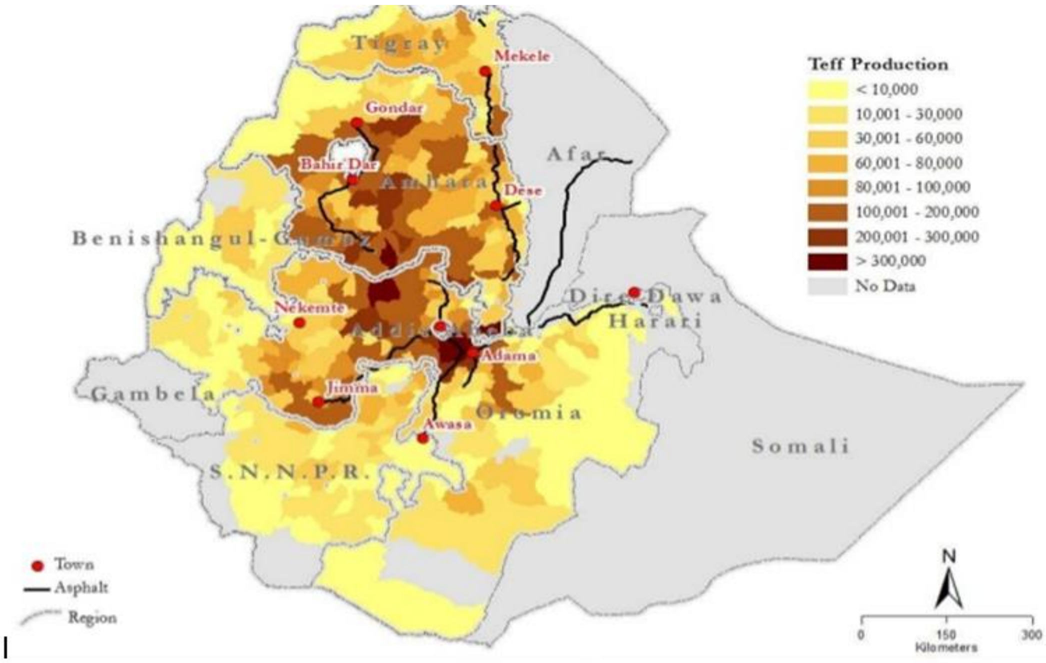


Figure 2.3: Major teff producing areas of Ethiopia

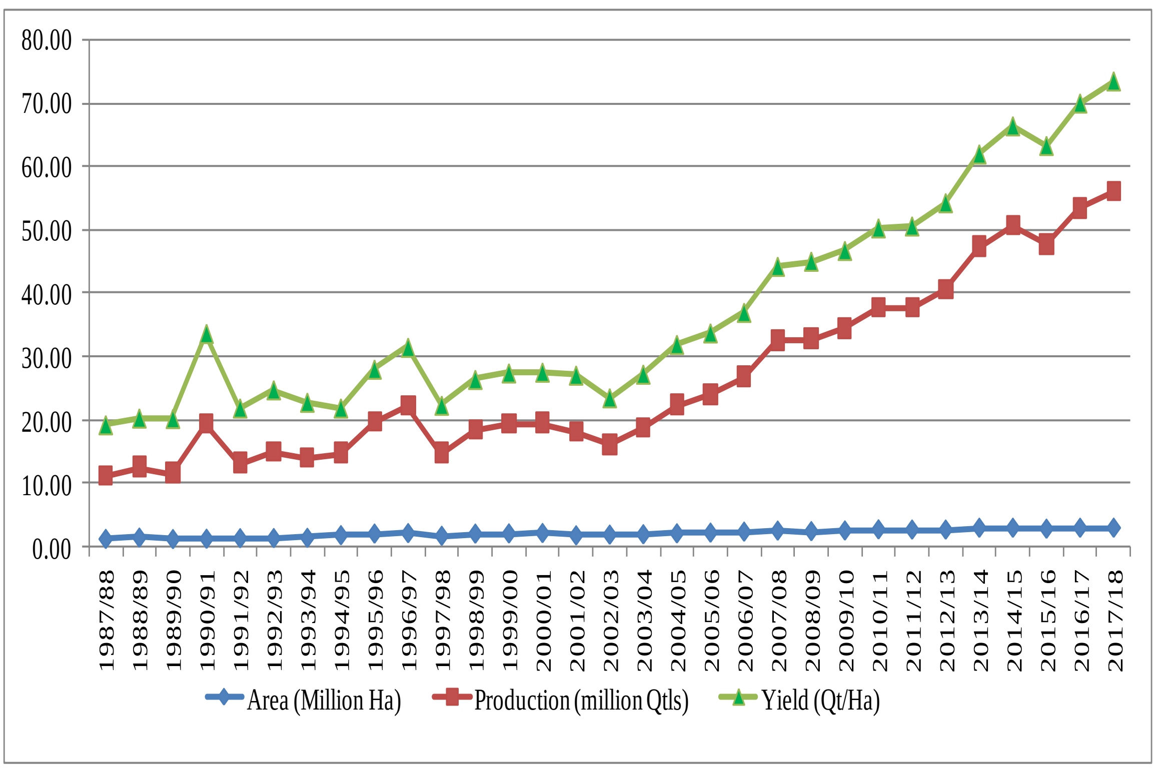


Figure 2.4: Trend of teff production over the period 1987/88 to 2017/18
Source: CSA, 1987/88 – 2017/18

2.3.4 Wheat production in Ethiopia

At global level, wheat is among the most important food crop with a production and supply volume of 750 million tons on about 220 million hectares during 2017. According to FAO (2017), a total of 7.5 million tons of wheat was being produced on a total cultivated area of 2.9 million hectares of land in the Sub-Saharan Africa (SSA) countries, with a share of 40% and 1.4% of production in Africa and at global levels, respectively. Among the major wheat producing and supplying countries in the SSA, South Africa, Ethiopia, Sudan, Kenya, Tanzania, Nigeria, Zimbabwe, and Zambia are the most important ones in descending order.

As has been stated above, Ethiopia is considered as the second biggest producer of wheat in SSA, next to South Africa with about 0.88 million ha cultivated land area of durum and bread wheat (White, *et al.*, 2001). In Ethiopia, wheat is considered as the fourth most important cereal crop in terms of both area cultivated and volume of production after teff, maize and sorghum (CSA, 2018). Wheat crop is largely grown in the highlands as well as midhighlands (Dega and Weyna Dega agro-climatic zones), which lie amid 7.05 and 13.3° N latitude and 37.5 and 42.2° E longtude, at an elevations ranging from 1,500 to 3,200 meters above sea level (Hailu, 1990). As a cool-weather cereal crop, the major wheat growing belts are Oromia (i.e., Arsi, Bale and Shewa) and Amhara (East and West Gojam) highlands of the country (Figure 2.5). The crop is mostly grown during the main rainy (long-rainfall) season from June - September and harvested from October through January. The crop also grows during the short-rainy season in all Shewa zones as well as in North and South Wollo zones, the season which contributes about 5 – 10 percent of cereal output.

Regarding the volume of production, Oromia and Amhara regions together accounted for 85.9 percent and 87.9 percent of the total cultivated area and production respectively in 2017/18. As a matter of fact, Bale and Arsi zones of Oromia and East and West Gojam of Amhara are specially recognized as wheat producing belts in the country during 2017/18. Although it is relatively low in terms of area and production level, wheat also grows in the regions of SNNP, Tigray, and Benshangul-Gumuz. Table 2.5 shows the major wheat producing regions in Ethiopia.

Table 2.5: Wheat production by regions in Ethiopia, 2017/18

Region	No. of Holders (million)	Area cultivated		Production		Yield (Qt/Ha)
		Hectare (million)	%share	(million Quintals)	% share	
Tigray	0.31	0.11	6.4	2.14	4.6	19.83
Amhara	1.65	0.55	32.8	14.05	30.3	25.33
Oromia	1.71	0.90	53.1	26.70	57.6	29.71
Benshangul-Gumuz	0.01	0.00	0.1	0.06	0.1	24.06
SNNP	0.53	0.13	7.5	3.39	7.3	26.66
Total	**4.21**	**1.69**	100.0	**46.34**	**100**	***

Source: CSA, 2018

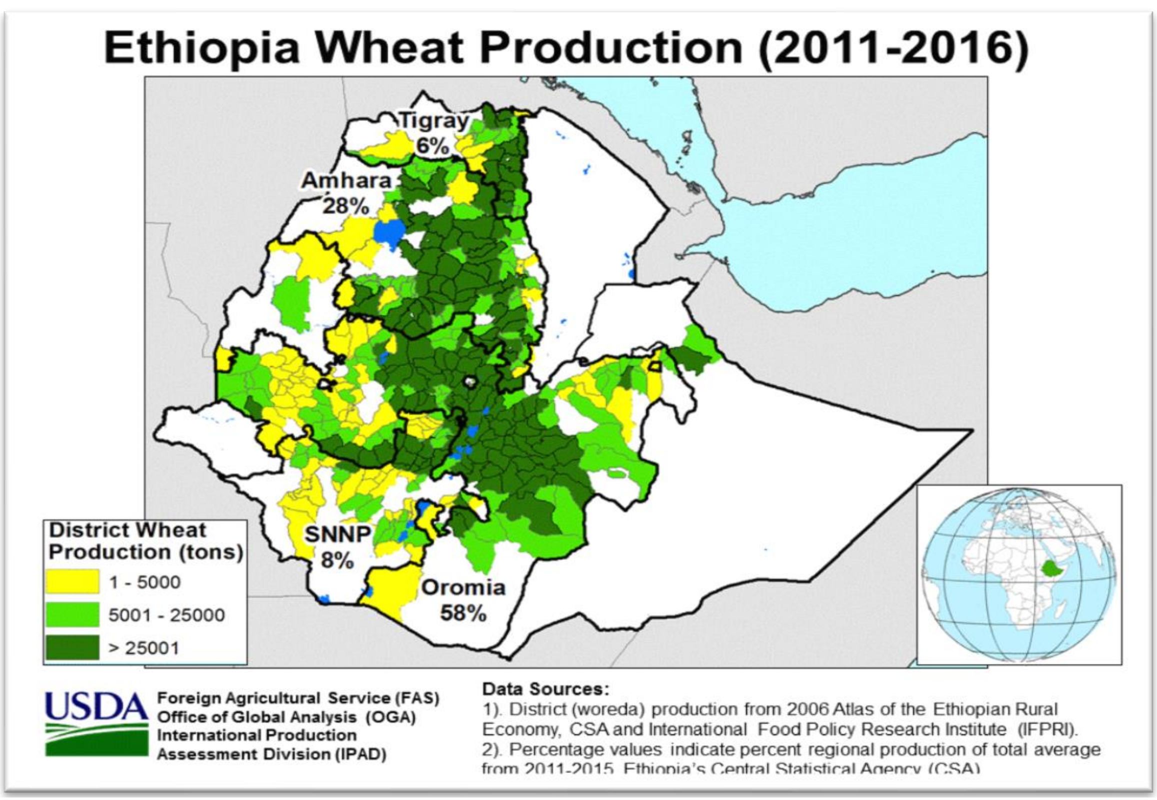


Fig. 2.5: Major wheat growing regions of Ethiopia.

Data shows that wheat production in the country has grown significantly over the past two decades. The notable growth can be attributed to the government extension programs and the different initiatives implemented to induce agricultural growth and ensure supply of food in the country. Figure 2.6 shows trend of wheat production over the period of 1987/88 to 2017/18. Production increased from around 10.72 million quintals in 2002/03 to 46.43 million quintals in 2017/18: an average annual growth of 22.2 percent. Yield of wheat also followed the same trend, its yield consistently increased from the level of 10.75 quintals/hectare in 2002/03 to 27.36 quintal /hectare during 2017/18. However, the increase in area cultivated under wheat crop during the same period is minimal, just 3.6 percent only.

From the above evidence, it can be concluded that increase in total wheat production was achieved due to improvement in yield of wheat as well as area expansion. The significant increase in wheat yield can be ascribed to improved use of fertilizers, improved seeds, pesticides, and better agronomic practices.

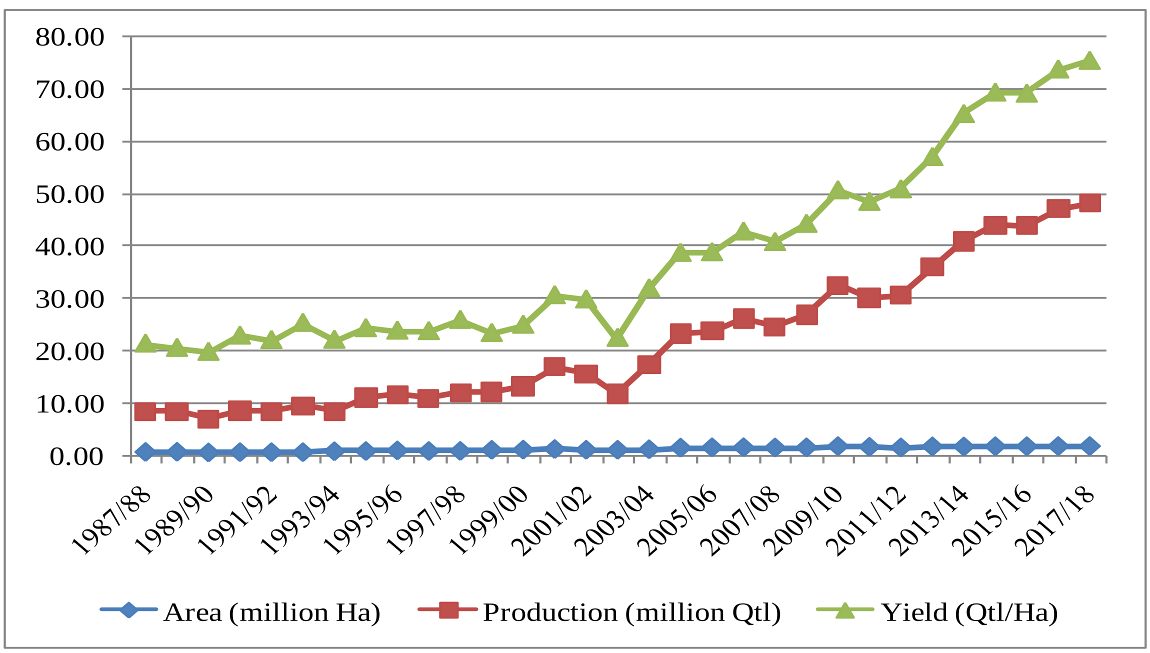


Figure 2.6: Trend of wheat production over the period of 1987/88 to 2017/18

Source: CSA, 1987/88 - 2017/18

2.3.5 Maize production in Ethiopia

Evidences show that maize (*Zea maize*) is considered as the most extensively grown staple food crop in the SSA; and occupies more than 33 million hectares of land area each production year (FAOSTAT, 2015). Per se, it covers almost 17 percent of the estimated 200 million hectares cultivated land area in SSA, besides being produced in diverse production environments. Maize is a staple food crop consumed by people with varying food preferences and socio-economic backgrounds.

According to Mandefro, *et al*.(2002), Ethiopia is considered as the third largest producer and supplier of maize crop in Africa, next to South Africa and Tanzania. It accounts for about 10% of the area cultivated, while its productive output is estimated to be about 12 percent of the production level of the region. Furthermore, the yield levels of maize crop are also exceeds the regional average yield level: about 1.7 metric tons/Ha compared to 1.5 metric tons/Ha for the whole Africa region.

In Ethiopia, maize crop is among the primary cereal crops; and ranks the highest in the country's total cereal crops volume of production and productivity, and second to teff (*Eragrostis tef*) in terms of area coverage (CSA, 2018). As a matter of fact, a total of 8.4 million tons of maize output (31.4 percent of the total cereal) has been produced on 2.13 million hectares (21 percent of the total area planted under cereals) of land owned by nearly 11 million small householder farmers during 2017/18 (CSA, 2018). As the most extensively grown crop in Ethiopia, maize is cultivated and grown under different agro-climatic zones and socio-economic conditions, and usually under rain-fed situations. The crop is mainly cultivated and grown in the main season known as *long-rainfall (Kiremt)*, which relies on May-September rainfall. The crop is also grown in minor rainy season locally known as *short-rainfall*, which makes it dependent on the rainfall between January and April. While maize is grown under rain-fed conditions during the main season (long-rain season), in contrast, maize crop is often grown under residual moisture during off-season (Mosisa, et al., 2012). Evidences reveal that maize is also grown during the short-rain season (Belg) accounting for 22 percent of area cultivated under maize crop as well as contributes about 9.5 percent of total maize production.

The bulk of the maize production and supply is realized from mid-altitude sub humid, followed by moisture stressed agro-ecologies. However, maize is worth mentioning that the highland and low altitude sub-humid agro-ecologies are not contributing most to the maize crop production currently. The primary reason is because there is lack of suitable varieties and limited knowledge about maize in those areas. Contrastingly, moisture stress and low altitude agro-ecologies represent considerable potential for the expansion of maize area. The geographic distribution of these broad agro-climatic zones is depicted in Figure 2.7.

Evidences show that maize crop is less tolerant to cold than teff, barley, and wheat crops. While teff can grow at elevations up to 2,800 masl, limited maize varieties grow above 2,400 meters. Furthermore, since maize crop has got a shallow root system, moisture can easily be available to the crop in the upper soil strata. In Ethiopia, maize crop requires an annual rainfall of 800–1,500 mm. Maize crop receives both bimodal and unimodal type of rainfall in the country; it receives unimodal rainfall in South-West, Western and North-Western parts of the country and *bimodal rainfall* type in the Central, Eastern and some Southern parts of the country.

Regionally, maize is mostly grown in the southwest and west parts of Oromia, west and northwest parts of Amhara, parts of the SNNPR, and Benshangul-Gumuz regions. Table 2.6 articulates the maize producing regions of Ethiopia. Available evidences portray that about 56 percent of maize production comes from Oromia region, followed by Amhara region with about 25 percent of total production (CSA, 2018). Minor maize producing regions include SNNP, with just a share of 14%, still less in Benshangul-Gumuz (2.4 percent), and lesser in Tigray (2 percent).

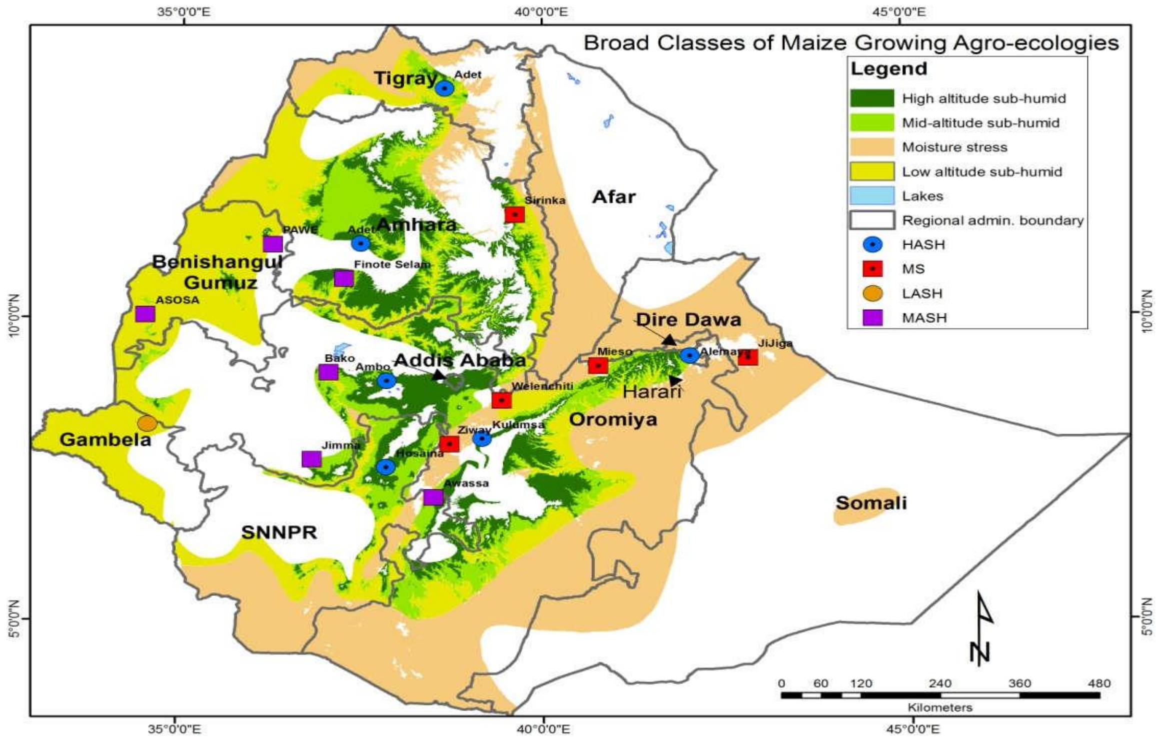


Figure 2.7: Geographic distribution of the broad maize agro-ecologies in Ethiopia

Table 2.6: Maize production by regions in Ethiopia, 2017/18

Region	No. of Holders (million)	Area cultivated		Production		Yield (Ton/Ha)
		Hectare (million)	%share	(million Quintals)	% share	
Tigray	0.66	0.06	2.9	1.59	1.9	2.559
Afar	0.01	0.00	0.2	0.14	0.2	3.203
Amhara	3.04	0.52	24.4	20.72	24.7	3.983
Oromia	4.92	1.15	53.9	46.77	55.7	4.078
Somali	0.07	0.02	1.1	0.57	0.7	2.416
Benshangul-Gumuz	0.21	0.05	2.4	2.03	2.4	4.013
SNNP	1.61	0.31	14.8	11.97	14.3	3.806
Gambella	0.00	0.00	0.2	0.13	0.1	2.648
Harari	0.02	0.00	0.1	0.03	0.0	2.420
Total	**10.55**	**2.13**	100.0	**83.95**	**100.0**	***

Source: CSA, 2018

Maize production has registered higher levels of growth over the last three decades. Figure 2.8 is a presentation of the trends in production of maize over the last three decades (1987/88 to 2017/18). Overall, the production levels for maize have greatly increased from 17.88 million quintal in 2002/03 to 83.96 million quintals in 2017/18, with average growth of 24.6 percent per annum. This increase is because ofarea expansion and increase in level of productivity, given the natural environment. Despite, the fluctuations in the percentage changes over the years, maize productivity has revealed a steady growth trend. As presented in Figure 2.7, the productivity of maize in 2002/03 was 15 quintals/ha while in 2017/18, it has grown to 39.4 quintal/ha, an annual growth of 10.8 percent. This steady growth is mainly attributed to continued government investment in maize research and development that have ensured improved availability of improved maize production technologies and practices.

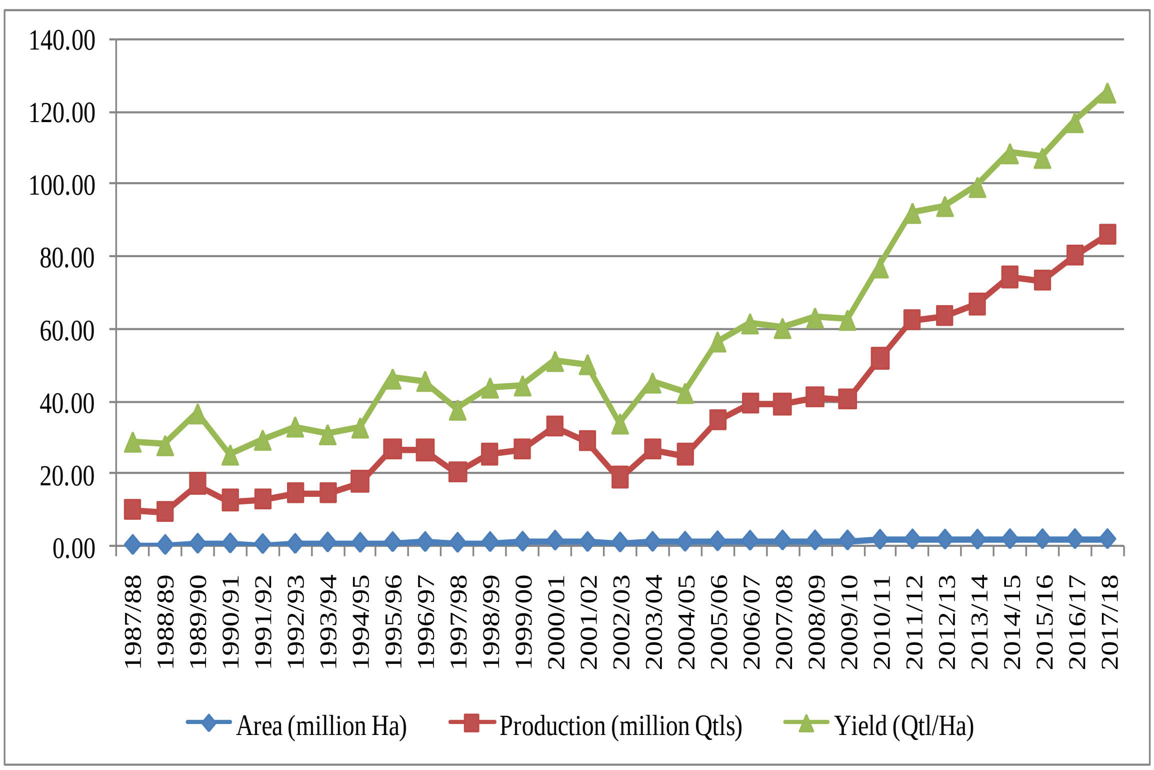


Figure 2.8: Trend of maize production in Ethiopia
Source: CSA, Agricultural Sample Surveys 1987/88 to 2017/18

2.4 Climate variability in Ethiopia

2.4.1 The climate system in Ethiopia

There is no gainsay that there is a nexus between climate system and rainfall; as such it is essential to comprehend the connection between both because of its value in agriculture cum economy of any nation. Per se, the important weather systems responsible for rainfall in Ethiopia are Sub Tropical Jet (STJ), Inter Tropical Convergence Zone (ITCZ), Red Sea Convergence Zone (RSCZ), Tropical Easterly Jet (TEJ) and The Somalia Jet (NMA, 1997). Accordingly, the weather system that cause rainfall for each of the seasons in Ethiopia is well elucidated by National Meteorological Agency (NMA, 1996) as described below.

Largely, evidences show that the country experiences moderately warm-humid as well as northeasterly winds throughout the *Bega season* (October – January). Such atmospheric masses start from the Saharan anticyclone as well as from the edge of the high pressure, scattering into Arabia from very elevated height over Central Asia (Siberia), or either of the two. However, once in a while, northeasterly winds might be interjected when the migratory lowpressure system arising in the Mediterranean area advances towards the eastwards and interact with the equatorial/tropical system. This subsequently leads to the rainfall in some parts of Central Ethiopia. Likewise, this infrequent development of the Red Sea convergence zone (RSCZ) impacts Costal areas.

All through short-rainfall, the season overlaps with the dominance of the Arabian high while it advances towards the north Arabian Sea. Essentially, the principal systems during the season are the evolution of thermal low over South Sudan; the origination and extension of disturbance over the Mediterranean, which can sometimes attract Easterly waves. Another significant system is the development of high pressure over the Arabian Sea; while some of the interface between mid-latitude depression and tropical systems is accompanied by troughs and the subtropical jet; lastly, there is an occasional development of the RSCZ.

Likewise, in the course of Kiremt, the airflow is specially marked by a zone of convergence in low pressure systems, as well as co-occur with the oscillatory Inter Tropical Convergence Zone (ITCZ), in addition to extending from West Africa through Ethiopia towards India. Also, main rain, likewise referred to as the long rainfall, producing systems during the season are Northward migration of ITCZ; development and persistence of the Arabian and the Sudan thermal low along 20^0N latitude; development of quasi – permanent high pressure systems over south Atlantic and south Indian ocean; development of tropical Easterly Jet (TEJ) and its persistence; and the generation of low level 'Somali Jet' that enhance low level southwesterly flow.

2.4.2 Rainfall Regimes in Ethiopia

Ethiopia is considered as a nation that is distinguished by diverse culture and weather conditions; which range from moist to highly-arid environmental conditions. In Ethiopia, prevailing seasons and rainfall regimes are normally classified based on mean annual and mean monthly rainfall distribution. In practice, there are three rainfall seasons in the country in terms of their importance for agricultural activities: viz. the first being the *long rainy season (Kiremt)* from June to September (J-S), the second is the *short rainy season (Belg)* from February to May (F-M), and the third is the *dry season (Bega)* from October to January (O-J) (NMA, 1996).

The passage of the ITCZ described above gives rise to the modal or the pattern of the seasonal rainfall occurrence among the different parts of the country. In this aspect, the rainfall regime in Ethiopia is characterized as *bi-modal type -1* (A), *monomodal* (B), *uni-modal* and *bi-modal type - 2* (C) systems influenced by the variations in the topography, seasonal cycles and opposing response to regional and global weather systems.

Based on the above rainfall occurrence and distribution patterns, the following four major rainfall regimes can be distinguished (see Fig. 2.9 for details):

(1) Regime A (bimodal type -1):- Normally comprises the central, eastern and northern part of the country experiences a ***bimodal rainfall*** pattern, in which these area usually are receiving the majority of their rainfall from the *Atlantic*, while some drives from *Indian Ocean*. The big rains between June and September (*long-rainy season)* come mainly from Atlantic while the light spring rains between February and May (*short-rain seasons*) come from the Indian Ocean. In each case, the amount of the rainfall and the length of of the rainy season decreases as one go further to the north. This area covers parts of Oromia, Amhara, Tigray, the highlands of Somali and western highlands of Afar regions.

(2) Regime B (unimodal):- The western and south-western parts of the country experiences unimodal rainfall pattern brought about by wind system that comes from Indian Oceans and merge with those coming from the Atlantic Ocean to give a continuous rain from March or April to October or November. The amount of rainfall and length of the rainy season normally decreases as one goes from south to northwest. This area covers western parts of SNNPR, Gambella, western Oromia, Benishangul-Gumuz, northwestern Amhara, and western parts of Tigray regions.

(3) Regime C (bimodal- type 2): This normally comprises Southern and Southeastern part of the country which experiences a bimodal rainfall pattern brought about by the wind system coming from the Indian Ocean from September to November (O-N) and from February to May (F-M). The most reliable rainy months are April and May. This part of the country normally represents the pastoral and agro-pastoral areas of the country, which receive *bi-modal rainfall* similar to regime B but main and short season rains at different time period. The area normally covers pastoral areas of SNNPR, Borena, Bale, and East Hararge zones of Oromia and pastoral areas of Somali region.

(4) The north-eastern parts of the country comprise part of the western escarpment of the Rift Valley and the adjacent Afar depression. The lowlands have only one rainy season during which only a little rain falls. However, the escarpment, particularly in the north, can have a third rainy season brought about by moist winds from Asia which has crossed the Arabian Peninsulla and cool as they rise over the Ethiopian escarpment. These can bring about mist and rain any time between November and February.

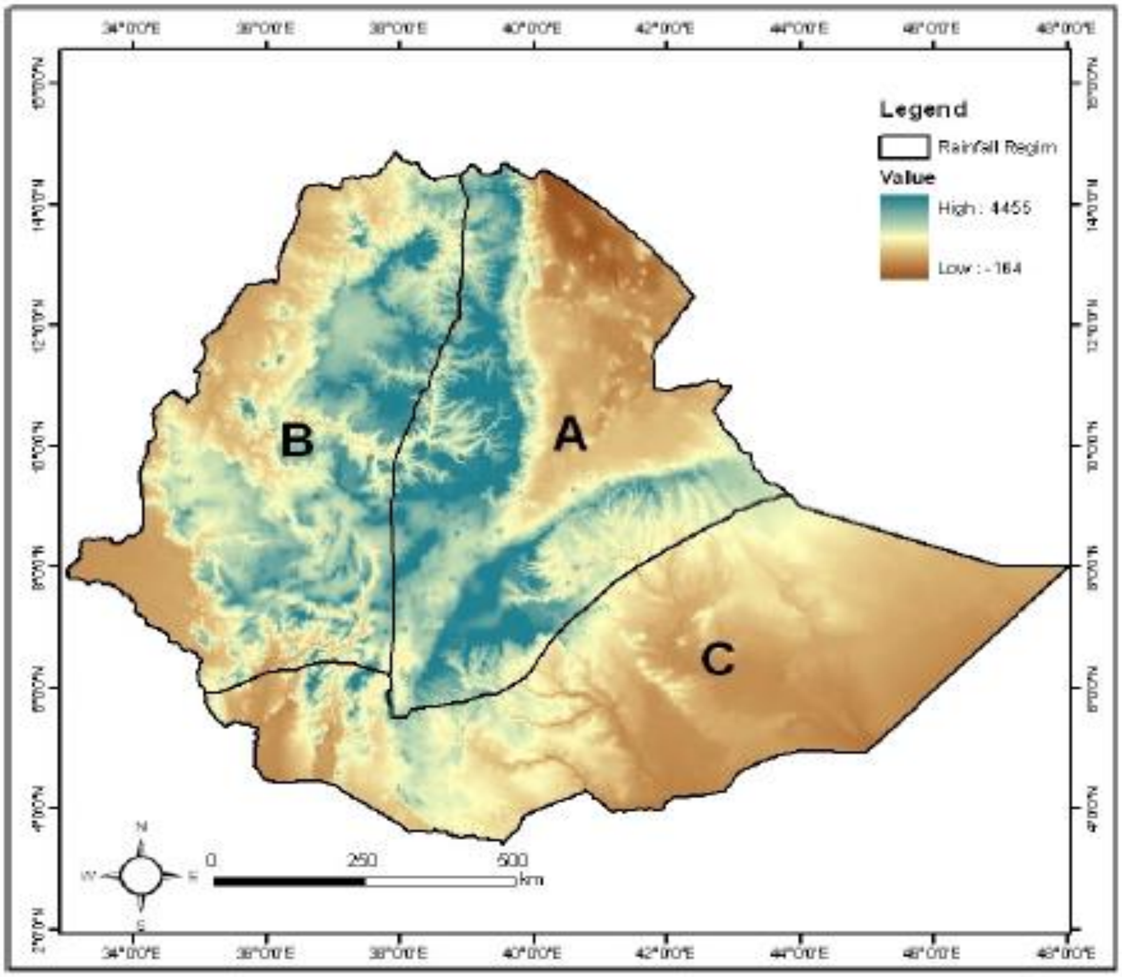
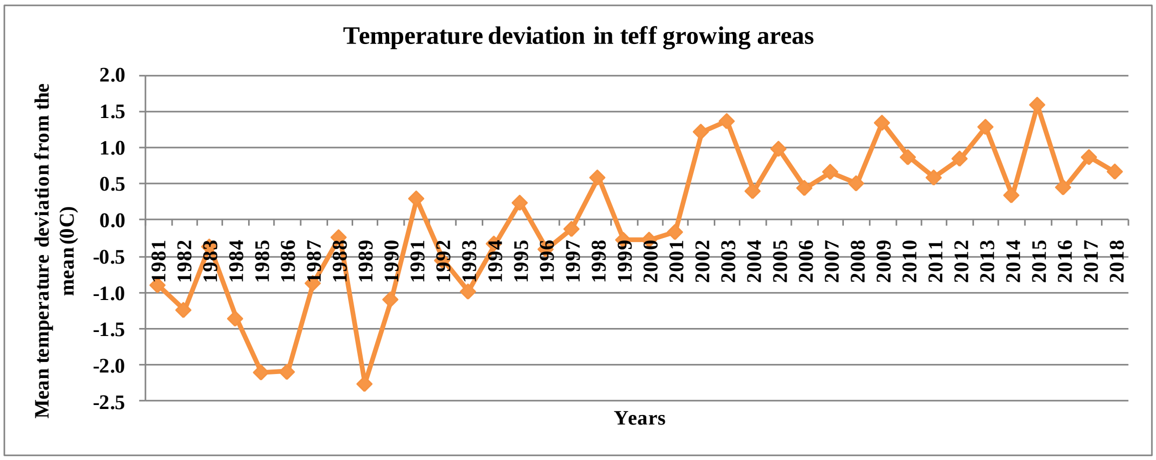


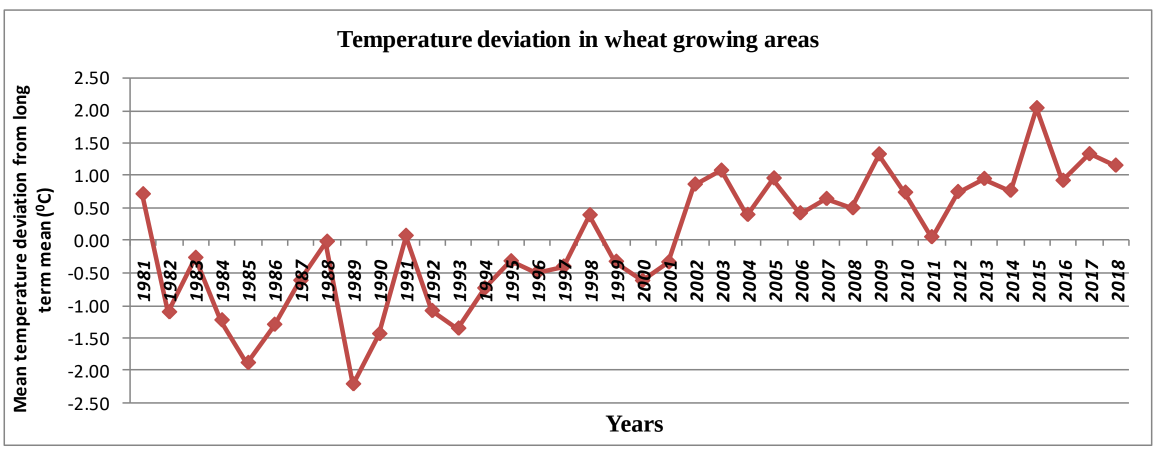
Figure 2.9: Topographic map of Ethiopia showing Rainfall Regimes (Modified from NMA, 1996)

2.4.3 Past and recent trends of climate in Ethiopia

A scrutiny of the past trends of weather situation in Ethiopia signifies that rainfall and temperature are dynamic, they are not static, but they have been changing over time. For instance, meteorological data from NMA (2019) verifies this fact; for it suggests that largely, Ethiopia has been experiencing increasing temperatures for the last 38 years (1981 to 2018) at an average rate of 5.2 percent, 2.3 percent, and 0.4 percent in the *teff*, wheat and maize growing areas respectively, consequently depicting a general warming temperature over time. Nevertheless, data revealed variability of temperature in teff, wheat and maize growing areas. Figure 2.10 shows year to year/yearly variability of temperature in teff, wheat and maize growing belts of the country. The temperature variations in teff, wheat and maize growing areas have been computed using data recorded in 20 weather stations located in high potential areas for teff, wheat and maize farming. The list of weather stations selected for this study is presented in Appendix 2.1.

The yearly variation of average temperature between 1981 and 2018 depicts a minute increase with fluctuations of up to -2.2^{0}C and +1.6^{0}C in teff growing areas, -2.2^{0}C and +2.03^{0}C in wheat growing areas, and -2.95^{0}C and +2.43^{0}C in maize growing belts.





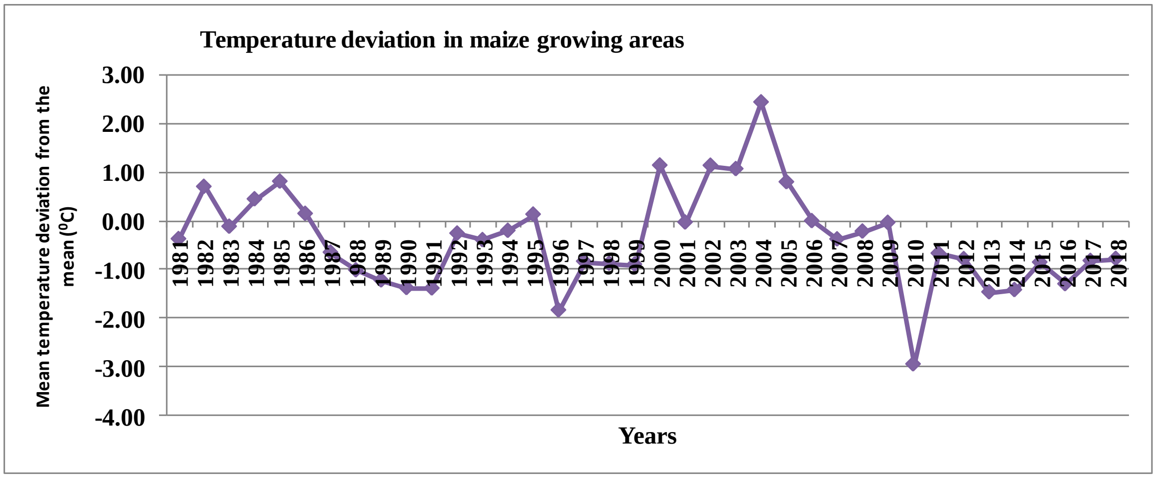
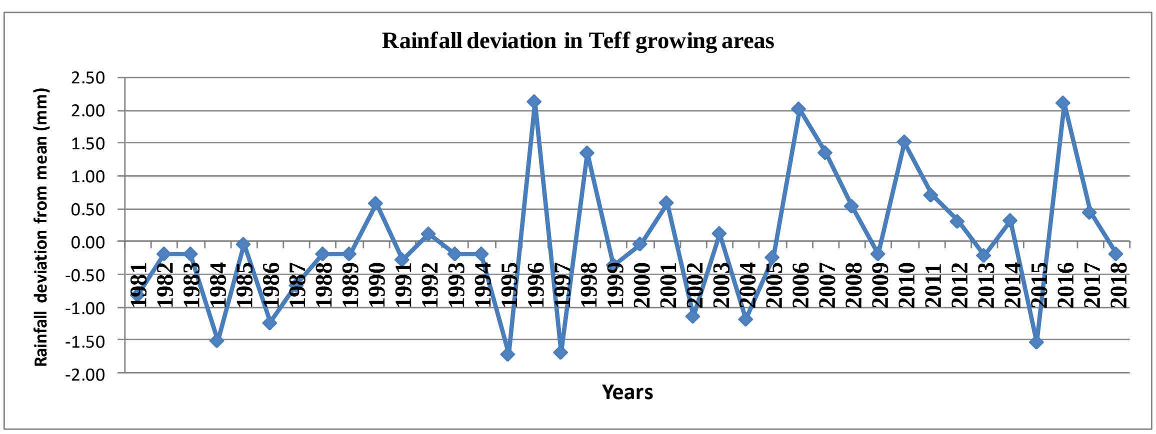
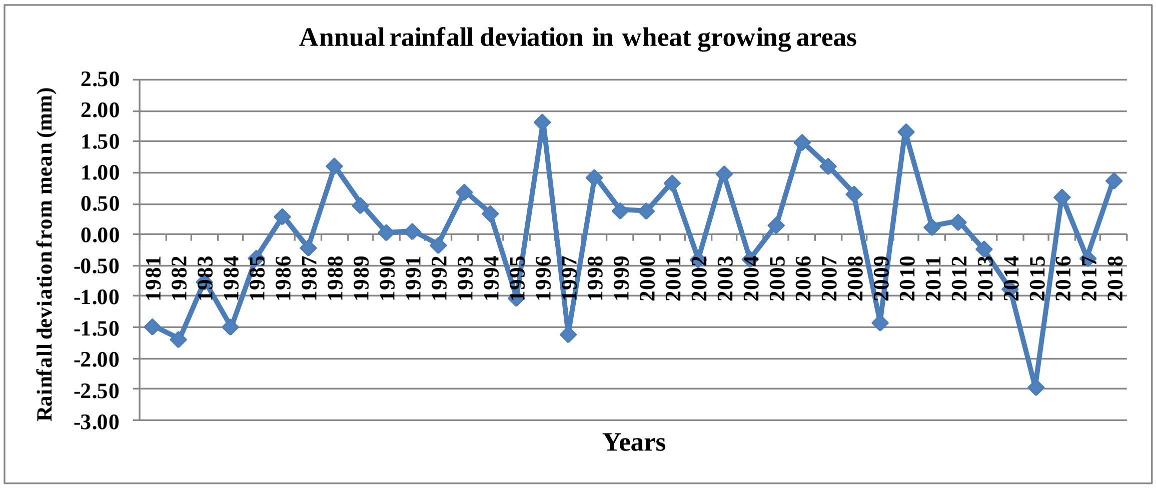


Figure 2.10: Annual mean temperature variations in wheat, teff and maize growing regions
Source: Ethiopian National Meteorology Agency, 2019

Similarly, the deviation in rainfall amount from the mean annual rainfall spanning through the period of 1981 and 2018 manifests a remarkably high level of variability, characterized by wet and dry conditions (for details see Figure 2.11 below). While the dry conditions are representing drought and famine periods, oppositely, the wet conditions do account for the flood conditions in the crop growing regions of the country. The changes observed stem from the atmospheric and oceanic circulation, mostly caused by differential heating of the sun on earth. Atmospheric-ocean circulations result into variation of climate every season and every year. Subsequently, the fluctuation evidenced the occurrence of extreme weather events that have been witnessed in the country. For instance, severe droughts occurred in 1983/84, 1994/95, 2003/04 and 2008-2010. Besides that, the country experienced a flooding in 2002, which is intricately linked to El Nino events.





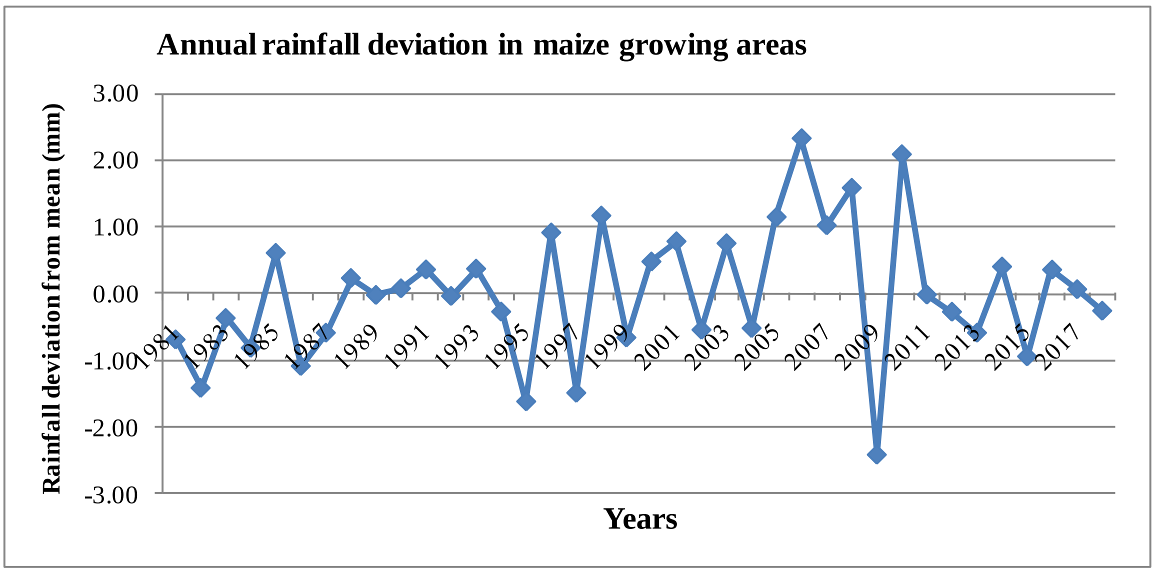


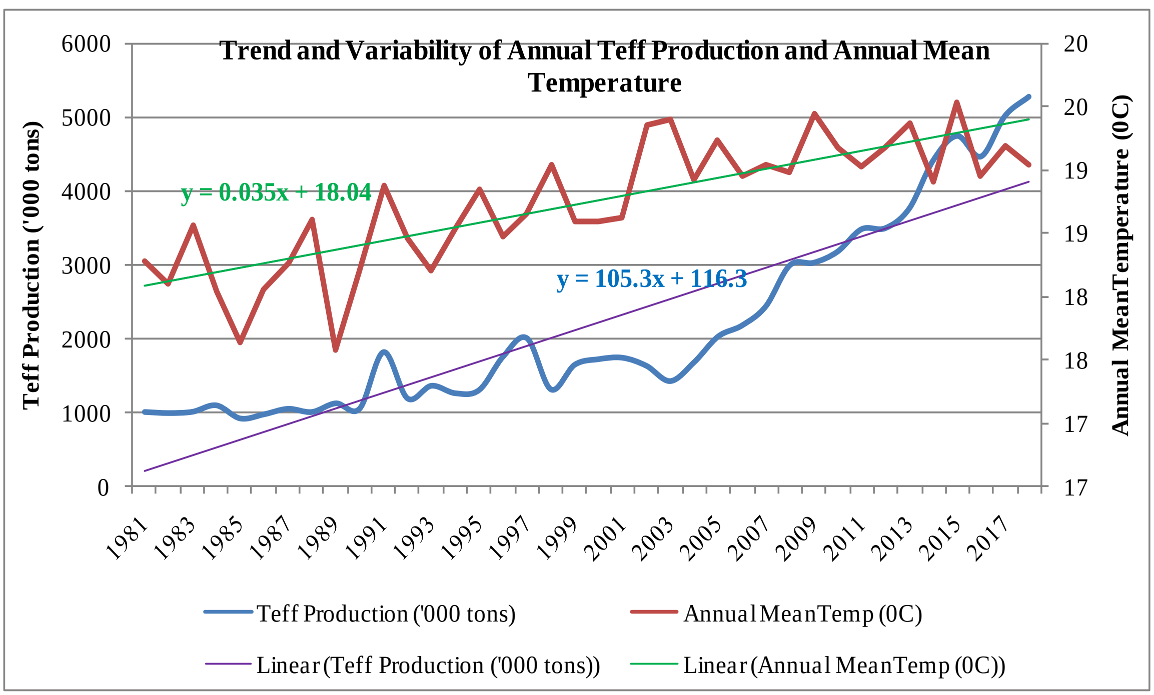
Figure 2.11: Annual mean rainfall variations in wheat, teff and maize growing regions

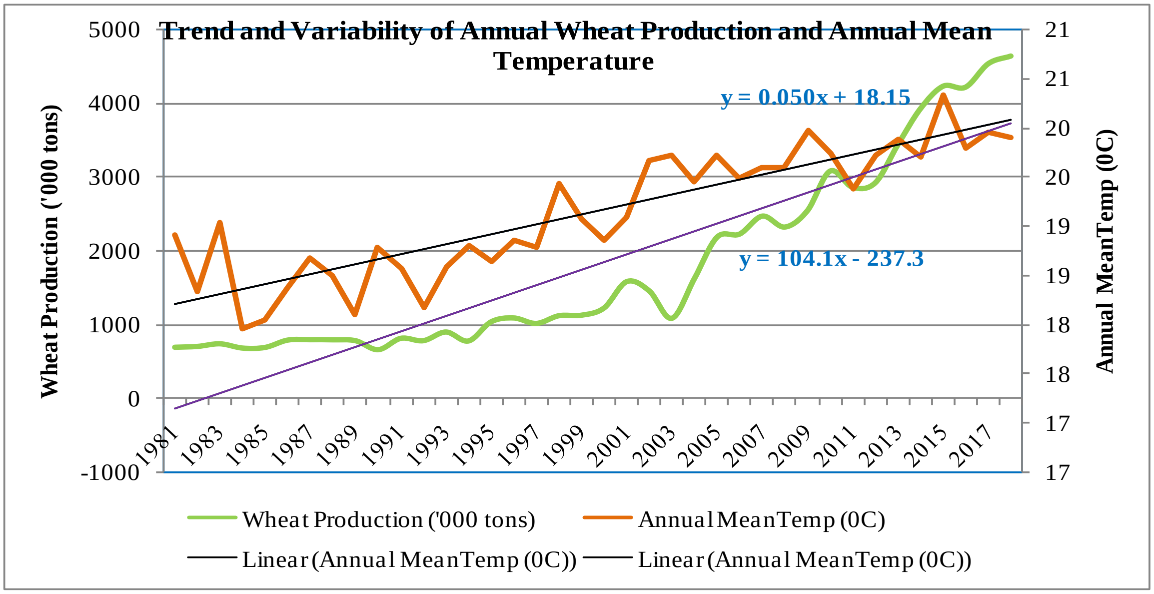
Source: Computed and constructed with data from National Meteorology Agency, 2019

2.4.4 Comparison of Trends of Annual Production and Climatic Variables

In this sub-section, comparison of the variations and trends in annual crop production vs mean annual climatic variables were made and presented. Such analysis will enable to compare the annual mean climate variables (rainfall and temperature) with the annual crop production variables in teff, wheat, and maize growing regions.

Figure 2.12 presents comparison of trends and variability of annual crops production and annual mean temperatures in Teff, Wheat and Maize growing areas. As can be seen from the figures, annual mean temperature has portrayed increasing trend in all crop growing areas, viz. teff, wheat and maize, which aligns with the global warming events. The analysis showed that temperature was being increasing with a magnitude of 0.04%, 0.05% and 0.03% in teff, wheat and maize growing belts. Equally, the result showed precence of high variability /fluctuations in temperature over the period 1981 to 2018 (3.8 decades). Similarly, the crops under study, i.e. teff, wheat and maize showed an increasing trend with a magnitude of 105.3%, 104% and 104% respectively over the observation period (38 years). Correspondingly, all the three crops had exhibited fluctuations from 1981 to 2003, during which most historical droughts were occurred. It can be seen from the figures that the variations in the annual production of crops directly associate with the relatively high variability in annual mean temperature. Furthermore, the relatively high increasing trend of all the three crops were partly attributed with adoption of modern technology (fertilizer, improved seed, chemical herbicides and pesticides, farming techniques), expansion of land area cultivated, and growth in population which accommodated the additional land put under cultivation.





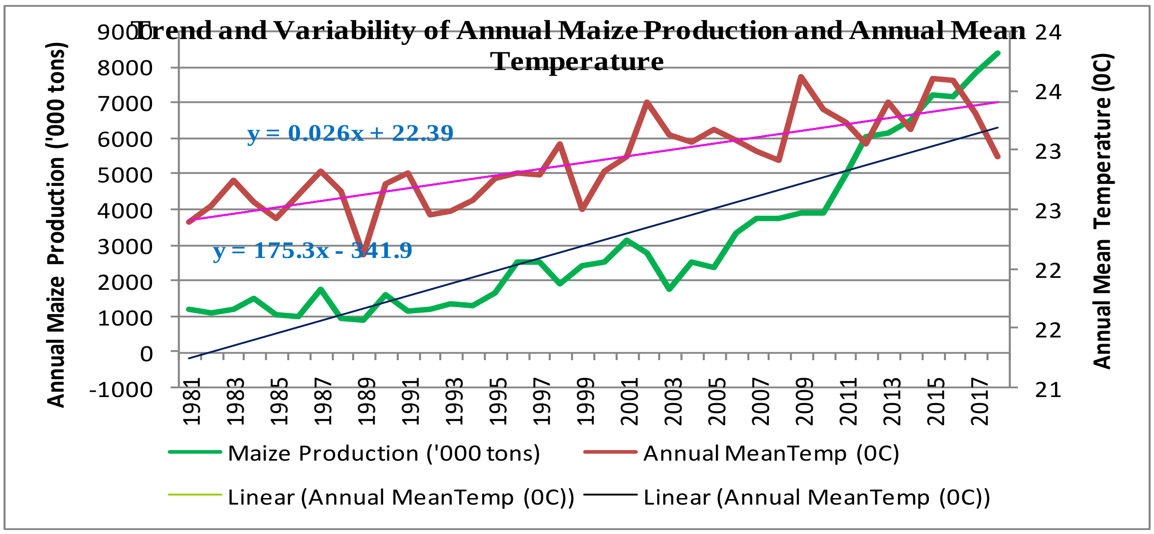
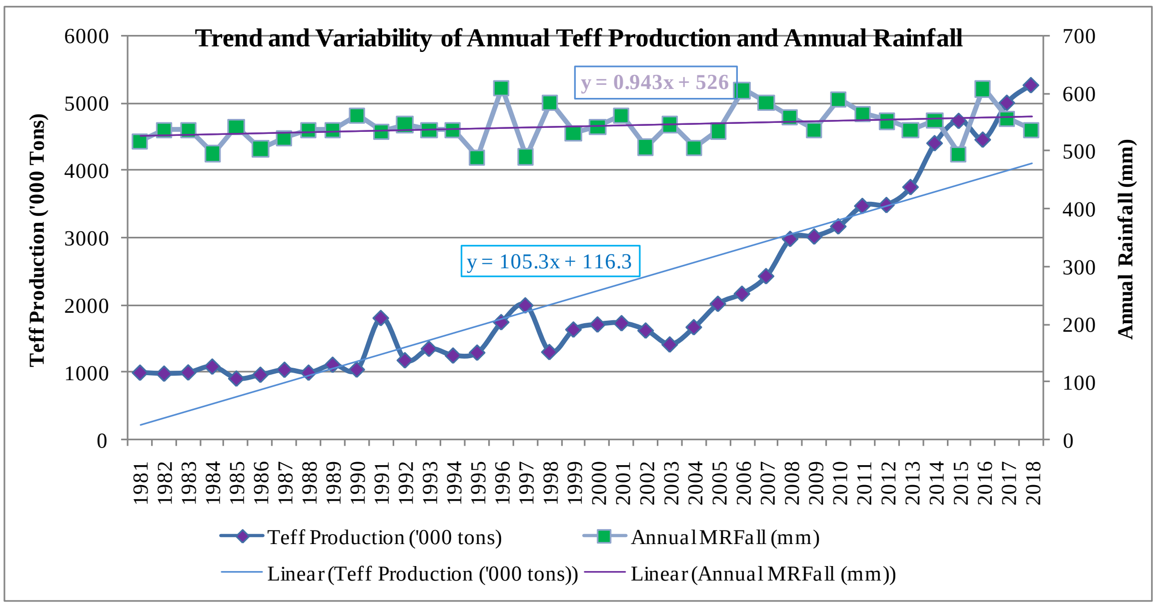
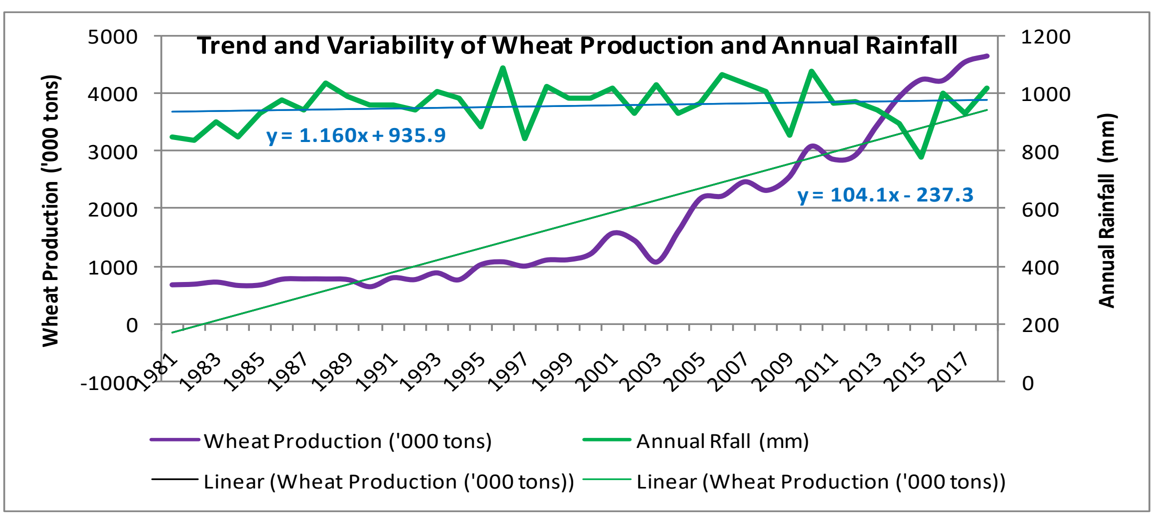


Figure 2.12: Comparison of Trend and Variability of Annual Crop Production and Annual Mean Temperature in Teff, Wheat and Maize Growing Areas

Source: Computed and Constructed from Raw Data from CSA and NMA, 2021

Moreover, comparison of annual mean rainfall and annual crop production in teff, wheat and maize growing belts has been made. Figure 2.13 presents comparison of annual crop production and annual mean rainfall in specific growing areas of crops selected for the study. The annual rainfall showed a slight increase over the study period of 38 years in teff and wheat growing areas with a magnitude of 0.94% and 1.16% respectively. However, the annual rainfall showed decreasing trend in maize growing areas with magnitude 0f (--0.78%). Correspondingly, annual production of teff, wheat and maize have shown increasing trend over the study period from 1981 to 2018, with magnitude of 105.3%, 104.1% and 175.3% respectively. As can be seen from the figures, the observed data shows that the annual productions of crops under study were increased sharply from 2004 to 2018. Conversely, both annual rainfall and annual production have exhibited fluctuation/ variability in all the three crops growing areas. The variation in annual rainfall was observed throughout the study period in the teff, wheat and maize growing belts. More pronounced variation in annual teff, wheat and maize production volume was seen from the period 1981 to 2003 which correlates with variations in annual rainfall in the study areas.





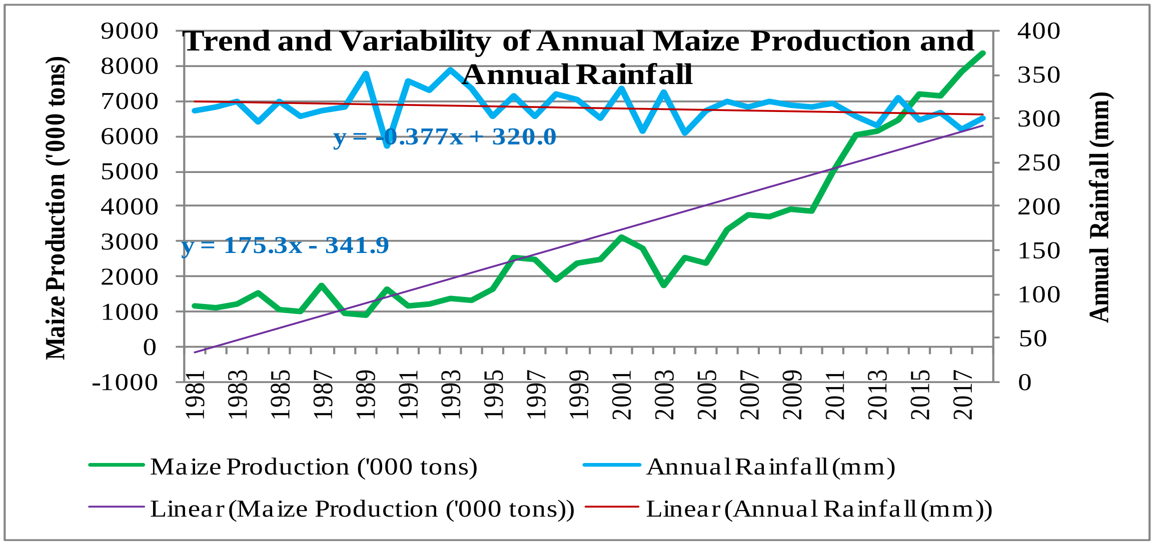


Figure 2.13: Comparison of Annual Crop Production and Annual Rainfall in Teff, Wheat and Maize Growing Areas

Source: Computed and Constructed from raw data from CSA and NMA, 2021.

In summary, detailed analysis of trends in and characterization of weather variables such as rainfall and temperature by season, crop and area of growing is presented in Chapter V of this study.

2.4.5 Vulnerability of Ethiopian agriculture to climate change

Evidences from review of previous studies show that Ethiopia is among the countries most vulnerable to changes and variability in climate factors. Consequently, changes in climate factors undoubtedly would affect the production and yield of the agricultural crops sector by diminishing the fertility of soils as well as increasing infestation of pests and crop diseases (Assefa *et al.*, 2006). Evenly, climate variability severely aggravates the scarcity of agricultural inputs and supply of improved crop seeds, besides leading to frequent drought and floods; the recurrence of these two can be ascribed to low use of irrigation facilities, population pressure, poverty, coupled with inadequate institutional capacity to design and implement appropriate adaptation and mitigation mechanisms to abate the effect of climate change (Assefa *et al.*, 2006).

Thence, it is evident that changes in climate is responsible for variability to weather variables such as rainfall, temperatures, concentration of carbon di oxide (CO_2), and rising temperatures and prolonged droughts. Pertinently, these weather variables have negatively affected the production of cereal crops of the country. Although farm households apply the factors of crop production such as chemical fertilizers, improved seeds, human labor etc. under the conventional rain-fed crop production systems to achieve increased agricultural crops outputs, their capacities to perform the business with competence often rely on the likely risks involved in crop production. The major drivers of these risks include variety of factors such as weather variables (rainfall, temperature, CO_2 emission, etc.), agro- ecological variables, farm practical and technical conditions (soil degradation, overgrazing, forest degradation) in the production environment and farm specific characteristics. Since the agricultural production business is primarily affected by weather, agroecological, and farm characteristics, they necessarily influence farmer's productive competence and their productivity. Despite the growing studies on the changes in climate factors, there exists scarcity of literature that deals with the influences of weather variables as well as agro-ecological variables on the yield and production of cereals at farm- and national-level in the country. Moreover, studies that were already carried out to assess the influence of weather variability on productivity and production of cereal crops in the various agro-ecological zones of the country are also inadequate.

Correspondingly, regarding the inevitability of changes in climate factors, it is apparent that these natural fluctuations can lead into more serious and contrary socio-economic consequences in the long-term. Exclusively, the farm production business can seriously be influenced by forecasted alterations in weather variables (temperature, rainfall, and CO_2). Available studies indicate that the influence of changes in climate variables on the farm production business would be found unevenly distributed across the regions of the country, while lowland areas are anticipated to be highly and adversely affected by the recurring changes (Stern, 2006).

Furthermore, latest projections clearly showed that unless appropriate measures that abate global warming are taken timely, global productivity of crops will assuredly be reduced by 15.9 percent by the 2080s; while a disproportionately large decline of crops productivity reach 19.7 percent in the developing countries (Cline, 2007).

In terms of changes in climate, Africa can be considered as one the most susceptible and unreasonably affected Continent in the world. According to FAO (2011), farming in Africa is primarly operationalized under conditions of rain-fed, amplified land degradation, and low levels of irrigation inputs (which is 6 percent compared to 38 percent in Asia). In view of this, it is evident that the economies of Sub-Saharan Africa have been tremendously susceptible to agroecological and economic shocks in the agricultural sector.

Ethiopia, as one of the Sub-Saharan African Country, relies heavily on rain-fed based farming although it contributes about 35 percent to the overall GDP of the country (PDC, 2018). Estimates indicate that cereals on an average accounted for 63 percent of the real value of crop output or about 20 percent of real GDP during the period 2005-2014. Among cereals, Teff is Ethiopia's most important cereal crop accounting on average for 19 percent of real value of crop output or 6.1 percent of real GDP. The other two major cereals, i.e. maize and wheat, accounted for 13 percent and 12 percent of real crop output, respectively (Bachewe, *et al.*, 2015).

Nevertheless, long term statistical data evinces that the agriculture GDP is highly affected by extreme rainfall events in the country. According to the World Bank (2020), climate variability is already negatively impacting livelihoods in the country and this is expected to continue. The report exemplified that drought is the single most destructive climate-related natural hazard in Ethiopia. In this regards, estimates suggest that climate change may reduce Ethiopia's GDP up to 10% by 2045, largely through drought-induced impacts on agricultural productivity (USAID, 2016). Economic impacts depend largely on the extent of annual weather variability and extremes, however recent major droughts have reduced the country's GDP by 1% to 4%, and rain-induced soil erosion has been estimated to reduce GDP by approximately an additional 1% (CGIAR, 2018).

On account of the above, so as to observe the effect of changes in climate factor on the performance of the economy of the country (GDP), mean rainfall has been associated to the movement of the economy (GDP) and agricultural GDP (AGDP) between the period of 1999 and 2018. Figure 2.14 explicates growth rates in real GDP and real AGDP with the long-run rainfall movement in the country. It is obvious from the graph that extreme dry rainfall has substantially affected the agricultural sector of the country during the recent years, first between 2002 and 2004, then spanning through 2011 and 2012, and lastly, from 2015 to 2016. Importantly, this evident strong susceptibility of the Ethiopian economy to variability in rainfall is largely due to the poor capacity of farming households in rural areas to adapt new and modern methods of farming. Rather they persistently hold on to old farming practices, mostly the oxen drawn traditional plough, low per capita farmland holding approximately less than one hectare per farm household, low level of technology use, and very poor marketing infrastructure facilities. All these have evidently become potential constrains to effectual production. Furthermore, the variability in availability of the hydrological possessions connected with worldwide and regional climatic inconsistency administered by complex land–atmospheric–ocean processes have adversely impacted the economy of the country.

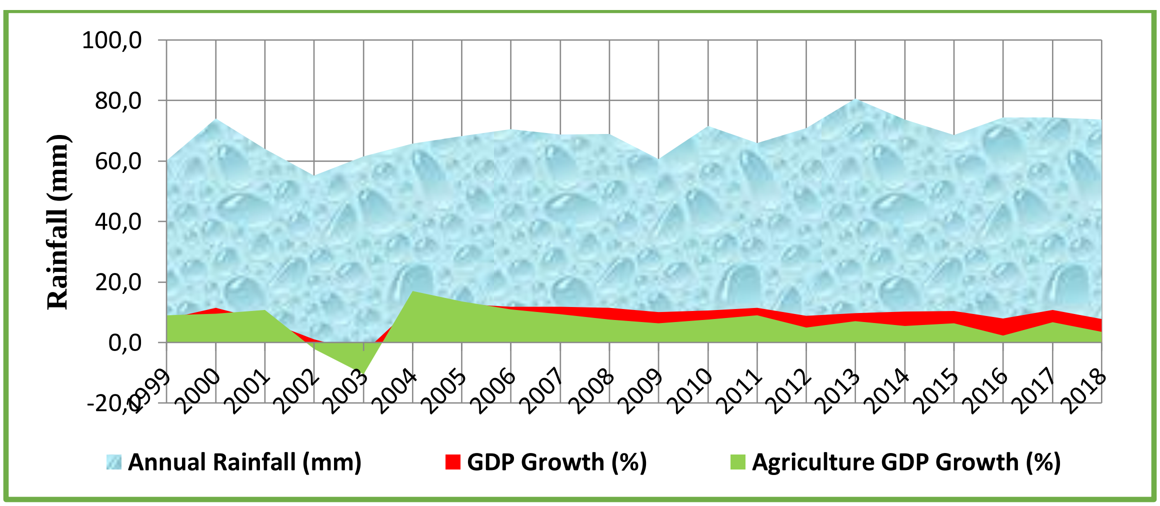


Figure 2.14: Rainfall, GDP growth and Agricultural GDP growth in Ethiopia
Source: Constructed by raw data obtained from WB Climate Portal and NBE (2018)

It has been assessed that the amalgamation of international, regional and sub-regional, as well as local climate drivers trigger deviations in climate over space and time cannot be rebutted. Congruently, some of the popular and central global climate drivers are the ENSO, PDO, and NAO. According to the assessment made by Anderson and Strahler (2008), these global climate drivers demonstrate that amongst all, ENSO is responsible for more than 20-30 percent global climate variability. This finding consequently rates ENSO as one of the crucial and key climate drivers for forecasting climate variability in the various parts of the world (RESCAP, et al., 2016).

Moreover, the ENSO is an intricate cyclic weather condition that manifests in a cyclic fashion, precisely between the periods of 3 and 7 years. While the warm period of ENSO is labelled El Niño; oppositely, its cold period is described as La Nina. El Niño represents the warming of the central and eastern Pacific or the entire Pacific basin, and its complex patterning adversely influences trade winds, which automatically affect atmospheric conditions and weather patterns. La Nina is the reverse cycle, and it pertains to the cooling of the central and eastern Pacific Ocean. Essentially, the workings of La Nina consolidate the normal circumstances in the Pacific. In addition, the notable stages in ENSO's necessarily influence the weather system in varying ways, which ultimately eventuate into biophysical and socioeconomic contrary impacts.

In Ethiopia, the long-season rainfall (Kiremt) responsible for the significant part (approx. 65–95 percent) of crop growing season is established by ENSO, also augmented by local climatic variable forcing (Korecha and Barnston 2007). Equally, it is assumed that droughts occurred during the main rainy season are connected to the warm ENSO episodes (Wagesho, et al, 2013). Some researches exhibited that the low frequency of variation in North Atlantic SST, identified as the North AMO, have been designated with mutually hot and chilly weather conditions during the last one and half century. Subsequently, it abides upon the pattern of rainfall of the globe that resulted into drought and storms (Enfield *et al*. 2001, Trenberth and Shea 2006) of erratic degree with noticeable effects in the North Atlantic regions. Similarly, its effect is apparent over the northern areas of this country. Taye and Willems (2012) confirmed that BENSO fluctuations that happen on the Pacific and the Atlantic oceans would greatly affect the precipitation distribution and amount around the areas of the upper Blue Nile basin of Ethiopia. AMO displays an incredibly potent and substantial connectivity to rainfall and stream flow throughout the dry season of the area.

As agriculture is a vast sector in Ethiopia, its contribution to the economy has been also perceived as enormous. This has been confirmed by the correlativity between variations in rainfall and agricultural value-added growth rates given in Figure 2.15. It is evident from the figure that every decrease in the amount of rainfall is accompanied by a drop in the growth of agricultural value added. The sharp decreases in the amount of rainfall during 1984, 1993 and 2002 coincided with the droughts and famines of 1984-85, 1993-94 and 2003-04 respectively. Thus, the dependence of the farming business and the overall economic growth on rainfall variables underscores the significance of timely and quantity of rainfall available in the in the country.

Some studies on CO_2 emission and concentration have discovered the harmful influences of changes in climate factors on the farming business and the overall performance of the economy in Ethiopia. For instance, a research carried out by Mulatu, *et al*. (2016) submits that CO_2 discharges would affect agricultural productivity in a negative way, including livelihood of farm households in Ethiopia. The study results equally showed that CO_2 concentrations have a contrary effect on the production of cereal crops such as teff, maize and wheat. However, the adverse effects of CO_2 concentrations have lead to significant decrease on farming factor productivity, particularly with respect to maize and wheat production. The reason for the adverse effect caused by CO_2 discharges is that greenhouse gas (GHG) can influence a change to the quantity and timing of rainfall, in addition to and increase in temperature.

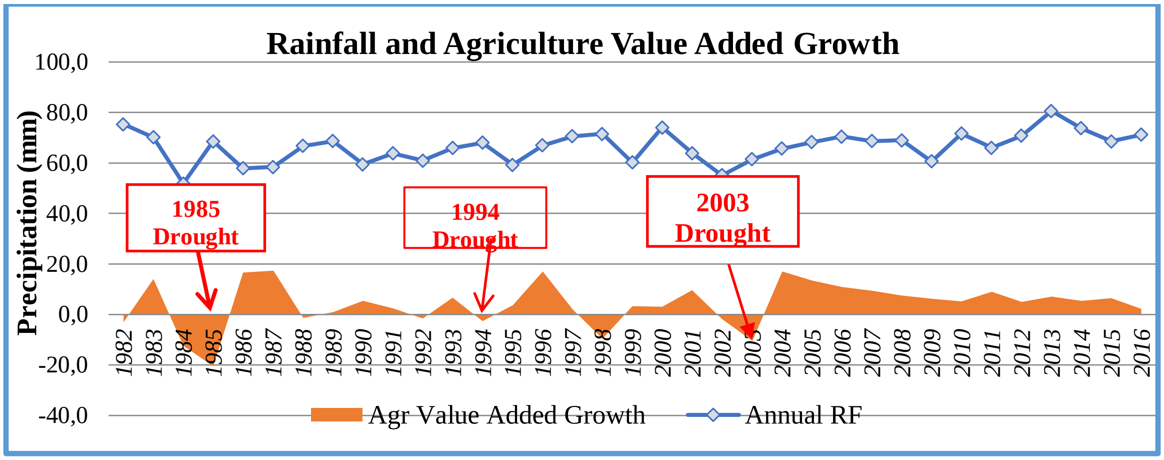


Figure 2.15: Rainfall and Agricultural Value-Added Growth in Ethiopia.
Source: Constructed using data obtained from WB Climate Portal and Trading Economics website (2018)

In Ethiopia, empirical data demonstrate that most CO_2 emissions are offshoots of agriculture sector through agricultural activities. Therefore, these CO_2 emissions comprise those green house gases (GHG) that released as methane (CH_4) and nitrous oxide (N_2O). They originate from enteric fermentation, synthetic fertilizers, including the compost left on grazing land, crop remainders and flaming savanna land, to point out just these. However, recently, the carbonate (CO_3) emissions resulting from agriculture activities have increased over the years. For example, there was an upsurge of CO_2 emission from agriculture from 20.13 teragram in 1981 to 99.43 teragram in 2018. This consequently evidenced growth of 295.7% over the period or 7.8% growth per annum (see Fig. 2.16 for details).

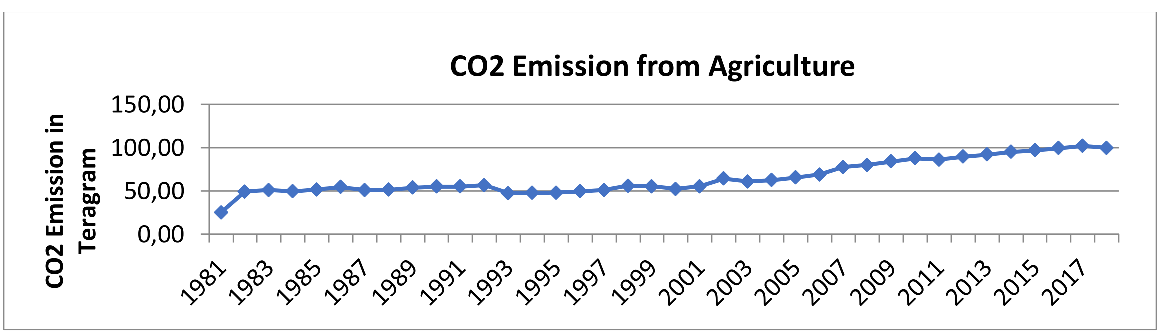


Figure 2.16: Trend of CO2 emission from agricultural activities
Source: Constructed from FAO data, 3018.

2.5 The climate change policy environment

The economy of Ethiopia relies heavily of on rain-fed agriculture. Subsequently, because of this dependency on rain-fed system, the country is necessarily subjected to the severe influences of variability in climate and weather factor extremes and its dictates. In order to cope with and adapt to the various climatic condition of the country, as well as to mitigate the tailgating challenges, the Government of Ethiopian had approved the Environmental Policy of the country on April 2, 1997, which has been stipulated by the Council of Ministers. Their specific objectives were to adopt preventive and protective procedures against land, air and water pollutions, in addition to guaranteeing active participation of the community towards ecological management, coupled with sensitizing the public with the knowledge they needed regarding their environments, amongst many others.

In addition to the 1997 environment policy, the government of Ethiopia (GoE) endorsed and adopted the UN Convention on Biological Diversity (UNCBD) conservation. Consequently, based on that endorsement and adoption, government has designed and is being implementing a National Biodiversity Strategy and Action Plan (NBSAP), the charge-coupled device (CCD), and relevant National Adaptation Plan (NAP), and United Nations Framework Convention on Climate Change (UNFCCC). Equally, in April 2016 the GoE signed the Paris Agreement on climate, which was sanctioned in March 2017. By the same token, the Ethiopian government prepared its First National Communication to the UNFCCC in 2001, while its Second National Communication came into existence in 2015, followed by a NAPA in 2007. Meantime, the EPACC (2010) was updated and in turn, replaced the NAPA with the with the sole objective of eliminating poverty, besides laying needed foundation that would also make possible a climate resilient path geared towards stable development. In addition to the aforesaid, Ethiopia has also submitted NAMAs to the UNFCCC.

Besides, Ethiopia has also integrated change climate objectives into the broader national plans and policies of the country. As growth and transformation plan (GTP) I & II aims to attain middle-income status by 2025, the framework from GTP I (2010-2015) was further modified, and the nation's CRGE strategy incorporated into the GTP II (2015/16 –

2019/20). Equally, the GTP II takes into cognizance the needs of Ethiopia to establish and ensure a lasting food security. On account of this, adaptation and mitigation programs are given priority so as to realize sustainable economic growth, coupled with the attainment of lower-middle income status, and exclusive of net increases in GHG emissions relative to 2010 levels.

Ethiopia's Climate-Resilient Economy (CRGE) Strategy is considered moderately exceptional mainly because it allows for the achievement of economic and climate change goals. The Secretariat for CRGE, with both the technical and financial unit established at the former Ministry of Environment, Forest and Climate Change (MoEFCC) and now replaced by Environment, Forest, and Climate Change Commission (EFCCC), and Ministry of Finance (MoF) provide a standardized guidance, as well as make available an ad hoc sector specific support to CRGE line ministries that are responsible to implement the strategy.

However, the share given to global GHG emission by Ethiopia is found very minimal. Nonetheless, emissions from agriculture and energy sectors doubled since 1994, and they are the major emitters in the country. Therefore, they are responsible for 85% and 15% of the total gas emission, respectively. The implication is that these sectors are plausible potential channels for mitigation. While some of the strategic directions endorsed by the government in its policy are clean development mechanisms (CDM) measures, derived from agriculture and hydroelectric plants, geothermal and wind turbine, including conservation of energy by means of efficient and switching of energy sources. The strategic directions also include the utilization of compact and efficient vehicles, interchanging means of transport to fuel efficient modes of transport, as well as using effectual stoves. It has been assessed that these directions align with the United Nations Framework Convention on Climate Change (UNFCCC) recommendations (MoFED, 2010).

2.6 Summary

This chapter has expounded on the significance of the agricultural sector to the economy of Ethiopian. However, it has been assessed that the Ethiopian agriculture sector performance was poor over the past three decades, despite the various policy and strategic interventions adopted under the different socio-political regimes. It has also been assessed that the poor achievement of the farming sector emanates from various socioeconomic and ecological constraints. The main socioeconomic constraints that impeded the achievement of the farming sector include: weak socio-economic and infrastructural set-ups; ineffective policies; soil degradation; deforestation; overgrazing of farmlands; population pressure; and low productive capacities and technologies to be applied in the farming sector. Conversely, the major environmental drivers encompass: droughts; frost, flooding; landslide; hailstorms; and infestation of insect pests.

Along the diverse agro-climatic zonation systems (i.e. *Wurch*, *Dega*, *Weynadega*, *Kola* and *Bereha*), different crop types and farm animal genus could be produced and reared as source of revenues for millions of smallholder farm householdsfarmers as well as pastoral communities residing in the country. It has been learnt from the assessment of past trends of rainfall and temperature that prevailed over the observation period that there exists an exceedingly high level of variation in climatic variables. Future forecasts of rainfall and temperature variables also exhibited that temperature would increase whereas rainfall would decrease.

Many studies show that most Ethiopian farmers are vulnerable to changes in climate, which are accredited to reliance on rain-fed agricultural production and high prevalence of poverty. It has also been learnt from review of past studies that the achievements of the key macro-economic measures such as GDP equivalently moves along with the course of precipitation; that means, fine precipitation means high-quality achievement of economic businesses and vice versa. Conversely, susceptibility owing to occurrence of poverty is ascribed to shortage of valuable, adaptive, tolerate, and mitigating strategies, equally at farm household and public levels.

CHAPTER III

CONCEPTUAL FRAMEWORK AND REVIEW OF LITERATURE

3.1 Introduction

This chapter presents the review of conceptual and theoretical framework as well as review of literature of previous studies conducted on the impacts of changes in climate on yield and production of cereal crops that are relevant to the current study. Each is taken in turn.

3.2 Conceptual and Theoretical Framework

This sub-section presents the conceptual and theoretical frameworks most often adopted in the examination and modeling of the influence of changes in climate variables as well as socio-economic variables on crop production and productivity.

3.2.1 Conceptual Framework

As conceptual framework, this investigation adopted the driver-pressure-state-impact-response framework to examine the impact of changes in climate on yields and output supply responses of teff, maize and wheat. This conceptual framework approach has adopted considering that it provides a structure within which to present the indicators needed to be furnish feedback to policy makers and planners in the field of environmental factors and the resulting impacts of the political choices made, or to be made in the future in an effort to reduce vulnerability climatic factors and restore resilience among the community. The framework was originally postulated by the OECD (1993) and the EEA (1995). As the name implies it interprets the interconnection between the five components that make up the framework, in addition to validating the complementarity between the causal relationships. As a result of its precise and effectual elucidation of causal relationship, the concept has been extensively used for the interpretation and evaluation of social and environmental setback of climate factors systems subject to influences of anthropogenic actions. This causal framework specifically presents a comprehensive description of the interactive transaction between society and the environment. This particular aspect of the conceptual framework articulates the extension designed by OECD so as to systematize and standardize the application of environmental indicators (OECD, 2003). The "driver" in the framework spells out how human activity, industry GHG emissions, natural variability, amongst others, exert "pressure" on the environment through GHG concentration, ice sheets shrinking, rise in sea level, and warming of oceans. Subsequently, as a result of this exertion, the "state" of the atmosphere is changed, which in turn eventuates into an alteration in mean temperature, precipitation or GHG accumulation in the atmosphere. Response, in this regard relates to the description of the community reaction, and not the ecosystem reaction. Accordingly, the explication of the societal response may give rise to the modifications of environmental policy. The eventual modification can encompass the introduction of taxes and improvement in the efficiency in reaction towards the changes.

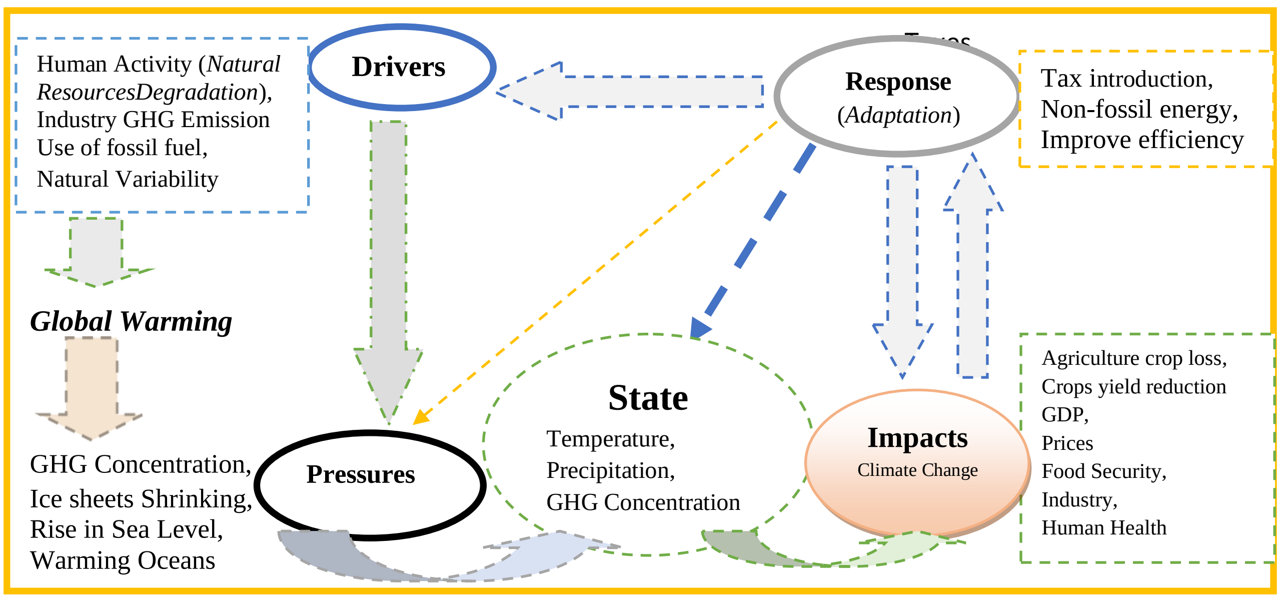


Figure 3.1: Conceptual framework for assessing impact of climate change
Source: Modified from Donnelly, *et al.* (2004)

Again, in 1999, the Ethiopian Energy Authority (EEA) expanded the framework, by including cursors of climate change drivers such as coal, oil and natural gass consumption and cursors of the "Impact" of changes in climate factors on the environment and ecological unit. Also included in the concept are agriculture, GDP, food security, industry, and human health. All these are represented in Fig. 3.1.

Meanwhile, in the current research, the investigator was focused only on the "Impact" part of the conceptual framework depicted below to assess impact of climate change on production and yield of selected crops.

3.2.2 Theoretical Framework

This sub-section deals with theories that expounds on decision making in agricultural production output, and climate change. The relevant theories are theories of climate change, production, profit maximization, and utility maximization. These theories are specially earmarked for explication because of their significance to the current study.

3.2.2.1 The Augmented Production Function

Neo-classical economic theory is a very vital tool that affords a precise and comprehensive evaluation of agricultural production. In economics, production is generally comprehended as the transformation of inputs into outputs. While inputs represent what is bought by a firm, that is, productive resources; oppositely, outputs are the goods and services produced by the same firm (Dewett and Chand, 1983). On a similar note, farm production depicts production of food, as well as fiber and livestock, through the employment of different kinds of inputs, which include improved seed, fertilizer, land, capital, labor, rainfall and other relevant inputs (Sadhu and Singh, 1983).

The central focus of **agricultural production in economics** is dealing with the quantitative relationships that are fundamental to production processes in agriculture. These associations have to do with input-output patterns and the various types of interactions between the individual inputs themselves and the products which contribute to the output. In addition, it is concerned with levels of factor costs and product prices, including the nature of production patterns, responsible for the realization of certain desired optimization, like profit maximization or cost minimization. Furthermore, the thrust of production economics covers all agricultural problems categorized under resource allocation and marginal productivity analysis.

As a matter of fact, in any production process, the output is dependent on the quantities of factors/inputs used, coupled with the proportions in which they are combined. Subsequently, these input-output relationships mark the starting point for a great deal of economic theory. The causal connection between physical output and the physical inputs utilized in the production process is described as ***production function*** (Sadhu and Singh, 1983). In production economics, production function can be defined as the physical association among production output (Y) and the various key inputs (X_1, X_2, X_3,….X_n) used in the production process. Essentially, production function articulates the association between production inputs and outputs (be it in agriculture or industrial manufacturing) by explicating the speed at which belongings (several inputs, X_j) are being converted into desired goods (single output, Y). The universal representation of the equation is specified as:

$$Y = f(X_1, X_2, X_3, \ldots\ldots.. X_n) \quad (3.1)$$

Where, Y stands for the quantity of farm output, X_1, X_2, X_3, ….. X_n capture the quantities of farm inputs. This equation indicates that total farm output Y depends upon the quantities, x_1, x_2, x_3, ……x_n of the factors X_1, X_2, X_3,…… X_n, respectively.

In the past, economists had drawn up several algebraic equation forms which can be employed to identify production functions. For instance, the following are the most common forms of production function: *Homogeneous Production Function, Cobb-Douglas Production Function, Linear Homogeneous Production Function, and Constant Elasticity of Substitution Function,* to mention just these.

3.2.2.2 Theory of Supply Response

Agricultural supply response is an expression that is used to elucidate the extent of production changes that results from changes on some significant variables, like output price, scale of production and prices of substitutes (Rao, 1989). Rao (1989) has the opinion that empirical estimates of elasticities depend both on the methodology adopted and on country specific factors relating to technology, economic structure and macro constraints. As a concept, it focuses on the clarification of the behavioral response of producers to changes in economic incentives (Nkang *et al.,* 2007). For instance, the extent of farmers' response to the changes in prices for a specific commodity is evaluated by the price-elasticity of supply of the relevant commodity itself. In economics price-elasticity of supply is defined as the proportionate change in amount of output supplied divided by the proportionate change in its own price (Kiiru, 2006). Economic theory stipulates that own-price elasticity of supply for any normal goods and services is expected to be positive (Nicholson and Snyder, 2008). It is evident from the various earlier studies that the price-elasticity of supply is always positive, which means that if suplly is elastic, the production process can enlarge output with no increase in cost or time holdup.

The approximation of farmer's supply response to price and other incentives was initially postulated by Nerlove in his seminal work in 1958 (Abiola and Ada-Okungbowa, 2012). In its simplest version, the Nerlove Price Expectations (P_t^e) and the supply function can be illustrated through the following equations:

$$X^*_t = a_0 + a_1 P_t^e + a_2 Z_t + U_t \qquad (3.2)$$

$$P^e_t = P^e_{t-1} + \beta(P_{t-1} - P^e_{t-1}) \qquad 0 < \beta \leq 1 \qquad (3.3)$$

$$X_t = X_{t-1} + \gamma (X^*_t - X_{t-1}) \qquad 0 < \gamma \leq 1 \qquad (3.4)$$

$$Ut \sim (0, \sigma^2_u),$$

Where,

X^*_t denotes desired acreage;

X_t is crop acreage under cultivation;

P^e_t is expected future price;

P_t is crop price;

Z_t is any other variable (weather);

U_t is a random residual; and

$a_0, a_1, a_2, \beta, \gamma$ are parameters.

Given that $0 < \beta \leq 1$, eq. (3.3) means that the present anticipated price $\boldsymbol{P^e_t}$ falls somewhere in between the last year's actual price $\boldsymbol{P_{t-1}}$ and the last year's anticipated price $\boldsymbol{P^e_{t-1}}$.

That is, the present year's anticipated price is being revised in proportion to the difference between actual and anticipated prices in the last year. If $\beta = 0$, the anticipation pattern is independent of the actual prices, and only one anticipated price for all time periods exists. If $\beta = 1$, the current year's anticipated price is always equal to last year's actual price.

Equations (3.2), (3.3), and (3.4) contain the long-term equilibrium and expected variables that are not observable. For the purpose of estimation, a reduced form that contains only observable variables may be written (after some algebraic manipulation) as follows:

$$X_t = \alpha_0\beta\gamma + \alpha_1\beta\gamma P_{t-1} + (1 - \beta + 1 - \gamma)X_{t-1} - (1 - \beta)(1 - \gamma)X_{t-2} + \alpha_2\gamma Z_t - \alpha_2(1 - \beta)\gamma Z_{t-1} + \gamma[U_t - (1 - \beta)U_{t-1}] \quad (3.5)$$

Essentially, the above reduced form represents the hypotheses and assumptions described above, although there might be possible to reach at the same reduced form of equation under a different set of hypotheses and assumptions.

3.2.2.3 Utility Maximization Theory

The utility maximization theory refers to the concept that individuals and farm house-holds seek to get the highest possible satisfaction from the economic decisions they are making. Utlity maximization implies expenditure minimization whenever preferences have local non-satiation (Mandy, 2017). According to Mohajan (2021), the original and modern concept of utility was developed in the late 18th century by the English moral philosopher, jurist, and social reformer, Jeremy Bentham (1748-1832). He provided the philosophy of utilitarianism that took for its fundamental axiom. In general, total utility can be maximized when marginal utility from the next unit consumed is zero (Saros, 2022). In case multiple products are being chosen, the condition for maximizing utility is that a consumer equalizes the marginal product per money spent. The condition for max-imizing utility is:

$$MUA/_{PA} = MUB/_{PB} \quad (3.6)$$

Where, MU is marginal utility and P is the price.

Consequently, the theory elucidates the consumption aspect of farm household's decision making process in prevailing markets. In practice, a farm household is considered as price-taker. In case a farm household is a price-taker in all the markets, then for every commodity and outputs the farm household consumes and produces, an optimal farm household production can be evaluated without considering leisure and consumption choices. The choice and uncertainty prevails when the decision maker has no objective knowledge about the probability of occurrence of the various possible states of nature. In economics, a price-taker is an individual farm household that must accept prevailing prices in the market, lacking the market share to affect market price on its own. In this case, all market participant farm households are considered to be price-takers in situations where all the establishments sell an identical product, there are no barriers to entry or exit, every farm household or company has a relatively small market share, and all buyers have full information of the market.

In cases the farm households are price-takers, decisions can be made on how to spend a fixed amount of income obtained from profit-maximizing production, to purchase combination of outputs that give the most satisfaction. The appropriateness of utilization maximization theory is validated through its recursive function by enabling sequential decision making, mainly because it incorporates profit and utility maximization components (Singh *et al.,* 1985).

In this theoretical model, the goal of a farm household is to harvest the highest possible satisfaction from the economic decisions they made. These decisions specifically refer to decisions such as the best possible number of hours used for labour to supply their labour, maximize the services received from consumer goods and services against the pre-set economic restraints.

In economic terms, a farm household maximizes utility through the consumption of all the available outputs and commodities (i.e., home-manufactures farm products, goods and services purchased from the markets) subject to full income, assets and output price constraints. The utility maximization model shows that if markets for assets and outputs prevail as well as all outputs and goods are tradeables, then prices are exogenous in which all production decisions are determined independent of the consumption decisions. Thus, the household production technique for the staple crop under condition of utility maximization theme can be specified as:

$$\text{Maximize } U = U(X_a, X_m, X_l) \qquad (3.7)$$

Where X_a are farm produced product, X_m is market-purchased good, and X_l is leisure. From the above model, utility is can be further maximized against cash income constraint as follows:

$$P_m X_a = P_a (Q_a - X_a) - P_l (L - F) - P_V V + E \qquad (3.8)$$

where P_m and P_a are prices of the market-purchased outputs and farm staples produced, respectively; Q_a is quantity of household's farm staples production; (Q_a - X_a) is the marketed surplus; P_l is the market wage; L is the labor input; F is family labour input; (L – F) if positive is hired labor and if negative, is off-farm labor; V is a variable farm input such as chemical fertilizer and improved seeds; P_v is market price of the variable input; and E is any non-labor, non-farm income variable.

As described above, a farm household may also face a time constraint, where that specific farm household cannot allocate extra time to the on-farm business, leisure or off-farm job than total time available to that specific household; which can be specified as:

$$X + F = T \qquad (3.9)$$

Where, T represents household's time, F represents off-farm time, and X represents time sepenton on-farm business. The farm household also faces production constraints or more specifically production techniques that portray association among farm inputs and outputs specified as:

$$Q = Q(L, A, K) \qquad (3.10)$$

Where, L represents number of labor input, A represents household's fixed land size and K is household's fixed capital stock.

In practice, the concept of utility maximization is guided by utility maximization rule. The utility maximization rule states that consumers decide to allocate their resources or maney income in a manner the last unit of resource or money invested or spent on each product or good bought yields the same quantity of extra marginal utility. This rule of utility maximization can be mathematically specified as:

$$\frac{MUx}{Px} = \frac{MUy}{Py} \qquad (3.11)$$

Where, MUx is the marginal utility derived from good x, Px is the price of good x, MUy is the marginal utility of good y and Py is the price of good y. As per the above model, the consumer is required to spend limited resource or money income on goods which shall give him the most marginal utility per unit of resource or money. The consumer is maximizing his total utility only when the ratio of MU/P is equal for all goods and services.

In the above elucidated models, the farm household is often considered to be price-taker in all the markets involved giving recurcive model. The three constraints prevailing among farm households in this regard can be collapsed into a single constraint. If cash income constraint is substituted into production constraint for Q_a and cash income constraint is substituted into time constraint for F in the previous equation, it yields a single constraint of the following form:

$$P_mX_m + P_aX_a + wXj = \mathrm{wT} + \pi \qquad (3.12)$$

Where π = $p_aQ(L, A, K) - wL$ and a measure of farm profits. In this model, the left hand side of the equation enunciates total household 'expenditure' on three items; i.e. market-purchased goods and services, the household's value of its own output, and the household's value of its own time in the form of leisure. The right-hand side of the equation, on the other hand, explicates the value of all the stock of time (wT) owned by the farm household. Furthermore, the addition for farm household comprises a measure of farm profits (p_aQ – wL) with all labor being valued at wage rate prevailing in the market, which considers the assumption of price-taking behavior in the labor market.

In all these equations, the farm household is expected to select the levels of consumption for the three products considered and the total allocated labor input as well as fertilizer and improved seed inputs for agricultural production businesses (Taffesse, 1998). In this context, the maximization of farm household utility subject to the newly established single constraint, with respect to X_a, X_m, X_l, L and V yields the following first-order equations:

$$P_a\frac{\partial Qa}{\partial L} = P_l = W \qquad (3.13)$$

…… equate to marginal revenue product of labor to the market wage

$$P_a\frac{\partial Qa}{\partial V} = P_V \qquad (3.14)$$

$$\frac{\partial U}{\partial Xa} / \frac{\partial U}{\partial Xm} = \frac{Pa}{Pm} \qquad (3.15)$$

$$\frac{\partial U}{\partial Xl} / \frac{\partial U}{\partial Xm} = \frac{Pl}{Pm} \qquad (3.16)$$

Equations 3.14 and 3.15 exhibit that farm households would weigh against marginal revenue output for labor and fertilizer inputs to their corresponding market prices. A significant characteristic of the two equations emanates from the fact that they contain only two endogenous variables, *L* and V. The other remaining endogenous variables, i.e. Xm, Xa, and XL, do not emerge in equations 3.13 and 3.14; given this, they have no effect on farm household's preference of *L* or V, provided that all second-order conditions are met. From this, one can understand from the system that the demand for farm labor and fertilizer can be ascertained as a function of prevailing prices (Pa, Pl and Pv,), the parameters of techniques the production function, and the fixed land area and quantity of capital.

Since equations, 3.13 and 3.14 designate standard conditions for profit maximization and 3.15 and 3.16 symbolize the standard conditions for utility maximization. To that effect, one can argue that farm household's decisions of production are in conformity with the profit maximization principle and sovereign from household's utility function.

3.2.2.4 Theory of Profit Maximization

Profit maximization is considered as the most important postulation used by numerous economists to formulate the various economic theories, such as price and production theories. Consequently, profit maximization forms the basis of conventional theories; it is regarded as the most reasonable and productive business objective of a firm. Apart from this, profit maximization helps in determining the behavior of business firms as well as the effect of various climatic and economic factors, such as precipitation, temperature, CO_2, prices, farm inputs (fertilizer and seeds), land, irrigation facilities, etc. in case of farm production.

According to the profit maximization theory, where MC and MR represent marginal cost and marginal return respectively; farm business maximizes its profits when it satisfies the two rules; (1) MC = MR, and (2) MC curve cuts the MR from below (Tripathi, 2019**)**. As per the rule, profit maximizing farm business can obtain optimum level of output when marginal revenue is equal to marginal cost. In other words, profit of a farm business can be maximized when marginal factor productivity (input and climatic factors) output are equal to marginal factor cost.

The profit maximization condition of a farm business can be expressed as:

$$\pi_Q = TR_Q - \mathbf{TC_Q} \qquad (3.17)$$

Where, π_Q is profit, TR_Q is total revenue, TC_Q are total costs, Q is quantity of the outputs obtained and sold. For the total profits of a farm business to be maximized in practical terms, the first derivative of the total profit function should be equal to zero. As a result, the equation (3.17) specified above can have the equation of the form:

$$\partial(TR)/\partial Q = \partial(TC)/\partial Q \qquad (3.18)$$

Where, $\partial(TR)/\partial Q$ and $\partial(TC)/\partial Q$ are the slopes of TR and TC curves respectively.

According to (Tripathi, 2019**)** any business decision taken by a farm will increase its profits if the following conditions prevail: (1) brings about increase in total revenue more than an increase in costs; (2) causes increase in revenue, costs remaining unchanged; (3) reduces cost more than it reduces revenue; and (4) reduces costs, revenue remaining the same.

3.2.2.5 Theory of Climate Change

Climate change can be considered as any alteration in the weather conditions over longer time which can be distinguished by distinct alterations in the mean or variability of its possessions (IPCC, 2014). Theories adopted by researchers and scholars on climate change have shown that it poses significant risks to crop productivity globally, regionally and nationally, and consequently evinced that agriculture is inherently sensitive to climatic conditions (Gezie, 2019). The thesis of this theory is that changes in climate result in crop damages, and this gives rise to low productivity. This is so because not only does temperatures rise, but rainfall patterns also become more variable, not mentioning the changes in extreme weather events, including reduction in water availability, and the increase in pest and disease pressures. On account of all the itemized contrariness stimulated by the instability in climate, individual and households' livelihoods and income of farmers are affected, which consequently eventuate into poverty and inequality (FAO, 2013). The researchers also submitted that greenhouse gas induced climate change is bound to further worsen the food security situation, particularly in the tropics because it will reduce agricultural productivity. Correspondingly, in Ethiopia, studies reveal that rainfall is expected to be irregular, which will surely affect food production negatively. Likewise, Von Braun (1991) has affirmed that a 10 percent decline in the quantity of precipitation under the long-run mean would result in a 4.4 percent decrease in Ethiopia's national food crop production and supply.

Equally various researches have assessed the validity of the theoretical aspects of climate changes imposing risks on agricultural productivity. For example, Nastis *et al.* (2012) noted that agricultural productivity diminished because of increase in temperature, during the last three decades, while precipitation had a positive effect on agricultural productivity in Greek. Differently, Mahmood *et al.* (2012) have recorded both positive and negative effects of weather variables (temperature and rainfall) on yield of rice, respectively, in Pakistan. Additionally, the same study projected that with increase in temperature by 1^0C and 3^0C, respectively, the yield of rice would increase by 2.09 percent and 4.33 percent. Quite oppositely, Acquah and Kyei's (2012a) research demonstrated that increase in rainfall and crop area expansion have had a positive and significant effect on mean maize yield while average yield of maize was adversely affected with increase in temperature in Ghana. Gupta, *et al.* (2012) equally carried out a macro level analysis to examine the impact of changes in climate on productivity of rice, sorghum, and millet crops in India. Through the application of Cobb-Douglas production functional model, the study has analyzed the impact of changes in weather variables on farm productivity both at regional as well as country level. The findings showed that changes in climate would likely diminish the yields cereals like rice, sorghum and millet crops.

In a different perspective, some researchers employed Stochastic Production Functional approach to assess the effect of weather factors on mean yield and yield variability of cereal crops (i.e., Poudel *et al.*, 2014; Acquah and Kyei, 2012b). For instance, Poudel *et al.* (2014) attested that precipitation and maximum temperature posed positive and significant impact on maize yield, while rice yield has been negatively affected by maximum temperature and precipitation in Nepal. The study however, posited that increasing precipitation decreased rice and wheat yield variability while minimum temperature was found helpful in the reduction of rice and maize yield variability. The findings of the study indicated that mean yield of maize and rice decreases as low precipitation and high temperature. The study also showed that mean yield of these crops was significantly affected by climatic conditions and the effects varied across crops. Likewise, Acquah and Kyei (2012b) discovered that maize yield was positively associated with cultivated crop area and negatively correlated with weather variables (rainfall and temperature) in Ghana. Per se, estimates imply that increase in crop area and temperature would as a matter of fact widen variability in yield of maize while increase in precipitation would diminish maize yield variability in Ghana.

Quite differently, Alam (2013) used ARDL model and ECM to assess the impact of changes in climate on productivity of agricultural crops. He incorporated CO_2 emission in the model and found that changes in climate have had negative impact on agricultural productivity and economic growth in India. Furthermore, the theoretical propositions with climate change that impose impacts and risks on sectors other than agriculture has been assessed. These propositions focused mostly on the risks caused by climate change and their drivers. Some of the theoretical propositions with changes in climate that most people have been familiar with are anthropogenic (man-made) global warming and human forces, apart from GHGs, ocean currents, and solar variability. Human induced emissions of GHG are climatic factors causing a disastrous increase in international temperatures. The actuator of global warming has been identified as the enhanced greenhouse effect, or the theory of *"anthropogenic global warming - AGW*" (IPCC, 2007). However, researchers in the past century have identified human activities, particularly the burning of fossil fuels and wood as well as cutting down or burning of forests that have led to the unabated increase of the concentration of CO_2 in the atmosphere by about 50 percent. Moreover, they projected that burning of fossil fuels and deforestation on a continuous base could double the amount of CO_2 in the atmosphere over the next century. Consequently so, ideally, the advocators of the AGW strongly argue that man-made CO_2 is the cause of crop failures, ocean coral bleaching, famines, droughts, floods, species extinctions, severe weather, spread of diseases, and literally hundreds of other catastrophes.

In contrast to the aforesaid view, another theory of climate change confirms that the influence of human beings on climate is not limited to its GHG emissions, but also has impacted change on the surface of Earth, through irrigating deserts, clearing forests, and building cities. Pielke (2009) expresses the theory as follows:

> Although the natural causes of climate variations and changes are undoubtedly important, the human influences are significant and involve a diverse range of first-order climate forces, including, but not limited to, the human input of carbon dioxide (CO2).

Basically, several of these “human forces” have local and regional effects on climate, which can be quantified as equivalent in nature or even far greater than the anthropogenic greenhouse gas emissions.

The next theory of changes in climate states that solar changeability is the reason for most or all the warming in the late twentieth century. The advocates postulate that the theory dominates changes in weather factors in the 21st century irrespective of man-made GHG emissions. Consequent upon that stance, they aver that lunar inconsistency drives changes in Earth’s climate. As a result they believe that positive feedback happens either through the effect of the solar wind on outer space rays, which automatically influences cloud formation, or on the oceans’ *thermohaline circulation* (THC). The affected THC in this process in turn will have influence on the sea surface weather condition such as the temperature and wind patterns.

3.3 Review of Literature

This sub-section presents a review of methodological and empirical literature. The review of literatures related to the study helps the researcher to understand the major aspects of the problem and to identify prevailing gaps in previous studies in relation to the current thesis. The methodological literature reviews highlights and test the different methodologies and models employed to examine the effects of changes in climate variables exerted on cereal crop production while the reviews of empirical literature present studies conducted on crop yield and output supply responses done at national, regional and global levels.

3.3.1 Review of methodological approaches

Assessment of various sources of published economic literatures indicates that a broad array of methodological approaches and models have been employed in the recent past to evaluate and test the likely economic impact of changes in climate on agriculture crop production processes. Some of the methodological approaches are reviewed and presented in the following sub-sections.

3.3.1.1 Approaches to Characterization of Climate Variables and Variation

The characterization of climate variables and their decisive variation have been studied and published by various researchers (Zelenáková, *et al.*, 2018; Befikadu, *et al.*, 2018). Zelenáková, *et al.* (2018) in their study employed Mann-Kendall method to detect the presence of trend in a time series data on weather variables (rainfall and temperatures) in Eastern Slovakia (1962–2014). This test is widely used in environmental science, as it affords a comprehensive interpretation because of its sability to account for omitted values as well as values lower than detection limit.

Equally, Befikadu, *et al.* (2018), applied nonparametric *Mann–Kendall (MK) test statistic* and *Sen's estimator test* at 5 percent significant level to assess tendencies in severe climate events over three agroecological Zones of Southern Ethiopia. They obtained data from three stations in Wolaita zone, spanning through the period of 1983 and 2014. Similarly, Daniel, *et al.* (2017) employed standardized precipitation index (SPI) in their trend analysis of rainfall and its variability for agricultural water management in Awash River Basin of Ethiopia. The index was used to observe the nature of the trends, and it allows to fortitude the desiccated and damp years in the record; mathematically computed as:

$$\mathbf{Z} = \frac{(\boldsymbol{X} - \boldsymbol{\mu})}{\boldsymbol{\sigma}} \qquad \textbf{(3.19)}$$

Where, Z is the standardized anomaly; x is an annual mean, μ is long-term mean and σ standard deviation. Further, the researchers used the coefficient of variation (CV) to measure the extent of variability in mean annual rainfall; which is calculated using the equation expressed as:

$$\mathbf{CV = (\sigma / \mu) \times 100} \tag{3.20}$$

Where, CV represents the coefficient of variation, σ, is standard deviation and μ is the long-term mean precipitation. The CV was used to evaluate the long-term disparity of damp season precipitation to that of individual years. The degree of rainfall variability measured by CV is categorized as less variable when CV<20 percent, moderately variable when CV ranges between 20 percent – 30 percent and highly variable when CV>30 percent, and CV from moderately variable is unitized as highly variable and susceptible to drought. CV is a unit-less normalized estimate of scattering of a probability distribution, which articulates the standard deviation as a portion of the mean and is utile when the concern is in the size of disparity that is relative to the size of the observation. The CV is a more useful basis of comparison than the standard deviation when comparing different years of rainfalls with different means.

It has been assessed that the above researchers whose findings were reviewed in this study have employed graphical and tabular tools to depit their findings in the reports.

3.3.1.2 Approaches to Estimate Impact of Climate Change on Crop Yield

Researchers have employed numerous models to evaluate the responses of crop yields to changes in weather variables. On account of that, these approaches are itemized into two broad distinct categories: structural and analogous approaches. Further, investigators have equally nominated other approaches fastened on the neo-classical theories to fill the gap which the other two approaches could not address.

Structural method captures key knowledge across multiple areas expertise in the field of natural science. Linking crop and economic models; it is an amalgam of farmers' economic decision and agronomic responses of plants. It is a model that enunciates detailed experiments, taking into consideration laboratory settings. These settings simulate varying and distinct changes in weather variables and other associated situations to model crop yield changes prevailing in specific regions. Results obtained from the process are then added to farmers' behavior based economic models to ascertain production and impacting factors. Largely the function of the economic models is to maximize the welfare producer and consumer, in relation to varied constraints supposed to be imposed on the model. The technique affords an approximation of the impact of weather and other interrelated factors on yield of specific crop varieties (Seo, *et al.,* 2006).

Oppositely, under this approach, effectual impacts of changes in climate conditions are directly integrated with yields of crops, which consequently give a comprehensive comprehension of the vital responses of crop yields to physical, economic, and biological factors, and adjustments to climate variables. Moreover, this approach enables the incorporation of adaptation techniques at farm level including management practices. These practices include changing of sowing dates, adopting relevant crop varieties, coupled with the enhancement or addition of irrigation, that are significantly vital for policy decisions and planning to mitigate the impacts of changes in climate variables.

However, the main difficulty associated with the application of the structural approach is on how to identify and integrate strategies and methods of adaptation to be employed by producers and consumers in the effort to respond to changes in climate, particularly in the long-run. The other disadvantage observed in the structural model is that deductions or extrapolations made based on findings from few locations and crops for the large farm areas and varied production systems may not be dependable. Such practice may lead to unrealiable results, subsequently defeating the purpose of the research. Basically, the results obtained from this method of analysis tend to hyperbolize damages caused by changes in climate (Mendelsohn, *et al*., 2000). Thus, although the models occupy a significant position regarding testing on scientific basis, but their utilization is constrained in most of the developing countries where experimentations are low and economic modeling practices are very weak (Seo, *et al.*, 2006).

In contrast to this approach, spatial analogue approach is a method that utilizes statistical and econometric estimation methods. The models are being employed to examine the likely effects of observed differences in climate and land values and agricultural production systems. Essentially, the approach studies differences in production over locations having different climatic conditions, to extrapolate the cost of differences in climate conditions will have. Through the usage of cross-sectional data, this technique assists the statistical and econometric approximation on how changes in weather variables (temperature and rainfall) might have affected crop production and associated incomes.

The advantage of this approach lies in the fact that changes in climate and responses of farmer are inherent in the analysis because they reflect on the utilized data. Despite that, one notable disadvantage of this model is that they do not give a comprehensive issues and cost of changes in irrigation infrastructures that may be vital to the reproduction of crops in warmer climates. Besides, the model does not take cognizance of changes in prices of output and input which are bound to occur from global production changes; and these changes may have a bearing on adaptation decisions at local farm business level successively (Adams, *et al.*, 1998).

The Ricardin model is among the extensively used spatial analogue models developed by Ricardo in 1817. The model states that, the value of land depicts the net productivity of farmland. The implication is that under conditions of perfect competition, the land value pointedly demonstrates the efficiency of the farmland's usage. In turn, this efficiency is impacted by changes in weather conditions.

The model affords an interconnection between impacts of climatic, socio-economic and ecological variables, and adaptation strategies and measures taken depending on market value of land. From the approximated regression coefficients of this model, the economic value of variables incorporated in the model can individually be ascertained. These regression coefficients are further utilized in projecting the impacts of future changes in climate and environmental factors. For instance, if market values of land are reckoned to be imperfect and defective, revenues or profits from farms are used as a substitute for values of land (Mendelsohn, *et al*., 2001 and Blanc, 2011).

However, despite its popularity, Ricardian approach is ladened with a few limitations. One of the central shortcomings is the presupposition of a perfectly rational agent whose objective is profit maximization. It is falsely assumed that farmers can identify climate change instantly, as well as possessing the capacity to rightly evaluate evolved changes in prevailing market, and consequently effectually adjust or regulate farming practices to permit utility maximization under existing and prevailing conditions. The implication of these assumptions is that farmers can access adjustment technologies to be used at any specified time (Mendelsohn *et al*., 2000). This is not actually feasible because of the existence of financial and political obstruction, capable of making such adaptation impossible. This is particularly apparent in areas where there is a very stiff competition for more profitable use of resources. Additionally, it has been found that farmers may find it impossible to instantly adapt a technology that scientist recommends solving their problems, irrespective of detecting even timely variability in climate as a result of varying reasons (Maddison, 2006). It follows that the impacts of changes in climate and related variables on net revenue are methodically prejudiced downwards where they are extremely low (Polsky, 2004). Again, the elemental assumption of perfect markets is not sustainable with respect to developing countries where the markets are not functioning well, when compared to United States' market, where the approach was first employed by Mendelsohn, *et al.* (1994).

Another restraint of Ricardian model relates to the use of land values for those farms near urban areas. Studies have demonstrated that in these areas modifications in land values are likely reflections of other factors. This implies that soil productivity due to alternative uses of land cannot be solely responsible for changes in the values of land. In addition, Ricardian model does not acknowledge changes in price. Congruently, Schimmelpfennig *et al.* (1996), equally opined that there is every likelihood that variations in climate could be responsible for a wide spread price changes, which in turn can give rise to incorrect estimation of land values. Likewise, according to Chao, *et al.* (2005) if there should be a change in prices because of local circumstances, approximations from the Ricardian approach would assuredly be biased. Moreover, the studies that rely on it for evaluation are often based on a year data, and this may not adequately represent other years. As such, the findings could be biased, particularly if there is any occurrence of a rare climatic, agronomic or economic condition during the period of investigation.

Alternative to the structural, spatial analogue, and Ricardian approaches, most researchers used production function to evaluate the effect of climate change on crop yield responses. For instance, Blanc (2011) utilized production function to appraise the influence of climate variation on crop yield in Sub-Saharan Africa. The study examined different functional models such as quadratic forms, which is included in the specification for weather variables, so as to ascertain non-linear weather effects on the yield of crops. In the study process, the interaction among climatic variables was conducted to gauge the possible impact of weather variable on cereal crops.

The most current analytical methods and models employed by various researchers to assess the impacts of climate fluctuations on agricultural crop productivity and output supply response in Ethiopia, Africa, and other parts of the world include the *production function* (Oloruntuyi and Adigun (2017) and Otitoju (2013)) and *autoregressive distributive lag* approaches (Onour, 2019; Mahrous (2018), etc).

Saei, *et al.* (2019) assessed the impact of weather variables on the average crop yield and variability of major grain crops (rice, maize, and wheat) in Iran over the period 1983 to 2014. They employed statistical method called the stochastic production functional model postulated by Just and Pope (1978). The fundamental thrust of this technique was considered that agricultural production function can be separated into two parts. While the first one is connected to the average crop yield level, the second is related to the crop yield variability. The common form of Just and Pope Production Functional model is specified as:

$$y = f(X) + h(x)\,\epsilon \qquad (3.21)$$

where; y is crop yield as dependent variable, and X involves explanatory variables. The estimated (X) gives the mean influence of the descriptive variables on crop yields; h(X) specifies their influence on the variability of crop yield. Anchored on Saha, *et al.* (1997) and Chen *et al*. (2004) a production function of the form below can be obtained:

$$y = F(X) + u = f(X, \beta) + h(X, \alpha)\, \epsilon \qquad (3.22)$$

where, y is crop yield (wheat, maize, and teff); X is descriptive variables (location, rainfall, temperature, and time period), and ϵ is the exogenous production shock with $(\epsilon)=0$ and $Var(\epsilon)=\delta\epsilon^2$. The application of this formula evinces that descriptive variables can influence the variability and mean of crop yield because $(y) = (X)$ $V(y)=Var(u)=h(.)$. The parameter estimation of (.) presents the mean effects of the descriptive variables on yield, but h (.) shows the impacts of the covariates on the variability of crop yield. In their study, they employed three functional forms, viz. quadratic, Cobb-Douglas, and translog forms, for the Just and Pope Production Function. Since a translog would violate the Just and Pope assumptions, the Cobb-Douglas, and linear-quadratic forms, both compatible with the Just and Pope assumptions were chosen for the estimation of average crop yield function.

The Cobb-Douglas function is specified as:

$$y = \alpha_0 + \alpha_t T + \Pi_j x_j^{\alpha j} \qquad (3.23)$$

Linear- Quadratic takes the Form:

$$y = \alpha_0 + \alpha T + \sum_j \alpha 1jxj + \sum_j \alpha_{2j} x_j^2 + \sum_j \sum k\ (k \neq j)\ \alpha_j k x_j k_j \qquad (3.24)$$

where jxj and kxk are descriptive variables concerned with weather variables, T denotes trend of time and $\alpha's$ implies coefficients. The justification for inclusion of time trend hinges onthe fact that it takes cognizance of technological progress in agriculture across the assumed time period.

Relatedly, Oloruntuyi and Adigun (2017) and Otitoju (2013) carried out analysis of the impact of change in climate variables on productivity of agricultural crops in Nigeria through the application of Cobb-Douglas production function, specified as:

$$Y_i = \boldsymbol{\alpha}_1 X_{2i}^{\alpha 2} X_{3i}^{\alpha 3} e^{ui} \qquad (3.25)$$

Where Y= crop output, X_2 = labor input, X_3 = capital input, u =stochastic disturbance term, and e =base of natural logarithm.

From the above equation, it is apparent that the relationship between output and the two inputs is nonlinear. However, if log-transformed the model, then it is denoted as:

$$\begin{aligned} \ln Y_i &= \ln\alpha_1 + \alpha_2 \ln X_{2i} + \alpha_3 \ln X_{3i} + u_i \\ &= \alpha_0 + \alpha_2 \ln X_{2i} + \alpha_3 X_{3i} + u_i \qquad (3.26) \end{aligned}$$

As stated by the researchers, the production function for the study was elucidated as follows:

$$Y = f\,(TEMP, RF, GOVE, L) \qquad (3.27)$$

Where: Y= Agricultural Output; TEMP = Temperature; RF = Rainfall; GOVE = Government Expenditure, and L = Labour. By adopting the above equation, as a model, they specified the model as:

$$\mathrm{Ln}Y_t = \ln\alpha 0 + \alpha_1 \ln TEMP_t + \alpha_2 \ln RFT_t + \alpha_3 \ln GOVE_t + \mu_t \qquad (3.28)$$

Ahmed *et al.* (2014) and Ali *et al.* (2017) explored the impact of changes in climate on productivity of cereal crops in Pakistan through the application of the modified production functional model. The general form of the production function they employed is portrayed as:

$$Y = f\,(Cl, NCl) \qquad (3.29)$$

Where, *Y* represents rice production per-hectare (yield), *Cl* denotes the vector of climatic variables, temperature, and precipitation, whereas *NCI* signifies the vector of non-climatic variables, such as fertilizer area under rice and technological change.

Differently, Chowdhury *et al.* (2015) investigated the impact of change in climate variables on yield of rice crop in Bangladesh employing time series analysis. They conducted the research so as to address the increasing vulnerabilities steming from changes in climate as well as the severely reducing yield of cereal crops due to global warming, which in return would threaten the country's food supply system. Following this, the study was carried out to assess the impacts of changes in climate variables on the yields of various varieties of rice crop in Bangladesh. A multiple regression model with OLS method has been used to measure the climate-crop yield associations using country-level time series data spanning from 1972 to 2014. They employed log-linear regression model and based on the distribution of the yields of three rice crops and other properties specified the following regression models:

The Aus Rice Model:

$$\mathrm{lnYAus}_t = \alpha_0 + \beta_1 \mathrm{lnmax}T_t + \beta_2 \mathrm{lnmin}T_t + \beta_3 \mathrm{ln}Train_t + \beta_4 \mathrm{ln}Hum_t + \varepsilon_t \qquad (3.30)$$

Where, 'lnYAus_t' is the natural logarithm of yield of Aus rice (in metric ton per hectare), 'lnmaxT ' denotes the log of growing season mean maximum temperature (ºC) from March - July, 'lnminT' illustrates the log of crop growing season mean minimum temperature (ºC) from March - July, 'lnTrain' signifies the log of crop growing season mean total rainfall (millimeter) from March - July, 'lnHum' captures the log of crop growing season mean humidity (%) from March - July, 'ε_t' means the disturbance term and 't' signifies the time variable (i.e., year).

The Aman Rice Model:

$$\mathrm{lnYAman}_t = \gamma_0 + \beta_1 \mathrm{lnmax}T_t + \beta_2 \mathrm{lnmin}T_t + \beta_3 \mathrm{ln}Train_t + \beta_4 \mathrm{ln}Hum_t + \omega_t \qquad (3.31)$$

where: 'lnYAmant' stands for the natural logarithm of yield of Aman rice (in metric ton per hectare), while 'lnmaxT' refers to the log of growing season average maximum temperature (ºC) from June to November; 'lnminT' is a denoteefor the log of growing season average maximum temperature (ºC) from June to November, 'lnTrain' denotes the log of growing season average total rainfall (millimeter) from June to November, 'lnHum' is a reference for the log of growing season average humidity (%) from June to November, 'ω_t' is the error term of Aman rice model and 't' is a denotation for the time (i.e., year).

The Boro Rice Model:

$$\ln YBoro_t = \Theta_0 + \beta_1 \ln \max T_t + \beta_2 \ln \min T_t + \beta_3 \ln Train_t + \beta_4 \ln Hum_t + \Psi t \qquad (3.32)$$

where: '$\ln YBoro_t$' points to the natural logarithm of yield of Boro rice (in metric ton per hectare), 'lnmaxT' means the log of growing season average maximum temperature (ºC) from November to May, 'lnminT' is a referent for the log of growing season average maximum temperature (ºC) from November to May, 'lnTrain' signifies the log of growing season average total rainfall (millimeter) from November to May, 'lnHum' is the log of growing season average humidity (%) from November to May, 'Ψ' is a symbol for the error term of Boro rice model and 't' is the time (i.e., year).

On the other hand, Onour (2019) carried out a study on the consequence of CO_2 concentration on the yield of cereal in Sudan. Therefore, to ascertain the long-term impacts of CO2 emission on yield of cereals in Sudan, the researcher utilized ARDL bound test for cointegration analysis. In the process of ARDL model estimation, he conducted estimation of unit root for each variable to identify the order of integration of the variables and the conventional ECM (error correction model) for cointegrated data. The ECM he employed is presented below:

$$\Delta yt = \beta 0 + \sum_0^p \beta i \Delta yt - i + \sum_1^{q1} \gamma \Delta x1t - j + \sum_1^{q2} \delta k \Delta x2t - k + \varphi zt - 1 + e_t \qquad (3.33)$$

Here, z, the "error-correction term", is the OLS residuals series from the long-run "cointegrating regression" specified as:

$$y_t = \alpha_0 + \alpha_1 x_{1t} + \alpha_2 x_{2t} + v_t \qquad (3.34)$$

He employed unit root tests to confirm that all the series he was working with excluded I(2) because ARDL model cannot coalesce with I(2) or higher order of integration. In order to present a clear elucidation, he substituted equation (3.30) and got the unrestricted ECM specification:

$$\Delta yt = \beta 0 + \sum_{0}^{p} \beta i \Delta yt - i + \sum_{1}^{q1} \gamma \Delta x1t - j + \sum_{1}^{q2} \delta k \Delta x2t - k + \Theta_1 x_{1t-1} + \Theta_2 x_{2t-1} + \Theta_0 y_{t-1} + e_t \qquad (3.35)$$

The difference was his replacement of the error-correction term, z_{t-1} with the terms y_{t-1}, x_{1t-1}, and x_{2t-1}. His assumption in the ARDL model was that the error terms in the above equation should be serially uncorrelated. To test the serial independence of the error terms he utilized the LM test to test for the null hypothesis that the errors are serially uncorrelated, against the alternative hypothesis that they are serially correlated. To perform the ARDL cointegration test on equation (3.35), he computed the F-test to check the hypothesis, H_0: 0 = 1 = 2 = 0; against the alternative that H_1 is not true. He did this to infer the absence of a long-run equilibrium relationship between the variables. This absence can be tested by testing for zero coefficients for y_{t-1}, x_{1t-1} and x_{2t-1} in equation (3.35). A rejection of H_0 reveals presence of a long-run relationship. A problem that have been addressed in the ARDL model is that exact critical values for the F-test are not applicable for a mix of cointegration orders of I(0) and I(1) variables.

Zhai, *et al.* (2017), Mahrous (2018), and Amponsah, et al. (2015) equally studied the impacts of changes in climate on wheat yield and cereals in China, Egypt, and Ghana, respectively employing an autoregressive distributed lag approach. In the ARDL model, the relationship between cereals and yield of wheat and the explanatory variables has been constructed as follows:

$$Y = f\ (M, F, A, P, T) \qquad (3.36)$$

The researchers have transformed all the explanatory and dependent variables into natural - log form to make equation (3.37) friendly estimable. The estimable form of the equation has been specified and presented as follows:

$$\ln Y = \beta_1 + \beta_2 \ln M + \beta_3 \ln F + \beta_4 \ln A + \beta_5 \ln P + \beta_6 \ln T + \mu \qquad (3.37)$$

However, the researchers did not investigate the various associations that exist among the variables between different years but centered only on the short- and long-run association existing among the variables over the period 1970 to 2014. Thus, this evidenced that, an ARDL model does not contain a year term. An ARDL in the equation (3.37) has been reformulated as follows:

$$\Delta \ln Y_t = \alpha_0 + \sum_{i=0}^{p} \alpha 1 i \Delta ln Y_{t-i} + \sum_{i=0}^{p} \alpha 2 i \Delta ln M_{t-i} + \sum_{i=0}^{p} \alpha 3 i \Delta ln F_{t-i} + \sum_{i=0}^{p} \alpha 4 i \Delta ln A_{t-i} + \sum_{i=0}^{p} \alpha 5 i \Delta ln P_{t-i} + \sum_{i=0}^{p} \alpha 6 i \Delta ln T_{t-i} + \beta_{11} Y_{t-1} + \beta_{12} M_{t-1} + \beta_{13} F_{t-1} + \beta_{14} A_{t-1} + \beta_{15} P_{t-1} + \beta_{16} T_{t-1} + \varepsilon_t \qquad (3.38)$$

Where, α_0 is a drift component, ε_t denotes an error term, and Δ represents first-difference operator. The ARDL method calculated the $(p + 1)^n$ to derive an optimal lag length for each variable, p is the maximum lags to be utilized. The summation signs stand for error correction dynamics while coefficients α_{1i}, α_{2i}, α_{3i}, α_{4i}, α_{5i}, α_{6i} symbolize possible short-run dynamics of the model's convergence to equilibrium. $\beta_{11} - \beta_{16}$ represents long-run correction coefficients that signify long-run relationship among the the explanatory and dependent variables. Once the long-run association between variables has been determined, the ECM can be approximated. Then, a general ECM of equation (3.39) is explicated as follows:

$$\Delta \ln Y_i = \alpha_0 + \sum_{i=0}^{p} \alpha 1 i \Delta \ln Y_{t-i} + \sum_{i=0}^{p} \alpha 2 i \Delta ln M_{t-i} + \sum_{i=0}^{p} \alpha 3 i \Delta \ln F_{t-i} + \sum_{i=0}^{p} \alpha\, 4 i \Delta ln A_{t-i} + \sum_{i=0}^{p} \alpha 5 i \Delta ln P_{t-i} + \sum_{i=0}^{p} \alpha\, 6 i \Delta ln T_{t-i} + \beta ECM_{t-i} + \varepsilon_t \qquad (3.39)$$

In realism, the last-period divergence from a long-run equilibrium would influence the short-run dynamics. In the above equation, the coefficient of ECM_{t-1}shows the rapidity of the modification by evidencing the speed of the variables returns to the long-run balance after a short-run shock.

3.3.1.3 Approaches to Estimation of Agricultural Output Supply Response

This segment elucidates different approaches employed to measure supply response of agricultural output. The supply response of agricultural crops to price and other variables was first undertaken by Nerlove in his seminal work in 1958 (Askari and Cummings, 1977). Estimates of the supply elasticity (short-run and long-run) based on the Nerlove model vary widely depending on the crop and region involved. Furthermore, the supply response elasticities are also important for policy decision regarding agricultural growth. The detailed specification of the Nerlove's structural supply model for specific crops has been described under sub-section 3.2.2.2.

Next to Nerlovian, numerous other studies have been carried out to examine the responsiveness of agricultural producers to price and non-price variables affecting agricultural production decisions. While supply response studies can be carried out for broadly aggregated agricultural commodities (Mythili, 2008; Muchapondwa, 2009; Obayelu and Salau, 2010), those for single commodities are more insightful for the formulation of appropriate sub-sector policies (Mose, 2007; Olwande, *et al.*, 2009; Ozkan, *et al.*, 2011).

Basically, the nature of agricultural production is such that the response to supply shifters is not immediate (Muchapondwa, 2009). First, supply responses of agricultural production are distinguished by biological lags between the use of agricultural inputs and agricultural output production periods. Secondly, factors such as technological and institutional constraints impede decisions on agricultural production from being fully accomplished in any specific time. Thirdly, the presupposition of perfect information is not so applicable to agricultural production practices as the environment is depicted by information asymmetries, particularly regarding prices (Muchapondwa, 2009). These reasons evidently demand the employment of dynamic models where a time variable is introduced to encapsulate these attributes.

As methodological approach, many researchers have used an ARDL model to measure the responsiveness of agricultural crops output to changes in climatic and non-climatic variables. Autoregressive distributed lag and production function models are the current and mostly used dynamic supply response models. While distributed lag models focuses on lagged explanatory variables; on the other hand, the thrust of autoregressive models, is to interpret the lagged values of the dependent variable (Gujarati, 1999). While distributed lag models denote that the effect of a unit change in the explanatory variable is distributed over a number of time periods, contrariwise, models that illustrate a lagged dependent variable, in accompaniment of lagged explanatory variables are labelled ARDL models.

Following the postulation of Kapuya (2010), a distributed lag supply model is based on the premise that the quantity supplied in the time *t* is represented as a function of the price received in the previous period *t-1*, that is:

$$Q_t = \alpha + \beta p_{t-1} + \mu_t \qquad (3.40)$$

Where: Q_t is the quantity supplied in period t

α is the intercept

p_{t-1} is the price paid in period $t-1$

β is the short-run elasticity that measures the degree of responsiveness of Q to a unit change

μ_t is the error term.

The effect of changes in one variable may have impact through several periods, this subsequently necessitated a distributive lag equation signified as follows (Kapuya, 2010):

$$Q_t = \alpha + \beta_0 p_{t-1} + \beta_1 p_{t-1} + ... + \beta_k p_{t-k} + \mu_t \qquad (3.41)$$

Where: $p_{t-k}$is the price received in time period k, $\forall k = 2, \dots$ n

n is the number of lags

β are parameters to be measiured on the variables denoted in the previous equation.

Nonetheless, the model above is prone to two major problems. The first one is multicollinearity; this stems from the fact that consecutive values of economic variables tend to be serially correlated. Furthermore, the application of ordinary least squares (OLS) technique automatesbiased and inefficient parameter estimates. However, on the grounds that the data are tested and found to be stationary or corrected for stationarity, then, OLS can still be utilized (Kapuya, 2010). The second challenge that researchers face is that it is problematic to decide the number of lagged values of explanatory variables to introduce (Gujarati, 1999). For instance, utilizing too many lagged values, can result into a problem of degrees of freedom. Thus, the result from the model becomes unreliable because with few degrees of freedom the analyst cannot confidently deduce that the sample adequately represents the population under study.

In recent years, researchers used various methodological approaches so to measure the impact of changes in climate on cereal output supply response. Chandio, *et al.* (2018) used time series based ARDL approach to assess the effects of fluctuations of weather factors on rice production in Pakistan covering the time priod from 1968 to 2014. The model used has been specified and resentatively described as follows:

$$\text{Rice Production} = \beta_0 + \beta_2 CO_2 + \beta_2 T + \beta_3 A + \beta_4 F + \varepsilon_t \qquad (3.42)$$

The linear combination equation (3.42) has been converted into log-linear regression equation so as to offer cvenient and proficient results in contrast to the simple linear regression model. The equation above can be transformed into log-linear form for convenience as follows:

$$lnRP = \beta_0 + \beta_1 lnCO_2 + \beta_2 lnT + \beta_3 lnA + \beta_4 lnF + \varepsilon_t \qquad (3.43)$$

where, RP represents rice production, CO_2 represents carbon dioxide gass emmission, T illustrates mean temperature variable, A exhibits area cultivated under rice crop, F describes fertilizers offtake and ε stands for standard error term. Now, in order to investigate the long-run interconnection between dependent and independent variables incorporated in the model, an ARDL bounds testing approach to cointegration equation (3.44) of the model is specified as:

$$\Delta \ln RPt = \beta 0 + \sum_{k=1}^{n} \beta 1k \Delta RPt-k + \sum_{k=1}^{n} \beta 2k \Delta \ln CO_{2t-k} + \sum_{k=1}^{n} \beta 3k \Delta lnTt-k + \sum_{k=1}^{n} \beta 4k \Delta lnAt-k + \sum_{k=1}^{n} \beta 5k \Delta lnFt-k + \lambda_1 \ln RP_{t-1} + \lambda_2 \ln CO_{2t-1} + \lambda_3 \ln T_{t-2} + \lambda_4 \ln A_{t-1} + \lambda_5 \ln F_{t-1} + \varepsilon_t \quad (3.44)$$

Based on an ARDL approach equation (3.44) is established for ordinary least square (OLS) method. The null hypothesis of this empirical model is tested as follows:

$$H_0 = \lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5 = 0$$

Against its alternative hypothesis is tested as follows:

$$H_1 \neq \lambda_1 \neq \lambda_2 \neq \lambda_3 \neq \lambda_4 \neq \lambda_5 \neq 0$$

In an effort to estimate the short-run relationship amid rice production and the explanatory variables (carbon dioxide emission, average temperature, area cultivated under rice crop, and fertilizers offtake), the researchers integrated an error correction model (ECM) into ARDL formulation. Then equation above is framed as:

$$\Delta \ln RPt = \beta 0 + \sum_{k=1}^{n} \beta 1k \Delta lnRPt-k + \sum_{k=1}^{n} \beta 2k \Delta lnCO2t-k + \sum_{k=1}^{n} \beta 3k \Delta lnTt-k + \sum_{k=1}^{n} \beta 4k \Delta lnAt-k + \sum_{k=1}^{n} \beta 5k \Delta lnFt-k + \alpha ECTt\text{-}1 + \varepsilon t \quad (3.45)$$

Quite differently, from Oparinde and Okogbue's (2018) approach, Solomon (2017) employed the conventional Cobb Douglas production function to examine the impact of CO_2 emission on total cereal production in Ethiopia. The production function is denoted as:

$$lnY_t = \beta_0 + \beta_1 lnL_t + \beta_2 lnF_t + \beta_3 lnCO_{2t} + e_t \quad (3.46)$$

where *ln* signifies natural log, *Y* is represents total cereals crop production; *L* enunciates land area cultivated under cereal production; *F* articulates fertilizer consumed; while CO_2 is a signification of carbon dioxide emission measured in K_t; β_0, β_1, β_2 and β_3 symbolize parameters to be estimated; t represents time in years, and e equals an error term.

Subsequently, in order to resolve any feasible problem of misspecification in this model, Vector Error Correction (VEC) is employed. Following postulation of Engle and Granger (1987), this error correction model can be specified and represented as:

$$\Delta LnYt = \beta 0 + \sum_{i=1}^{mi} \beta_{1i} \Delta LnY_{t-1} + \sum_{i=0}^{mi} \beta_{2i} \Delta LnL_{t-1} + \sum_{i=0}^{mi} \beta_{3i} \Delta LnF_{t-1} + \sum_{i=0}^{mi} \beta_{4i} \Delta LnCO_{2t-1} + \delta \varepsilon_{t-1} + \eta_t \quad (3.47)$$

Where βs are unknown parameters that need to be estimated, Δ sign indicates change (e.g.,$Y_t - Y_{t-1}$), m denotes the lags length, δ describes the speed of adjustment in the parameters, $\varepsilon_{t-1}$is a description of one-period lag for the error correction term; and η points to disturbance term with zero mean.

Vikas and Goyal (2018) also estimated acreage response for major crops in Haryana, India. The study relied on time series data for the following periods: between 1966 and 67 to 2008-09 on area, production, and productivity of major crops (Rice, wheat, bajra, gram, rapeseed, and mustard, etc.). Subsequently, the researchers utilized a long-run acreage response function, which is represented as:

$$LnA_{it} = \beta_0 + \beta_{i1} LnHP_{it-1} + \beta_{i2} LnHPS_{it-1} + \beta_{i3} LnY_{it-1} + \beta_{i4} LnR_{1,it-1} + \beta_{i5} LnI_{it-1} + \beta_{i6} LnA_{it-1} + \varepsilon_{a,it} \quad (3.48)$$

Where the subscript i stands for different crops; LnA_{it} is the natural log of area planted under the i^{th} crop in the year t; $LnHP_{it-1}$denotes the natural log of lagged harvest price of the i^{th}crop; $LnHPS_{it-1}$refers tothe natural log of lagged harvest price of the substitute crop for i^{th}crop; LnY_{it-1} represents the natural log of lagged average yield of the i^{th}crop; $LnR_{1,it-1}$ is the natural log of pre sowing month rainfall of the i^{th}crop; $LnIit\text{-}1$is the natural log of lagged irrigated area under the i^{th}crop; $LnAit\text{-}1$ illustratesthe natural log of lagged area under the i^{th}crop; β_{i1}, β_{i2}, β_{i3}, β_{i4}, β_{i5}, and β_{i6} are denotations of the long-run coefficients of the i^{th}crop; and $\varepsilon_{a,it}$are the error terms assumed to be white noise.

Shakoor *et al.* (2017) and Kavinya *et al.* (2014) separately investigated how the production of maize respond to changes in climate in Pakistan and investigated response of maize hectarage to price and non-price incentives in Malawi, respectively, using ARDL model and vector auto regression (VAR) model. The model employed by Shakoor *et al.* (2017) and Kavinya *et al.* (214) on maize crop response to weather and related input factors have been described and specified as:

$$MZP = \beta_1 + \beta_2 AU + \beta^3 FR + \beta_4 CD + \beta_5 WA + \beta_6 AT + \beta_7 ATX + \beta_8 ATM + \beta_9 ARN + U_i \qquad (3.49)$$

Where MZP symbolizes maize crop production, AU is land area cultivated with maize crop, while FR depicts chemical fertilizer quantity consumed in maize crop, CD expresses credit use in maize crop, WA indicates availability in water variable, AT typifies mean temperature in ^{0}C, ATX equates with mean maxTemperature in ^{0}C, ATM points to mean minTemperature in ^{0}C, and ARN correspond to mean precipitation in millimeter.

Eregha, Babatolu and Akinnubi (2014) researched the impact of changes in weather variables (rainfall and temperature) on cereal crops production and supply in Nigeria over the period 1970 and 2009. In their research, they adopted the standard distributed-lag model as tool of analysis. The form is interpreted as:

$$Outp_t = \Theta_1 + \phi_{11} temp_t + \phi_{12} rain_t + \phi_{13} cab_t + \mu \qquad (3.50)$$

Where *Outp* = output of selected crops; Θ_1= intercept; $\phi_{11} - \phi_{13}$ = coefficients; μ = error term, Temp = temperature (^{0}C); rain = rainfall (mm); and cab = carbon emission (Kt).

The model as dynamic error correction model is further specified as:

$$\Delta Outp_t = \alpha_0 + \alpha_1 \sum_{\alpha=\infty}^{n} \Delta outp_{t-1} + \alpha_2 \sum_{\alpha=\infty}^{n} \Delta temp_{t-1} + \alpha_3 \sum_{\alpha-\infty}^{n} \Delta rain_{t-1} + \alpha 4 \sum_{\alpha=1}^{n} \Delta cab_{t-1} + ecm_{t-1} \qquad (3.51)$$

Where ecm_{t-1} indicates error correction term, one-period lagged residual of static regression and 'Δ' stands for the first difference of the model.

Likewise, Janjua, Samad and Khan (2013) and Agba *et al.* (2017) studied climate change and agriculture in Pakistan and the impacts of climate change on crop output in Nigeria, respectively, utilizing ARDL model and ECM for co-integrated models using time series secondary data. The general specification of ARDL model as recommended by Pesaran (1997) with n lags for variable Y and m lag for variable X is represented as:

$$Y_t = \alpha_0 + \sum_{i=1}^{n} \alpha i Yt - i + \sum_{i=1}^{m} \beta i\, Xt - i + U_t \qquad (3.52)$$

More generally, the specification of ARDL form of ECM is presented as:

$$\Delta Y_t = \alpha_0 + \sum \beta j Yt - i + \sum \beta j Xt - j + \Psi ECM_{t-1} + \varepsilon_t \qquad (3.53)$$

In the equation above, Ψ represents the speed at which parameter adjusts itself, the sign of which must be negative for significant ECM model. The Error Correction Term in this model proposes that any departure from the long-run equilibrium of variables can be corrected in each of the period under consideration. It also recommends on how much time it will take to return to the long-run equilibrium position. ECM_{t-1} represents the residuals that inherited from the estimated co-integration model.

The association of wheat production with the explanatory variables is defined as follows:

Wheat Production = f (CO2, Temp, Precip, Water, Area, Agr.Credit, Fertilizers, Technology) (3.54)

This linear amalgamation of the equation is then converted into log-linear model which subsequently represent appropriate and effectual results in contrast to the simple linear model. The converted log-linear specification is presented as:

$$lnWheat = \beta_1 + \beta_2 ln\mathrm{CO2} + \beta_3 ln\mathrm{Temp} + \beta_4 ln\mathrm{Precip} + \beta_5 ln\mathrm{Water} + \beta_6 ln\mathrm{Area} + \beta_7 ln\mathrm{AgCr} + \beta_8 ln\mathrm{Frt} + \beta_9 \mathrm{lnTech} \qquad (3.55)$$

The specific form of the ARDL model adopted for the current study to find the long-run association among the dependent and explanatory variables is presented as:

$$lnWheat_t = \alpha 0 + \sum \alpha 1 lnWheat\mathrm{t} - \mathrm{i} + \sum \alpha 2 lnPrecipt - i + \sum \alpha 3 lnTemt - i + \sum \alpha 4 lnWatert - i + \sum \alpha 5 lnCO2t - i + \sum \alpha 6 lnAreat - i + \sum \alpha 7 lnAgrCr_{t-i} + \sum \alpha 8 ln\mathrm{Frt}_{t-i} + \sum \alpha 9 lnTech_{t-i} \qquad (3.56)$$

Whereas the short-run dynamics of ARDL model equation can be specified as follows:

$$\Delta lnWheat_t = \beta0 + \sum \beta 1\Delta lnWheat_{t-i} + \sum \beta 2\Delta lnPrecip_{t-i} + \sum \beta 3\Delta lnTemp_{t-i} + \sum \beta 4\ ln\Delta lnWater_{t-i} + \sum \beta 5\ \Delta lnWater_{t-i} + \sum \beta 5\Delta \ln CO2_{t-i} + \sum \beta\ 6\Delta lnArea_{t-i} + \sum \beta\ 7\Delta lnAgrCrt_{t-i} + \sum \beta 8\Delta lnFrt_{t-i} + \sum \beta 9\Delta \mathrm{lnTech}_{t-i} + \Psi ECM_{t-I} \quad (3.57)$$

Dumrul and Kilicarslan (2017) and Akanni and Okeowo (2011) conducted studies to evaluate the effects of climate change on agricultural production in Turkey and Nigeria, via the empirical model of the form:

Agricultural GDP = f (rainfall and temperature) (3.58)

The functional form of the model is presented as:

$$AGDP = \beta_0 + \beta_1 Rain_t + \beta_2 Temp_t + \varepsilon_t \quad (3.59)$$

Where AGDP is the agricultural GDP as measured Agriculture, value added (% of GDP), Rain is rainfall as measured mm and Temp is the temperature as measured °C. t is the time trend and ε is white noise error term. The parameters β_1 and β_2 are denotations of the long-run elasticities of Agricultural GDP about rainfall and temperature, respectively.

They employed an ARDL bounds testing approach to determine the long-run nexus between Agricultural GDP, Rainfall and Temperature. The mathematical illustration of the ARDL approach is presented below:

$$\Delta AGDP = \beta_0 + \beta_1 \sum_{i=1}^{n} \Delta AGDPt - 1 + \beta_2 \sum_{i=1}^{n} \Delta Tempt - i + \beta 3 \sum_{i=1}^{n} \Delta Raint - 1 + \beta_4 AGDP_{t-1} + \beta_5 Temp_{t-1} + \beta_6 Rain_{t-1} + \varepsilon_t \quad (3.60)$$

Where Δ indicates change, n signifies the optimum delay lengths.

In order to investigate the short-run relationship between the variables, the error correction model anchored on the ARDL approach is validated as follows:

$$\Delta AGDP = \gamma_0 + \gamma_1 \sum_{i=1}^{nl} \Delta AGDPt - 1 + \gamma_2 \sum_{i=0}^{n2} \Delta Tempt - i + \gamma 3 \sum_{i=0}^{n3} \Delta Raint - i + \gamma_4 ECM_{t-1} + \varepsilon_t \quad (3.61)$$

Where ECM (-1) term is a lagged value of the residual of model in which the long-term relationship is obtained; ECM(-1) represents the speed of adjustment parameter which is projected to be negative.

Conversely, many researchers employed Cobb-Douglas Production Function to estimate response of crop production to changes in climate and non-climatic factors. For instance, Zaied and Zouabi (2015), and Raza and Ahmed (2015) utilized econometric Cobb-Douglas Production Function to evaluate the economic impacts of climate change (pre-cipitations and temperature) on Tunisian olive output, analyze the impact of climate change on cotton productivity in Pakistan; respectively. The Cobb-Douglas production functional model the researchers adopted in its exponential form has been specicied as:

$$Y_{it} = F\,(L, K, RL, TM) = L^{\alpha 1i}K^{\alpha 2i}RL^{\alpha 3i}TM^{\alpha 4i} \qquad (3.62)$$

Where: Y, L, K, RL and TM are representations of quantity of olive production, number of labor, inputted capital stock, amount of rainfall, and temperature variables respective-ly. The researchers transformed the above model into logarithm (ln) form and obtained an equation augmented by a residual term that to account for specific unobserved factors, whereby they utilized time series quantitative annual data to calculate the model:

$$\ln Y_{it} = \alpha_{1i}\ln L_{it} + \alpha_{2i}\ln K_{it} + \alpha_{3i}\ln RL_{it} + \alpha_{4i}\ln TM_{it} + \varepsilon_{it} \qquad (3.63)$$

3.3.2 Review of Empirical Literature

Various studies were carried out to assess the effect of changes and variability in climate using different models, particularly the agronomic approach or statistical estimation ap-proach in different agro-climates and countries. However, the results vary due to the methodology employed, crop types under consideration, and the region selected and stud-ied on the specific thematic area currently under consideration. This sub-section presents the reviews of literatures relating to the changes and variability in weather variables, and their impacts on yield of crop and output supply in Ethiopia, Africa and other parts of the world.

3.3.2.1 Characterization of Climate Variables and Their Variation

Characterization of weather factors such as precipitation, temperature and CO_2 becomes very important for apricultural business planning and making decisions that minimize risks in the production businesses. To this effect, many researchers have studied the trends and variabilities of climatic factors in Ethiopia, Africa and other parts of the world.

Asfaw *et al*. (2018) and Daniel *et al*. (2017) studied variability and trend analysis of rainfall and temperature using time series secondary data in north central Ethiopia and Tana Basin, in Ethiopia, respectively, using CV and Standardised anomalies. The research carried out by Daniel *et al*. (2017) in the Awash Basin areas of the country showed that higher variations of rainfall existed in the short-rainfall season than in the long-rainfall sesean (main season) in all the stations selected for the study, even though main-rain season (Kiremt rainfall) contributed the highest percentage of rainfall in the Basin. The results also indicated that the stations in the basin have experienced more dry seasons than wet seasons, especially in short-rainfall. The probability of dry season occurrence for short-rainfall is therefore higher than the one observed in the Kiremt season. Equally, the short-rainfall season rainfall and LGP manifested a declining pattern in most of the selected stations, although it is not statically significant. However, the long-rain (Kiremt season rainfall) and crop growing period evinced a non-significant increment in several weather stations of the study areas.

Befikadu *et al*. (2018) and Arragaw and Woldeamlak (2017) equally assessed the changes experienced in the indices of severe weather variables (temperature and precipitation) based on the changes taken place in the lowland, mid-land, and highland AEZs in the Wolaita Zone of Southern Ethiopia and in the central highlands of Ethiopia, respectively, and found nearly related findings. In particular, Arragaw and Woldeamlak (2017) conducted a spatial and temporal trends and variability in weather variables (precipitation and temperature) in the central highlands of Ethiopia over the period 1983 to 2013. They found a rising trend in the long- rain season (June - September), although statistically insignificant, consequently maintaining a match with this current work.

In similar fashion, Zelenáková, *et al*. (2018) and Padhiary, *et al*. (2018) analyzed trends in precipitation and temperatures in Eastern Slovakia using data series for 53-year period from 1962 to 2014 as well as over Jaraikela catchment in India, respectively; and reported similar findings. In particular, Padhiary, *et al*. (2018) studied the inconsistency and long-term trends observed in climatic factors such as monthly, seasonal, and annual precipitation, temperature (maximum, minimum, and mean) over the Jaraikela catchment of India. The result of trend analysis in this regard has shown considerable raise in average annual rainfall and temperature at most of the stations under observation and although no clear trend is found in monthly and seasonal analysis of rainfall and temperature. The study provided a pattern of maximum, minimum, and mean temperature as well as precipitation that can be utilized for sensitivity examination in the supply of and demand for water in the catchment area.

In the same vein, Oza and Kishtawal (2014) have examined the long-term and short-term fluctuations in the Indian Summer Monsoon (ISM) rainfall and temperature over North East India (NEI) in Eastern Himalayan region. The researchers utilized Rainfall data to inspect the period of 1871–2012, and temperature data for the period between 1901 and 2007. The results of the assessment indicated a declining trend in the Indian summer monsoon precipitation at all India level, as well as in North East India. Even in NEI, the rate of decrease was steeper towards the east. The maximum temperature in the NEI was increasing during all the four seasons at a rate of between 0.5 to 1.6o C / 100-years. The increase was highest in winter months and lowest in pre-monsoon season. However, no consistent direction of change emerged in the examination of minimum temperature data. The investigation revealed that between the period of 1960 and 1970, that decade was a critical time point from where the reversal of trend in climatic variables was noticeable.

3.3.2.2 Climate and Crop Yield Studies

Many researchers have conducted studies on the likely impact of climate change on yield of cereal crops in Asia (Farook and Kannan, 2017; Chowdhury *et al.* 2015) and reported comparable findings. Chowdhury *et al.* (2015) examined the effect of change in climate variables on yield of rice in Bangladesh. The researchers employed time series method of analysis on three different rice crop species: Aus, Aman and Boro. Subsequently, the empirical results revealed that the yield of Aus rice was significant; implicating that those climate variables included in the model can explain some of the disparity in the yield of Aus rice. Also, the value of adjusted R^2 implied that 33 percent of the total variation in the yield of Aus rice can be clarified through the climate variables in Bangladesh, which was included in the model. The results also indicate that (seasonal average) maximum temperature, rainfall and humidity are statistically significant at 10 percent, 5 percent and 1 percent level, respectively. Furthermore, the results specified that the rainfall and humidity portrayed positive association with the yield of Aus rice, while Aus yield was negatively related with maximum temperature. To this end, it can be rightly attested that an increase of average maximum temperature will necessarily reduce the yield of Aus rice further. Contrastingly, it was discovered that rainfall and humidity were beneficial for the Aus yield. The research however concluded with the fact that minimum temperature could not determine the yield of Aus rice as the coefficient of lnminT was statistically insignificant.

The Aman rice is almost entirely rain-fed crop and is grown in the season of monsoon. Thus, the results of the regression model signified that seasonal rainfall and humidity were statistically significant at 10 percent and 1 percent significance level individually and impacted Aman rice yield positively. However, maximum temperature portrayed a negative contribution to the yield of Aman rice, besides being statistically significant at 5% level. Oppositely, minimum temperature was statistically insignificant and had no influence in any respect on the Aman yield. Likewise, the approximated value of adjusted R^2 proved that about 31 percent of the total variations in the Aman yield of rice can be explicated by the climate variables included in the research.

Additionally, regression results for the Boro Rice Model depicted that seasonal average maximum temperature and rainfall negatively coalesce with Boro rice yield and found highly significant at 10 percent level. The implication of this finding is that rise in maximum temperature and rainfall could give rise to an adverse effect on Boro yield. Howbeit, average minimum temperature and humidity determined the yield of Boro rice, and therefore significant at 5% and 1% level, respectively. Furthermore, the value of adjusted R^2 signified that the long-run overall model aptly harmonized as the explanatory variables, that is, climatic variables can explicate and account for over 46 percent of the total variation in the yield of Boro rice, such as the dependent variable.

On the one hand, it was also revealed that 1 percent increase in growing season maximum temperature and rainfall on average would reduce the yield of Boro rice by 1.68 and 0.18 metric ton/hectare, respectively. On the other hand, 1 percent increase in minimum temperature and humidity on average could result into a raise in Boro rice yields by 3.50 and 5.03 metric tons/hectare, respectively.

3.3.2.3 Crop Production Supply Response Studies

Evidences reveal that agricultural supply response studies have trapped the attention of many researchers in Ethiopia, Africa and other parts of the world. Towards this end, Chandio, Jiang and Magsi (2018) and Dumrul and Kilicarslan (2017) examined climate change impact on rice production in Pakistan and economic effect of changes in climate on agricultural crops in Turkey, respectively using ARDL Model. They found almost comparable as well as mixed results. Dumrul and Kilicarslan (2017) analyzed economic effect of changes in climate change on agricultural crops in Turkey using a time series secondary data covering the period of 1961-2013. The effect of weather variables on agricultural GDP in Turkey was approximated employing Autoregressive Distributed Lag (ARDL) approach. The study showed that the increase in precipitation positively influences agricultural GDP, while in contrast, increase in temperature negatively affects agricultural GDP. On that ground, the researchers argued that it was needful to establish policies, strategies, plans and programs to combat climate change and minimize its adverse effects in Turkey. The study equally recommended the production of agricultural products suitable for the increase in temperature in Turkey should be supported and the farmers should be aware of the adaptation to climate change.

Furthermore, numerous researchers have conducted studies to assess the supply response of cereal crops to changes in climate in Africa (Agba, *et al,* 2017; Aninagyei and Appiah, 2014). In particular, Agba, *et al* (2017) on their part found that rainfall had positive and significant association with crop output supply in the short-run while CO_2 emission had negative impact on crop output supply in the long-run in Nigeria.

Aninagyei and Appiah (2014) analyzed the effects of rainfall and temperature variability on the production of grain crops in Akim Achiase, Ghana. They observed that even though favorable rainfall and temperature are necessary inputs to the growth cycle of grain crops, yet the analysis of the data did not reflect the estimated relationship between the two climatic elements and the quantity of grain crops produced in Akim Achiase, Ghana annually. Nonetheless, the finding evidenced that rainfall and temperature were not the sole determinants of the survival of grain crop survival, hence the significant higher yields recorded. They further argued that researchers should equally take cognizance of other factors like the fertility of the soils and farming methods when examining the relationships between climatic variables and food crop output.

Eregha, Babatolu and Akinnubi (2014) and Kavinya *et al.* (2014) studied effect of changes in climate on crop output supply in Nigeria and Malawi, respectively. All of them found related results. In particular, Kavinya *et al.* (2014) on their part concluded that lagged hectarage allocated to maize and number of labor in a household in Malawi manifested positive and significant impact on maize output supply whereas the availability of labor stimulated a decrease in amount of land allocated to maize in current season, respectively. Further, lagged maize market prices and weather variables played a significant role in influencing the smallholder farmers' decision in land allocation. They also found that only maize price policies and market interventions are not sufficient to effect a change in smallholders' land allocation decisions in the case of staple food production since farmers are unresponsive to price factors, but responsive to non-price incentives.

3.3.3 Overview of Reviews, Advantages and Disadvantages of the Models Employed

All of the preceding reviews of literatures were focused on researches that examined the effect of climate and non-climatic variables on various crops in different parts of the world. It has been assessed that most of the researchers have critically addressed the issues of climate change and the impacts they have of yield of cereal crops both in the long- and short-run. However, the studies reviewed did not address issues of mitigation and adaptational approaches and strategies to be undertaken to reduce the adverse effects of climate change, which should be the focus of future research.

The review revealed that some studies have also been carried out on the impact of climate change on output and yield of cereal crops in Ethiopia. However, the studies in Ethiopia were limited to specific regions and pocket areas. Most of the studies conducted few regions and pocket areas have also considered only temperature and precipitation out of the various weather variables. Therefore, this study used nationally aggregated production data on teff, wheat and maize crops using long term secondary data that is sufficient enough to capture changes in climate and its variability. The current study also included CO_2 emission as one of limiting factor in crop production. The study has also addressed the shortcomings prevailing in literature on the thematic area of climate change in Ethiopia by incorporating both climate variables (rainfall, temperature and CO_2 emission) and non-climatic variables to assess their effects on teff, wheat and maize production using long-term historical data.

The reviewed literatures also revealed that researchers have critics on the various models employed to estimate the intended variables under consideration. They have cited advantages and disadvantages of the models being employed. The advantages and disadvantages cited by the researchers have been briefly discussed under the linear trend regression approach, Cobb-Douglas Production functional approach, and autoregressive distributed lag approaches as follows.

3.3.3.1 Linear Trend Line and Regression Models

Researchers have assessed the technical suitability of linear trend line or Sen's slope test and identified potential advantages and disadvantages to apply on measuring effect of rainfall, temperature and yield (Meals, *et al.* 2011). The identified advantages of the analytical approaches include: trend lines can employ data coming from single monitoring station, do not require calibration, applicable for large data series, and are useful for the situations with long lag times. Conversely, the disadvantages cited include: usually requires long continuous data records, difficult to account for variability, and they provide no insights into causes of trend.

3.3.3.2 Cobb-Douglas Production Functional Models

It has been assed that Cobb-Douglas functional form has been abundantly used by many economists since it has the advantage of algebraic tractability and of providing a fairly good approximation of the production process (Yu, *et al.*, 2010; Sadoulet and de Janvry, 2003; Reynès, F., 2011). Furthermore, the Cobb-Douglas functional approach has additional advantages; (i) first, there is an exact dual relationship between the Cobb-Douglas production and profit functions, (ii) second, it can handle multiple inputs in its generalised form, (iii) thirdly, the estimated coefficient of an input from a linearized Cobb-Douglas function is the direct elasticity of the input, and (iv) forth, it allows for easily introduction of different levels of elasticity between production factors. Conversely, the main limitations of Cobb-Douglas function are: (i) to impose an arbitrary level for substitution possibilities between inputs, and (ii) it is not possible to combine the different factors due to the scarcity of factors and due to their indivisibility (Bhanumurthy, 2002; Reynès, 2011).

3.3.3.3 Autoregressive Distributed Lag Models

In the literature reviewed, many researchers have the opinion that autoregressive distributed lag (ARDL) model has got both advantages and disadvantages in its application (Oxera, 2010; Adekoya and Razak, 2019). The ARDL model has the following advantages: (i) it can accommodate very general lag structures as well as can easily be extended to incorporate both time series and panel data, (ii) its ability to generate sufficient lags for variables in the model and its superiority to sufficiently provide for the means to ascertain residual correlation, and (II) it is capable of providing the short-run and long-run at the same time. Conversely, the models of ARDL type are likely to have difficulties in successfully identifying the 'correct' relationships between the variables in the data which contain a unit root, as issues of spurious correlation may arise.

Summing up, capitalizing the advantages of the models reviewed; the investigator adopted Linear Trend Line or Regression model, Augmented Cobb-Douglas Production model, and Autoregressive Distributed Lag model in this study.

CHAPTER IV

RESEARCH METHODOLOGY

4.1 Introduction

In this chapter, the research design adopted, empirical models, and analytical techniques employed in the investigation were presented. Additionally, description of the type and sources of data, the statistical techniques employed to test the hypotheses proposed for the study are presented. This chapter presents the various statistical and econometric methods that were employed for data analyses.

4.2 The Research Design and Approach

This study employed the quantitative research approach whereby secondary time series data were utilized. Quantitative research approach refers to a research method where measurable numerical data are collected and analyzed to make predictions and test casual relationship between variables. Likewise, quantitative secondary data research approach is a research method that uses already existing secondary data available from various sources. It involves collection of quantitative data from existing data sources such as published government resources, libraries, internet and research reports. In this study, the researcher used an inductive reasoning approach, where he identified research problem, formulated hypothesis, set research objectives, collected data on variables relevant to the research problem, conducted analysis and generated conclusions, and finally verified or proved the hypothesis.

4.3 Data Types and Sources

In this study, time series data were used. The variables that were selected for this study comprised of weather variables (rainfall, temperature and CO_2) and agro-economic variables such as area of land cultivated under the specific crops, irrigated area under crops under study, price of the crops under study, fertilizer and improved seed consumed for production of the selected crops. The data required for this study were collected from government documents such as the annual sample survey reports and websites, which included: Ethiopian Central Statistical Agency (CSA), Ethiopian National Meteorological Agency (NMA), Ethiopian Grain Trade Enterprise and National Bank of Ethiopia. Furthermore, some data gaps were obtainedfrom FAOSTAT database, and other relevant international organizations. Data on output and yield of three major crops (*teff*, wheat, and maize) were used. These three cereal crops are of agricultural significance accounting for about 67% of the area cultivated and about 68% of the total volume of cereal production during the 2017 production season (CSA, 2017). Nationally aggregated data on land area cultivated to the selected crops, production of crop outputs, and yield per hectare of the crops selected for this study were mainly compiled from CSA Agricultural Sample Survey reports over the period 1981 to 2018 (38 years). Any gap in these data variables was complemented from FAOSTAT database.

The data on weather variables such as *temperature and rainfall* for the observation period of 1981 to 2018 were collected from the National Meteorological Agency (NMA) of Ethiopia. Weather data from twenty one (21) representative weather stations that were based in the major crop growing regions of the three selected cereal crops were collected. Average monthly data for *Short-rainfall Season* (***Belg***) (February - May) and main crop growing season, *Long-rainfall season (M**eher**)* (June - September) were computed. An aggregated average/ pooled data at national level for both crop growing seasons were calculated by taking average of weather stations selected for each crop over the period of 1981 to 2018. In total, 21 weather stations were selected, 12–13 stations were classified for each crop growing belt selected for this study.

Agricultural inputs data on fertilizers and improved seeds were collected for each cereal crop from the Agricultural Sample Survey, Farm Management Practice reports of CSA. Any gap in the data was complemented from reports of Ministry of Agriculture and Agricultural Inputs Supply Enterprise of Ethiopia.

Historical prices of agricultural outputs on the three selected crops were compiled from FAOSTAT database, CSA, EGTE and other relevant organization for the period of 1981 to 2018. Both producer price index and producer price data for crop output were collected.

4.4 Data Cleaning and Diagnostic Tests

The data were checked for completeness and recorded in an excel spreadsheets for further analysis using statistical softwares.

There could be severe consequences if models are mis-specified in regression analysis unless diagonistic tests are taken before estimation. In order to tackle these concerns, researchers should perform several model misspecification tests so as to test the validity of the supply response models selected for the studies. These diagnostic tests included: test for normality, heteroskedasticity, serial autocorrelation, and stability of long-run coefficients. The suitability of the specification of models was also tested using a Ramsey RESET test, while the consistency and strength of the estimated coefficients were evaluated using CUSUM and CUSUM of Squares tests.

4.5 Empirical Models Specification

In this study, different approaches were employed to examine the effect of weather variables such as rainfall, temperature and CO_2 and socio-economic factors on selected cereal crop yields and outputs.

It has been assessed that researchers have adopted different models to examine the impact of changes in weather variables on crop yields and outputs. Among the models, Autoregressive distributed lag model, Production Functional Model, the Ricardian Model, and Crop Yield Model are most extensively used to analyze the relationship between climate change and response of crop yields or outputs.

The methodological approaches and models employed in this study have been described briefly in the following sub-sections.

4.5.1 Climate Characterization and Analysis of Models

In order to address the *first objective* of the study, under the main objective of analyzing the impact of climate change on the yields of selected cereal crops, analysis of trends in climate variables (temperature and precipitation) and year-to-year/yearly variation of precipitation and temperature were characterized using standardized anomaly of rainfall (ΔR_t) or temperature (ΔT_t) as well as coefficient of variation for each variable under study.

To investigate the nature of trends in rainfall, temperature and CO_2 data series, linear trend lines was fitted for both annual and seasonal situations. The linear trend line is given by:

$$R_t = \alpha + bR_t \quad \text{for rainfall, and} \qquad (4.1)$$

$$T_t = \alpha + bT_t \quad \textit{for temperature.} \qquad (4.2)$$

$$CO_{2t} = \alpha + bCO_{2t} \quad \text{for } CO_2 \qquad (4.3)$$

Furthermore, the long-term standardized anomaly of precipitation (ΔR_t) for a given locality or pool of locations over a period t is given by:

$$\Delta R_t = R_t - \bar{R}_t / \sigma, \qquad (4.4)$$

Where: ΔR_t is normalized anomaly of rainfall, R_t is the mean rainfall for year t, $\bar{R}_t$ is the long-term mean over a period under study, and σ is the normalized deviation of mean rainfall over the long-run (period under study).

Similarly, the long-term standardized anomaly of temperature (ΔT) and CO_2 (ΔCO_2) for a given location or pool of locations over a period t is given by:

$$\Delta T_t = T_t - \bar{T}_t / \sigma, \qquad (4.5)$$

$$\Delta CO_{2\,t} = (CO_{2\,t} - \overline{CO}_{2t})\sigma, \qquad (4.6)$$

Where: ΔT_t is normalized temperature anomaly for period t, T_t is mean annual temperature for year t, $\bar{T}_t$ is long-term mean temperature over a period under study, $\Delta CO_{2\,t}$ is normalized CO_2 anomaly at period t, $CO_{2\,t}$ mean annual CO_2 for year t, $\overline{CO}_{2t}$ is long-term mean CO2 over period under study, and σ is the standard deviation of annual mean temperature for the long-run (over a period of observation).

Furthermore, the inter-seasonal variability of national level aggregated weather variables (precipitation and temperature) were evaluated using coefficient of variation (CV), which is expressed as:

$$CV_{R,T} = 100 \times \sigma / \bar{R}, \bar{T} \tag{4.7}$$

Where: $CV_{R,T}$ represents the coefficient of variation of aggregate precipitation/ temperature variables, σ is the standard deviation of precipitation or temperature data series, and $\bar{R}, \bar{T}$ are mean rainfall and temperature data series observed in teff, wheat and maize growing areas.

In order to characterize climatic factors (precipitation and temperature) data records of 20 selected weather stations have been aggregated/pooled and arranged by crop seasons (*belg* and *meher*) in a manner convenient to estimate their trends and anomalies. Then, analysis and interpretation of the results have been carried out using equations specified above (i.e., 4.1 – 4.7), descriptive analysis and graphics were used to visually portray the results.

4.5.2 Agriculture Crop Yield Models

In order to address the *second objective*, an augmented Cobb-Douglas Production Model has been employed to examine the effect of changes in climate and socio-economic variables on the yield of crop. *Crop yield* refers to crop production per area of land under specified crop in quintals per hectare. In this study, three cereal crops, viz., teff, wheat and maize were selected and included in the model. According to data obtained from CSA (2018), these cereal crops covered nearly 67 percent of the aggregated agricultural cropped area during 2017 production season.

In line with the production theory described in Chapter III, it was assumed that the relationship among the explanatory variables (climatic and socio-economic) and dependent variable (crop yield) takes non-linear form. Thus, the empirical model applied in this current study was also assumed to take non-linear form. To investigate the effect of changes in weather factors on average yield of cereal crops, most studies employed stochastic production functional model postulated by Just and Pope in 1978 (Acquah and Keyei, 2012a). In this study, an augmented Cobb-Douglas production functional model has been employed. This model has advantages over other models as it is simple to estimate and interpret the coefficients as well as its appropriateness in situation of small size of observations. This model presupposes that farm production is a function of many variables (endogenous and exogenous) such as area cultivated under crops, area irrigated under specific crop, improved seeds, fertilizers, etc. The Cobb-Douglas production model (Gujarati, 2004), can be specified as:

$$Y_i = AX_i^{\beta i}e^{\varepsilon} \qquad (4.8)$$

Where, Y_i is a dependent variable (yield of *teff*, wheat and maize), X_i are observations of the independent variables incorporated in this study, and β_i are regression parameters, A is the intercept, e is base of natural logarithm, while ε is the disturbance term with zero mean and constant variance. The non-linear form of the model specified can be predicted employing OLS with natural log on both sides of equation (4.6), which represents log-linear form. It is evident from the model specified that estimates of this form of production function will give straight elasticities of the variables. The log-linear form of the Cobb-Douglas production function in this regard is given by the equation:

$$\ln Y_i = \beta + \beta i \sum_{i=1}^{n} \ln X_i + \varepsilon i \qquad (4.9)$$

Where lnY shows crop yield (quintal per hectare), X is vector of farm inputs including fertilizer, improved seed, irrigated area, etc. However, time series data were unavailable for some of the farm inputs like farm machinery, and laborers. In its functional form, the Cobb-Douglas production function under equation (4.9) can be specified as:

$$\ln Y_{it} = \alpha_0 + \beta_1 \ln La_{it} + \beta_5 \ln Fert_{it} + \beta_6 \ln IS_{it} + \beta_7 \ln Irrga_{it} + \varepsilon_{it} \qquad (4.10)$$

Where, lnY_{it} signifies the natural log of yield of a given crop (quintal per hectare), $lnLa_{it}$ is natural log of cropped land area under i^{th} crop, $lnFert_{it}$ is natural log of fertilizer used under each crop, IS_{it} denotes natural log of improved seed used under i^{th} crop, and $Irrga_{it}$ represents natural log of irrigated land area under i^{th} crop.

Climate factors are further assumed to be an input factor for growth of crops in the Cobb-Douglas production model (Nastis *et al.* 2012). The climatic variables considered in this study were rainfall and temperature, where mean minimum temperature for *Short-season rainfall* (February - May) and *Long-season rainfall* (June - September), mean maximum temperature for *Short-* and *Long-season rainfall*, as well as mean rainfall for *Short-season rainfall* and *Long- season rainfall* were considered. The ε is the usual disturbance term in-dependently and identically distributed. After incorporating climatic variables, equation (4.8) in its log-linear form has been specified as:

$$lnY_{it} = \alpha_0 + \beta_1 lnLa_{it} + \beta_6 lnFert_{it} + \beta_7 lnIS_{it} + \beta_8 lnIrrga_{it} + \beta_2 lnSSRain_{it} + \beta_3 lnLSRain_{it} + \beta_4 lnMinTemp_{it} + \beta_5 lnMaxTemp_{it} + \varepsilon_{it} \quad (4.11)$$

Where: lnY_{it} is the natural log of yield of a given crop (quintal per hectare), $lnLa_{it}$ is natural log of cropped land area under i^{th} crop, $lnRainbel_{it}$ is natural log of *short-rainfall* season rainfall, $lnRainmeh_{it}$ is natural log of *long-rainfall* season rainfall, $lnTempMin_{it}$isnatural log of annual minimum temperature recorded during cropping seasons, $lnTempmax_{it}$isnatural log of annual maximum temperature recorded during cropping seasons, $lnFert_{it}$ is natural log of fertilizer used under each i^{th} crop, $lnIS_{it}$ is natural log of improved seed used under i^{th} crop, $Irrga_{it}$ is natural log of irrigated area under i^{th} crop, i = 1, 2, 3 corresponds to teff, wheat and maize crops selected for this study, t = time period from 1981 – 2018, α_0, β_1, β_2, β_3, β_4, β_5, β_6, β_7, and β_8 are unknown parameters to be estimated, and $\varepsilon_{it}$is the error term. To estimate the Cobb-Douglas production model specified by equation 4.9, ***MedCal- Version 19.1 software*** **and** ***SPSS 24 Statistical package*** were used.

In agricultural production models, it is customary to estimate marginal impact of variables (covariates) included in the formulated models. In practice, the marginal product of a business is defined as the the additional output created as a result of additional input placed into the production firm. In production economics, it is also refered to as marginal physical product, or MPP. In practical terms, this might mean the additional ton of wheat produced on a farm business once it hires an extra farm employee. In general, marginal product can mathematically be specified as:

$$MP = \frac{\Delta Y}{\Delta X} \tag{4.12}$$

Where, MP is marginal prduct

ΔX is change in the farm's use of the input,

ΔY is change in quantity of output produced (ignoring external cost and benefits).

In a similar fashion the marginal impact (MIM) of a given covariate (input) such as land area cultivated on particular yield of crop is estimated at its mean and specified as:

$$MIL_m = \frac{\Delta YQ}{\Delta Lm} = \frac{\partial YQ}{\partial Lm} \tag{4.13}$$

Where, MILm is marginal impact of land at its mean; ΔY_Q or ∂Y_Q represents change in yield of relevant crop; and ΔL_m or ∂L_m is change in mean cultivated land area.

The elasticity of an output or yield quantity with respect to relevant covariate or input can also be estimated, which is the ratio of the marginal impact of the concerned covariate or input at its means (MIL_M or MIF_M) to the mean of the covariate or input (ML_a or MF_Q). As such, the elasticity of crop yield with respect to cultivated land area ($e_{YQ.La}$) will be estimated as:

$$e_{YQ.Lm} = \Delta Y_Q/\Delta L_m * ML_a/Y_Q \tag{4.14}$$

If its value is less than unity, then the comparable percentage change in yield will be lower than the proportional change in covariate (input La); if it is more than unity, the percentage change in output will be higher than the proportionate change in the covariate (input La);

and If it is unity, then the proportionate change in output will be equal to the proportionate change in covariate (input La).

The agro-economic factors included in the above model as explanatory variables were area cultivated under crop, price of specific crop under consideration, fertilizers and improved seed used in specific crop, irrigated area put under specific crop.

From climate factors, *short*- and *lon-season* rainfall, crop growing period mean minimum and maximum temperatures, and CO_2 were included in the model and analyzed. Infact, the explanatory changeables are anticipated to have both straight and tortuous influences on the yield of crops considered in the current study, especially under condition of rainfed agriculture. Ergo, mean crop growing period temperature and rainfall data series were included in the model specification.

Although labour and mechanization are important explanatory fariables in crop production, they are not included in the models as data on these inputs are not available on consecutive and time series basis. No regular surveys are being conducted on these two variables.

4.5.3 Output Supply Response Model

In order to attain the *third objective* of this study, an analysis of crop supply reaction to the alterations in climatic factors has been conducted. To analyze the supply responses of the selected cereal crops to the changes in weather and non-weather variables, an ARDL model, also known as bounds testing cointegration method initially constructed by Pesaran, *et al.* (2001) was employed as a model that sufficiently examine the effects of climate as well as socio-economic explanatory variables on supply of teff, wheat, and maize outputs. The ARDL model provides an efficient platform to test and estimate *long-run* associations based on real time series secondary statistical data (Hassler and Wolters, 2006) while the model also being perfectly suited for *short-time series* (Duasa, 2010). According to Pesaran, *et al.*

(2001), ARDL model provides flexibility in analyzing variables of different orders of integration.

The common form of an ARDL model with specified lags (p) for variable Q and lag (q) for variable X is specified as:

$$Q_t = \alpha_0 + \sum_{i=1}^{p} \beta_i Q_{t-i} + \sum_{i=0}^{q} \beta_i X_{t-i} + U_t \qquad (4.15)$$

Where, Q_t represents quantity of crop supplied (teff, wheat, and Maize) in year *t*, Q_{t-i} represents quantity of crop output (teff, wheat and maize) supplied in year *t-i*, X_{t-i} represents quantity of explanatory variables in year *t-i*, and β_0, β_i, … are *long-run* coefficients of inputs incorporated in the model, *p* and *q* represent lag lengths, and U_t is disturbance term.

In this study, the association among the teff, wheat, and maize production and climate as well as socioeconomic variables is assumed to take the following functional form:

$$Q_t = f\,(PrCrop_t, La_t, IrrigA_t, Fert_t, ImS_t, RF_t, Temp_t, CO_{2t}) \qquad (4.16)$$

Where; Q_t is observations on relevant crop output measured in tons; $PrCrop_t$ is the price of relevant crop output in ETB,, La_t is land area cultivated under the relevant crop, $IrrigA_t$ is irrigated area under (teff, wheat or maize), $Fert_t$ is fertilizer consumed under each of the crop production, ImS_t is improved seed of (teff, wheat or maize), RF_t is seasonal rainfalls (short- and long-season) measured in millimeters, $Temp_t$ is the crop growing period mean temperatures (MinTemp and MaxTemp) measured in degrees Celsius, and CO_{2t} is CO_2 emission in time t measured in teragrams.

The above linear combination equation (4.16) can be transformed into log-linear model so as to make the model well fitting and competent compared to the simple linear model; which can be specified as:

$$lnQ_t = \beta_0 + \beta_1 lnPrMz_t + \beta_2 lnLa_t + \beta_3 lnIrrigA_t + \beta_4 lnFert_t + \beta_5 lnImS_t + \beta_6 lnSSR_t + \beta_7 lnLSR_t + \beta_8 lnMinTemp_t + \beta_9 lnMaxTemp_t + \beta_{10} lnCO_{2t} + \varepsilon_t \qquad (4.17)$$

Where: $ln SSR_t$ is log short-season rainfall in mm, $ln LSR_t$ is log long-season rainfall, lnMin-Temp is log minimum temperature in ^{0}C, lnMaxTemp is log maximum temperature in ^{0}C, and $ln CO2$ is log CO2 as defined above, ε_t is the statistical stochastic disturbance term with zero mean and stable variance, uncorrelated with independent variables and their earlier knowledge.

The specific ARDL model employed to find out the *long-run* association among the relevant variables was specified as:

$$\ln Q_t = \alpha_0 + \sum \alpha_1 \ln Qt\text{-}i + \sum \alpha_2 \ln La_{t-i} + \sum \alpha_3 \ln PrMz_{t-i} + \sum \alpha_4 \ln IrrigA_{t-i} + \sum \alpha_5 \ln Fert_{t-i} + \sum \alpha_6 \ln ImS_{t-i} + \sum \alpha_7 \ln SSR_{t-i} + \sum \alpha_8 \ln LSR_{t-i} + \sum \alpha_9 \ln MinTemp_{t-i} + \sum \alpha_{10} \ln MaxTemp_{t-i} + \sum \alpha_{11} \ln CO_{2t-i} + \varepsilon_{t-I} \quad (4.18)$$

If the variables included in the model are found cointegrated, there exists an error correction representation. Indeed, the *short-run elasticity* coefficients can be estimated employing the following Dynamics ARDL Error Correction Model (ECM):

$$\Delta \ln Q_t = \beta_0 + \sum \beta_1 \Delta \ln Q_{t-i} + \sum \beta_2 \Delta \ln La_{t-i} + \sum \beta_3 \Delta \ln PrW_{t-i} + \sum \beta_4 \Delta \ln IrrigA_{t-i} + \sum \beta_5 \Delta \ln Fert_{t-i} + \sum \beta_6 \Delta \ln ImS_{t-i} + \sum \beta_7 \Delta \ln SSR_{t-i} + \sum \beta_8 \Delta \ln LSR_{t-i} + \sum \beta_9 \Delta \ln MinTemp_{t-i} + \sum \beta_{10} \Delta \ln MaxTemp_{t-i} + \sum \beta_{11} \Delta \ln CO_{2t-i} + \psi_i ECT_{1-i} + u_i \quad (4.19)$$

where ψ_i represents the speed of adjustment (ECM term) which determines the deviation of Q_t from the long-run equilibrium level.

The lags length was being established using standard industrial classification (SIC) and Hannan-Quinn Criteria (HQIC). The ARDL models specified above has been estimated using ***Eviews 9 software and SPPS Version 24***.

4.5.4 Forecast of Future Impacts of Climate Change on Yields of Selected Crops

Forecasting of weather factors such as precipitation and temperature are very important task to the agriculture sector to provide information that farmer producers, planners and decision makers can use to reduce weather-related losses and enhance social benefits. In order to forecast the future effects of changes in climate on the yield of selected crops, researchers have developed and used several models. Cobb-Douglas Functional model is well-known and as such, it is extensively used in forecasting future impacts of climate change on crop yields. The Cobb-Douglas functional approach, which describes an empirical relationship between the various inputs in the production process, could be used as it effectively fit the actual production, to a large extent (Yuan *et al.*, 2009).

To forecast the future alterations in minimum and maximum climatic variables (temperature and precipitation) the following equation has been used:

$$\Delta Y = [((\frac{\partial Y}{\partial R}) * \Delta R) + ((\frac{\partial Y}{\partial T}) * \Delta T)] * 100 \qquad (4.20)$$

Where, Y is the yield, R is the rainfall, and T is the temperature; ($\partial Y/\partial R$) and ($\partial Y/\partial T$) are identified by the equations of the model.

4.6 Method of Estimation

The models described above and other relevant ones have been extensively examined, while the best fit models to the time series data of crop output and yield, including climate and socio-economic variables were selected and employed for this study. The supply responses of teff, wheat, and maize output models in this study have constantly been estimated using OLS if the disturbance term (ε_j) has zero mean, constant variance, and no multi-collinearity among the independent variables and their previous lagged values. Indeed, models selected for this study have been estimated using annual time series secondary data spanning over 1981 to 2018.

In estimating the ARDL model, four main steps are involved: (i) determine whether or not the variables are stationary or not employing ADF; (ii) choose optimum lag length for the model; (iii) test existence of co-integration using bounds testing approach; and (iv) estimate the ARDL model to obtain short-run and long-run coefficients.

4.7 Time Series Properties

Since the current study used time series data, test for unit root and existence of cointegration has been conducted using appropriate methods and tools, before estimation of the equations involved. Details of the tests are presented in the following sub-sections.

4.7.1 Testing for Stationarity of Data

Unit root tests are commonly used at the beginning of econometric time series analysis. Therefore suitable tests for different situations have been proposed in the literature. The presence of unit root was tested using two most popular tests employed in time series data; (1) ADF and (2) PP tests. ADF test for stationarity in series y has been estimated employing equation:

$$\Delta y_t = \mu + \beta_t + \gamma\, y_{t-1} + \sum_{i=1}^{p} \emptyset_i \Delta y_{t-1} + \varepsilon_t \qquad (4.21)$$

Where μ is the constant, t is the time period, i represent lag length in Δy_{t-i}, p is maximum number of lags determined using AIC and SC, and ε_t is the stationary disturbance term.

The null hypothesis H_0: $\gamma = 0$ (unit root) has been tested against the alternative hypothesis H_A: $\gamma < 0$ (no unit root). If **the Null Hypothesis is rejected (**$\gamma = 0$**)**, we say that our series is integrated of order 0 and write **the series y_t as I(0).** If **the Null Hypothesis** is **not rejected (**$\gamma < 0$**)**, we take the first differences dyt and test the new series for a unit root. If the new series dyt is stationary then we say that our **series is integrated of order 1**, that is we need to differentiate once to transform our non-stationary series to stationary and write y_t as I(1) (also dyt as I(0)).

The time series secondary data collected for this study have also been brought to a PP test which has a higher power. In this regard, the PP test would be specified as:

$$\Delta Y_t = \theta_0 + \sum_{i=1}^{m} \delta_i \Delta Y_{t-i} + \varepsilon t \qquad (4.22)$$

Where ΔY_t is 1st difference of the dependent variable; i is lag length; $i=1, 2, \ldots, m$; θ and δ are regression parameters to be estimated and ε_t is disturbance term. The null hypothesis of, H_0: $\delta_i = 0$ (unit root) was tested aligned with the alternative, H_A: $\delta_i < 0$ (no unit root). If the calculated test statistic value is > than the decisive value at 5% level of significance, then the null hypothesis was not rejected (stationary). If the computed value is < the critical value, then H_0 is not rejected (stationary). If H_0 could not be rejected, then the time series variable is regarded as contained a unit root and hence non-stationary, otherwise it is considered as stationary.

When unit root test outcomes show a mixtures of I(1) and I(0) variables or all variables are I(1) then the ARDL model is appropriate to apply. The ECM model is designed when all variables are I(1). Specifically, if a time series has a unit root (non-stationary), it shows that a systematic pattern that is unpredictable and cannot be used at levels since there is likelihood of giving spurious results. Then it is recommended to go for first difference test, and if found stationary, the series was an I(1). If all variables included in the study yield I(0), then it is recommended to go for OLS, if all variables included yielded I(1) with cointegration it is recommended to go for VECM, if all variables revealed I(1) without cointegration, go for VAR, if the variables yielded a mixture of I(0) and I(1), it is recommended to go for ARDL. But for a mixture of I(1) and I(2), none of above methods described can be used.

4.7.2 Cointegration analysis

Testing for cointegration is simply testing the stationarity of the disturbance (error) term in the cointe-grating equation. Though a single time series is non-stationary in practice, yet the linear combination of two or more time series can be stationary; therefore, these variables are called cointegrated. Cointegration reveals a secular and steady equilibrium relationship. When estimating an econometric model with non-stationary variables, these variables have to be cointegrated in order for the model to be meaningful. The Granger Theorem states that if two series are non stationary (i.e. I(1)), there can be a linear combination of the two series that is stationary.

Cointegration relation must involve at least two I(1) variables and therefore I(0) variables may also be included in the cointegrating equation (Hatanaka, 1996). Indeed, the test for cointegration involves running a regression of each crop output on climate and other control variables. Once cointegration is established employing the model with at least two I(1) data series, then one can also add I(0) variables in the ARDL model. Addition of I(0) variables does not alter I(0) characteristics of the disturbance (error) term (Hill *et al.,* 2012) to be tested.

For cointegration analysis, this study uses the Akter and Seung-Jee (2011) procedure which is considered multivariate case to avoid the identification problems and estimate the long-run impact. The first step in the procedure is to define an unrestricted vector autoregression (VAR). For cointegration test it is especially important to select proper order of VAR. The procedure for multivariate cointegration is based on the following form of VAR model:

$$X_t = A_1X_{t-1} + \ldots + A_kX_{t-k} + U_t \qquad (4.23)$$

Where X_t is a (n × 1) vector of I(1) variables which contain both endogenous and exogenous variables, A_i are (n × n) matrix of parameters, $U_t$is (n × 1) vector of white noise errors. Each equation specified in (4.21) above can be estimated by the OLS since each variable in the A_t is regressed on the lagged values of its own as well as all other variables in the system.

To examine the hypotheses of integration and cointegration, equation (4.23) can be transformed into the following VECM form:

$$\Delta X_t = \delta + \Gamma_1\Delta X_{t-1} + \ldots + \Gamma_{k-1}\Delta X_{k-1} + \Pi X_{t-1} + \psi Z_t + U_t \qquad (4.24)$$

Where $\Delta X_t = X_t - X_{t-1}$, Ztis a (q × 1) vector of stationary I(0) exogenous variables, δis a (n × 1) vector of parameters (intercepts), and ψ is a (n × q) matrix of parameters.

In equation (4.22), Γ_i and π are (n × n) matrices of parameters which provide information about short-run and long-run modifications respectively to alterations in X_t. The term ΠX_{t-1} is error correction mechanism that provides information on long-run equilibrium association among independent variables in X_t. For this term equation (4.24) differs from the VAR model. In the above equation, Π matrix is named as the long-run effect matrix of the error correction mechanism, which is a outcome of two (n × r) matrices α and β, i.e., $\Pi = \alpha\beta'$. In the model, α is the error correction term which ascertains the pace of modification in ΔX_t so that large value of αindicates rapid adjustment and vice versa.

However, β is the matrix representing the cointegrating associations among the non-stationary factors in X_t. The number of cointegrating association can be represented by the rank of the matrix Π, denoted as r. there are three probabilities for ranking. If rank $r$is zero, then the variables will not be cointegrated, i.e., the model will be comparable to a VAR model in the first differences; if $0<r<$n, then the variables will be cointegrated; and if $r = n$, then the variables will be stationary, i.e., the model will be comparable to a VAR model in levels. All the cointegration analyses have been conducted employing Eviews 9 econometric software.

4.8 Ethics Considerations

The researcher has taken care of ethics about other peoples' quality of life. He fully complied with all the policies, rules and procedures of UNISA, complied with resources and supervision at UNISA laboratory where found necessary. He took care in demonstrating high level of integrity without any form of compromise. He was obliged to obtain the necessary clearances (university research authorization letter). He also carefully considered the following ethics:

The researcher adhered to avoid plagiarism and fraud; he maintained confidentiality and anonymity of relevant information. The researcher has made every effort to avoid imparting any physical or psychological harm to subjects; he has high regard to conform to the principle of voluntary and informed consent, and he complied to use resources received from

UNISA and other institution for the current study and didnot divert any to other purposes, but strictly used it for this research. He also focused on demonstrating a high level of academic freedom.

The investigater hopes to publish this thesis as a way of publicizing the results so that the outcomes can be read and used among captivated stakeholders such as students, government decision makers, and other researchers, which can be considered as valuable study outome for contribution to existing knowledge and literatue.

CHAPTER V

CHARACTERIZATION OF RAINFALL, TEMPERATURE, CO_2, AND CROP YIELD IN ETHIOPIA

5.1 Introduction

Chapter V presents the analyses of the trend and variability of climatic variables as well as crop yield variability in teff, wheat and maize growing areas on aggregate/pooled and spot location basis. The examination included rainfall trend during *short-rainfall* and *long-rainfall* seasons, temperature over crop growing period, annual CO_2 emission from agrictulture, normalized anomaly of rainfall, temperature and CO_2 over a long period of time. The analysis of crop yield variation over long-period of time has also presented in this chapter. Further details of content the content of the chapter have been elaborated and presented in this chapter.

5.2 Trends of climate in Ethiopia

The study defines three periods namely, February to May (FMAM), June to September (JJAS), and October to January (ONDJ). The FMAM is partially a semi dry period (*Short-rainfall* season) in many parts of the country, which launch before the main rainy season. Nevertheless, this season also becomes main rainy season in mid-highlands and lowland belts of the South and Southeastern parts of the country such as lowlands of Bale, Giji, Borena, and Guji zones of Oromia region, Southern Somali region, and some agro-pastoral and pastoral zones of SNNP regions. The JJAS is the main-rainy season (*long-rainfall* season) which starts with onset of long rains in June in most parts of the country. The third period (ONDJ) is the dry season (Bega) in most parts of the country, which comes after the main rainy season which starts with the long dry season from November. However, this season becomes the second rainy season for the South and Southeastern parts defined above. Bearing this in mind, the analysis of climate pattern and trends in Ethiopia has been conducted using time series secondary data.

5.2.1 Pattern and Trend Analysis of Rainfall in Crop Growing Areas

The pattern and trend analysis of the *short-rainfall* and *long-rainfall* seasons has been carried out for areas growing teff, wheat and maize crops. As explained in Chapter II of this study report, the *short-rainfall season (Belg)* normally covers the central parts of northern highlands (North and South Wollo zones, and North Shewa zones), the central (Shewa zones), the Southern mid-highlands (SNNP region), and the eastern highlands (Afar, East and West Hararge zones) of the country (see Fig. 5.1). Conversely, the *long-rainy season (Meher)* covers the Southwestern (highland zones of SNNP region), the Western (Gambella, Western Oromia, and Benishangul-Gumuz regions); Northwestern highlands (Awi, Gojam and Gondar zones), Central and Highlands of Northeastern (all Shewa zones, North and South Wollo zones, Southern Tigray zones and highlands of Afar region); Eastern highlands (East and West Hararge zones, and the highlands of Somali region) and Southeastern (Arsi and highlands of Bale) parts of the country.

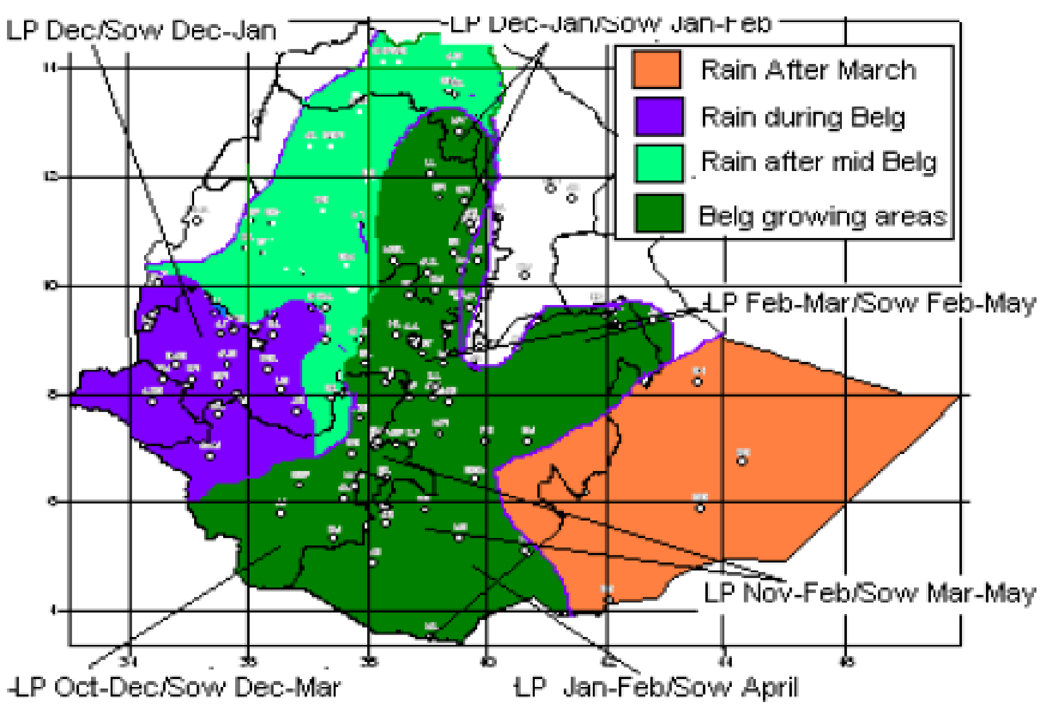


Figure 5.1: Belg Season Crop Growing Areas of the Country

The rainfall data used in this analysis were taken from 21 weather stations as recorded by the National Meteorology Agency (NMA) of Ethiopia. Table 5.1 depicts the descriptive data estimates of rainfall in teff, wheat and maize growing areas. Spatially, the raw data obtained from NMA of Ethiopia represents 21 weather stations; rainfall data of 12-13 stations have been aggregated/ pooled for each of the crops selected for this study.

Accordingly, the crop growing period mean rainfall (Feb. – Sept.) over the teff, wheat and maize growing areas were 543 mm, 479 mm, and 156 mm, respectively. Seasonally, the mean *short- rainfall season* rainfall in teff, wheat and maize growing areas were 227 mm, 195 mm, and 65.5 mm, respectively. Equally, the mean *long-rainfall season* rainfall amount in teff, wheat and maize growing areas reached a level of 859 mm, 764 mm, and 247 mm, respectively. The results indicate that teff and wheat growing areas receives relatively the highest rainfall amount while maize growing areas receives lowest rainfall over both *short*- and *long-rainfall* seasons.

As has been portrayed in Table 5.1, the *long- rainfall season* in the crop growing areas contributes the highest rainfall amount, displaying existence of elevated concentration of precipitation among the rainfall seasons. Further, *short-rainy* season that lasts from the months of February to May also constituted a considerable quantity of rainfall.

Figure 5.2 depicts the pattern and trend of *short-rainfall* and *long-rainfall* season in teff growing areas over the period of 1981 to 2018. The pattern of short-rainfall and long-rainfall in teff growing areas shows that short-rainfall season is decreasing while long-rainfall season is increasing over time in teff growing areas. A linear trend line has been fitted to both rainfall seasons' data so as to identify the extent and direction of changes in both short- and long- rainfall season in teff growing areas. The result signifies that the amount of short- rainfall season has a decreasing trend with a magnitude of (-) 0.47mm (negative), but statistically insignificant. Oppositely, the long- rainfall season revealed an increasing trend with a magnitude of 2.87 mm (positive) and highly significant at 1%

level in teff areas over the observation period (Table 5.2). This implies that as time passes over, there is a significant increase (2.868 mm/year) in the amount of long- rainy season in teff growing areas. The positive and significant rise in rainfall during *long-rain* season becomes very important in teff production as all teff farming practices (from seed bed preparation to harvesting) take place during this season rather than the *short-rainy* season. The teff growing belts are normally located in the mid-highlad and upper-lowland areas with mean *long-rainfall season* rainfall amount of 858.7mm; which is relatively above the water requirement of teff crop. This rainfall amount might be considered as suitable condition for teff crop production provided that other inputs as well as technical requirements are fulfilled. Nevertheless, in case the rainfall amount exeeds the optimum level requirement it will affect the yield and production of teff. The result of this study agrees with that of Hayelom, *et al,* (2017) who analyzed trends of weather variables in the Southern Tigray of Ethiopia over the period of 1981-2010; their study equally reported an increasing and significant trend in summer (long- rainfall) season. Similarly, Birara, *et al* (2018) have conducted trend and variability analyzed of weather factors in the Tana basin area of Ethiopia. The researchers utilized data obtained from selected weather stations between the periods of 1980 to 2015. In their study, they observed an increasing and significant trend in precipitation in Kimerdengay (3.94 mm/year) and Addis Zemen (2.5 mm/year) the weather stations during the *long-rainfall* season. Also, Arragaw and Woldeamlak (2017) have analyzed spatio temporal variability and trends in weather variables (precipitation and temperature) over the central highlands of Ethiopia covering the period from 1983 to 2013. Afterwards, they found a rising trend in *long- rainfall* season (from June - September), although statistically insignificant; consequently maintaining a match with this current work refults. In contrast, the investigation results of Asfaw, *et al.* (2018) contradict with the results of this present study. They examined the trend of weather variables (precipitation and temperature) in the northcentral Ethiopia (Woleka Sub-basin) covering the period of 1981 to 2015, but have observed a declining annual and *long- rainfall* season (kiremt season) with a magnitude of (-)1.503 and (-) 1.312, respectively. These results were statistically significant.

Table 5.1: Descriptive Statistics of rainfall in teff, wheat and maize growing areas

Variables	N	Minimum	Maximum	Mean		Std. Dev	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. E	Statistic	Statistic	Std. E	Statistic	Std. E
Crop Season Rainfall (Feb-Sep) _TGA*	38	476	611	542.75	5.627	34.685	0.227	0.383	-0.475	0.750
Short- Rainfall Season _TGA	38	153	347	226.84	7.172	44.214	0.761	0.383	0.770	0.750
Long- Rainfall Season _TGA	38	701	969	858.66	11.032	68.005	-0.391	0.383	-0.497	0.750
Crop Growing Period Rainfall (Feb-Sep)_WGA**	38	391	544	479.28	5.839	35.991	-0.444	0.383	-0.177	0.750
Short- Rainfall Season _WGA	38	97	315	194.75	6.934	42.746	0.531	0.383	1.022	0.750
Long- Rainfall Season _WGA	38	615	871	763.80	11.964	73.752	-0.461	0.383	-0.904	0.750
Crop Season Rainfall (Feb-Sep)MGA***	38	134	178	156.36	1.509	9.303	0.086	0.383	0.334	0.750
Short-Season Rain-fall_MGA	38	41	96	65.51	1.923	11.854	0.160	0.383	0.612	0.750
Long-Season Rain-fall_MGA	38	210	286	247.22	2.896	17.851	0.160	0.383	-0.208	0.750

*, ** *and* *** *represents teff growing areas, wheat growing areas and maize growing areas, respectively*

Source: Computed based on raw data from NMA of Ethiopia, 2019

As expressed above, the study result signified that the quantity of *short- rainfall* season in teff growing belt portrayed a decreasing trend, although statistically insignificant. The reason for moderately declining trend exhibited in *short- rainfall* season can be due to the changes experienced in climate factors that lead to global warming and reduced rainfall. The decline in trend of *short- rainfall* season in the eastern, south and southwestern parts of Ethiopia is originated by the parallel relentless warming of the South Atlantic Ocean and Sea Surface Temperature (SST) over the tropical eastern Pacific Ocean that influence ENSO esipodes. These have been confirmed by some researchers such as Seleshi and Zanke (2004). Seleshi and Zanke (2004) investigated the changes in important weather variables based on data from 11 key weather stations located in various climatic zones of

Ethiopia between 1965 and 2002. They reported a declining short-season rainfall in eastern, south, and southwestern Ethiopia due to warming of the South Atlantic Ocean, change in SST over the tropical eastern Pacific Ocean, and warm El Ni˜no–southern oscillation episodes.

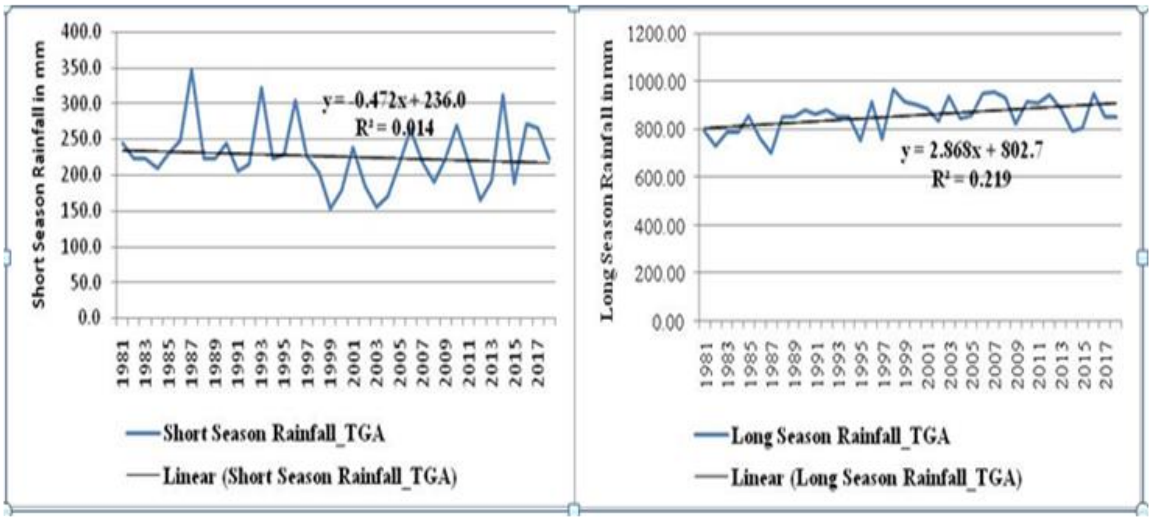


Figure 5.2: Trend of *Short- and Long-Rainfall* in teff growing areas, 1981 – 2018

Source: Computed based on raw data from NMA of Ethiopia, 2019.

Table 5.2: Linear trend testing statistics for rainfall data set in teff, wheat and maize growing areas over 1981 - 2018

Variables	β (slope)	St. Error	t-Stat	Adjusted R^2	PIF
Short-Season Rainfall_TGA	-0.472	0.658	-0.718	-0.013	1.000
Long-Season Rainfall_TGA	2.868**	0.900	3.187	0.20	1.000
Short-Season Rainfall_WGA	-1.954*	0.603	-2.161	0.09	1.000
Long-Season Rainfall_WGA	2.464**	1.027	2.399	0.114	1.000
Short-Season Rainfall_MGA	-0.227	0.710	-0.320	-0.025	1.000
Long-Season Rainfall_MGA	-1.280	1.050	-1.220	0.013	1.000

* and ** indicates 5% and 10% significance level, respectively

Source: Author’s Computation based on raw data from NMA, 2019

Figure 5.3 shows the trend of short-rainfall and long-rainfall observed and recorded in Motta weather station, one of the main teff growing belts in the country. The rainfall in both short-rainfall and long-rainfall seasons articulated a decreasing trend over the period under study. The rate of decrease is relatively higher during *long-rainfall season* (-3.182) than short-rainfall season (-0.686). Wherefore, the result of this station is in line with the result of national aggregated/pooled rainfall data series. Conversely, the estimate for short-rainfall demonstrated positive and increasing trend (1.75) in Debrezeit Station while *long-rainfall* earmarked a decreasing trend (-2.005) in the same station, which is also among the main teff growing belt in the country (see Fig.5.4). The result in Motta and Debrezeit stations imply that a 1% change over time would lead to a decrease in amount of long-rainfall season (main crop season) rainfall by 3.18mm and 2.005mm, respectively. However, the trend of long- rainfall season in Motta and Debrezeit stations contradicts that of pooled/aggregated 12 stations' trend since *long-rainfall* season in both stations portrayed a decreasing trend over the observation period. Quite differently, the trend of short- rain season in Motta station coheres with that of pooled 12 stations' result, for both enunciate decreasing trend. In opposition to this, the trend of the short- rainfall season in Debrezeit station negates that of pooled 12 stations' trend since short- rainfall season of the former station portrayed an increasing trend.

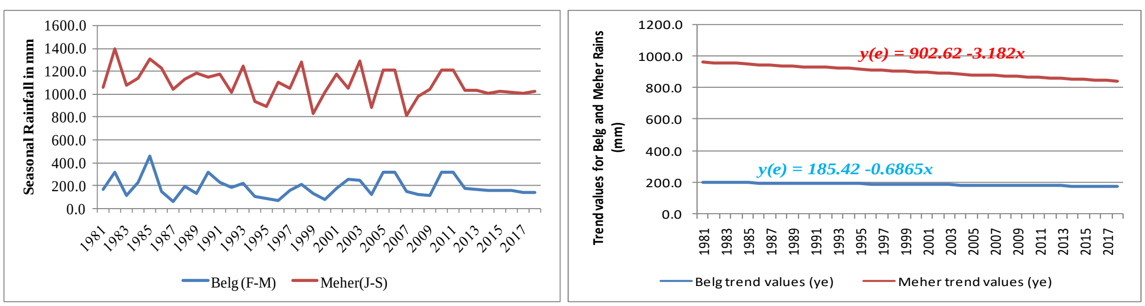


Figure 5.3: Trend of Short-rainfall and Long-rainfall in Motta Station, major TGA
Source: Computed based on raw data from NMA of Ethiopia, 2019

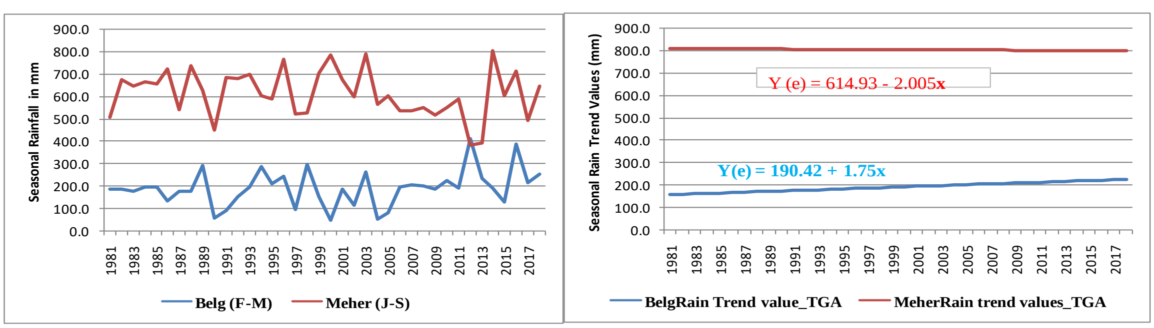


Figure 5.4: Seasonal trend of rainfall in Debrezeit Station - TGA, 1981 - 2018
Source: Computed based on raw data from NMA of Ethiopia, 2019

In this study, the rainfall pattern and trend in wheat growing areas has also been assessed. Figure 5.5 is a graphic representation of the plot of *crop growing season* (Feb-Sept), *short- rainfall season* (Feb-May), and *long- rainfall season* (June-Sept) pattern and trend in wheat growing areas between 1981 and 2018. The result indicates that short- rainfall season manifested a negative (decreasing) trend while the long-season rainfall recorded a positive (mounting) movement over the observation period in wheat growing belts. The rate of change in magnitude (trend) is -1.954mm during short-season rainfall and 2.464 mm during long-season rainfall. The trend slope rates estimated are found statistically significant for both the short-season and long-season rainfalls at 5% and 1% level of significance, respectively (see Table 5.2). From this study finding, it can be concluded that a declining rainfall during *short-rainfall season* affects the wheat farming practices as the seedbed preparation task is being taken place during this season. Contrarily, the increasing trend of rainfall during *long-rainfall season* is beneficial for wheat crop production system since most of the farming practices like final seedbed preparation, seeding/ planting, weeding, and grain filling processes takes place during this season, provided the rainfall amount did not exceed optimum level. In case the long-season rainfall amount exceeds optimum level, it will result in flooding, landslide, removal of top soil, etc. all of which affect the yield and production of wheat crop. Consequently, the increasing trend in long-season rainfall aligns with the suitable condition for wheat crop production as the crop grows in highland (Arsi, Bale and East Gojam) and mid-highlands (all Shewa, Gondar, and South Wollo) areas as well as the mean *long-season rainfall* amount coincide nearly with the maximum water requirement of the wheat crop. The findings of this study partly align with the result of Dagne's (2018) research. His study in Sekota area of Ethiopia detected a decreasing trend of 19 mm and 14 mm during short-rain season and long-rainfall seasons, respectively. The results also correspond with Arragaw and Woldeamlak (2017) whose research results have portrayed increasing and significant trends in rainfall during long- rainfall season, but greatly variable, decreasing and non-significant trend in rainfall during short- rainfall season through time in the Dega and Woinadega agroecologies of central highlands of Ethiopia.

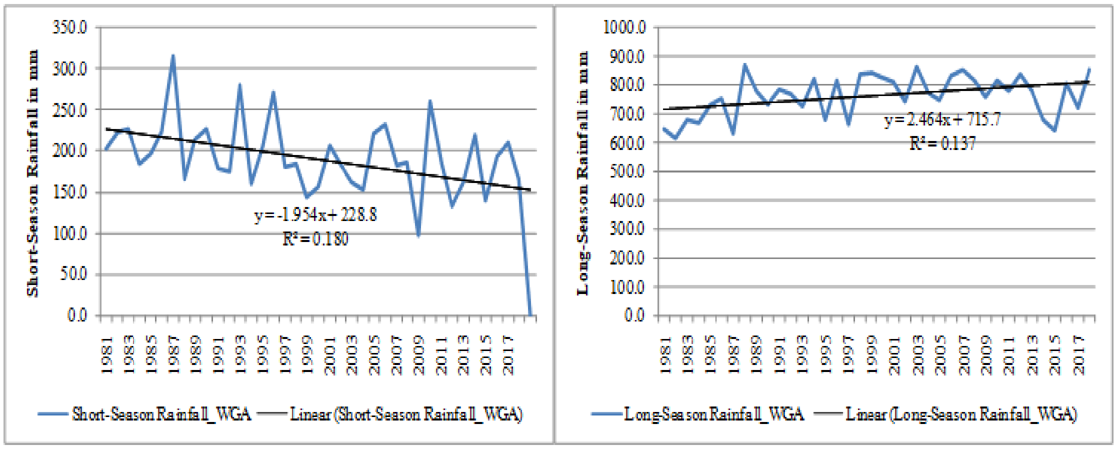


Figure 5.5: Trend of seasonal rainfall in wheat growing areas, 1981 – 2018
Source: Author's Computation from NMA of Ethiopia, 2019

Below is Figure 5.6 which presents the pattern and trend of crop growing season (Feb-Sept), *short-rainfall* season and *long- rainfall season* over the period of 1981 to 2018 in maize growing areas. A reading of the pattern deliberately reads that the national level aggregated/ pooled rainfall of 13 weather stations exhibit a decreasing trend for both *short-rainfall* season and *long-rainfall* season in maize growing belts. In contrast, the rate of decrease was more significant during long-rainfall season than short-rainfall season, both parameters being statistically insignificant. The rate of change was -1.28 mm for long- rainfall season and -0.227 mm for short- rainfall season (see Table 5.2). This result implies that both shor- and long-rainfall seasons affect the production of maize crop over periods since maize farming practices take place during both seasons because of maize crop is a long-cycle crop in nature. In maize farming, all the seedbed preparation and planting activities take place during short-rain season while weeding, second round fertilization, crop grain filling activities tak place during long-rainfall season. This shows that both short- and long-season rainfall become important inputs in the production of maize crop.

The study finding maintains a parallel with the findings of Dagne (2018) who carried out a study in Sekota Woreda and discovered a decreasing trend during both *short- rainfall season* and *long- rainfall season*. The result highlighted the rate of change as -1.998 mm/year for short- rainfall season and -1.456 mm/year for the long- rainfall season. The results of the present study also align with the study findings of Rosell and Holmer

(2007) as well as that of Arragaw and Woldeamlak (2017). They disclosed that *short-rainfall season* is more variable than the *long- rainfall season* in most parts of Ethiopia.

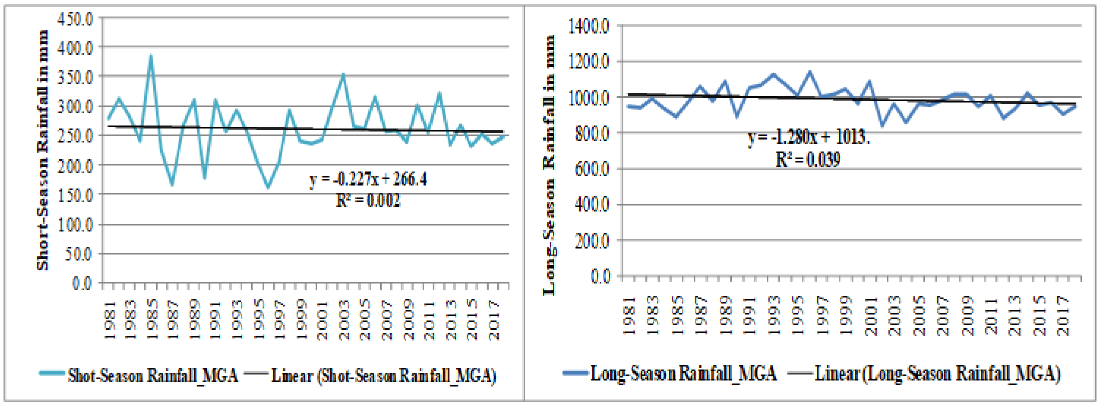


Figure 5.6: Trend of seasonal rainfall in maize growing areas, 1981–2018

Source: Author's Own Analysis of data from NMA of Ethiopia, 2019

Provision of some variability indices for some time intervals would make more meaning in analyzing data on climate factors given that climate change is about variability in the weather parameters over time. Consequently, the pattern and trend in seasonal rainfall in crop growing areas over time has also been examined in decadal based intervals so as to understand more about the variability in weather parameters. Figure 5.7 presents pattern and trend of the decadal short-season rainfall in teff and wheat growing areas. The graph depicts that short- rainfall season decreased over the first five years, shift direction and increased upto the seventh year, and then starts decreasing till the nineth year of each decade in a similar fashion. Moreover, long- rainfall season revealed a slight rising tendency in the wheat growing areas and a slight decreasing trend in maize growing areas over each decade, still on a similar note. Figure 5.8 substantiates this discovery. In general, the decadal short-season rainfall exhibited relatively pronounced fluctuations or variations than that of long-season rainfall over each of the decades in all crop growing areas.

In contrast to the information presented in Table 5.2, Table 5.3 enunciates decadal trend line slopes (mm) of seasonal rainfall in crop growing areas. It is notable that short-season rainfall exhibited decreasing trend in all crop growing areas over the second decade

(1991-2000) with magnitudes of -7.114 mm, -4.748 mm and -5.912 mm per decade for teff, wheat and maize growing areas respectively; however all are statistically insignificant. The short-season rainfall further showed a decreasing trend over all decades in maize growing areas; but statistically insignificant. The trend values of short-season rainfall showed an increasing trend in the first (1981-1990), third (2001-201) and fourth (2011-2018) decades in teff and wheat growing areas, but all are insignificant.

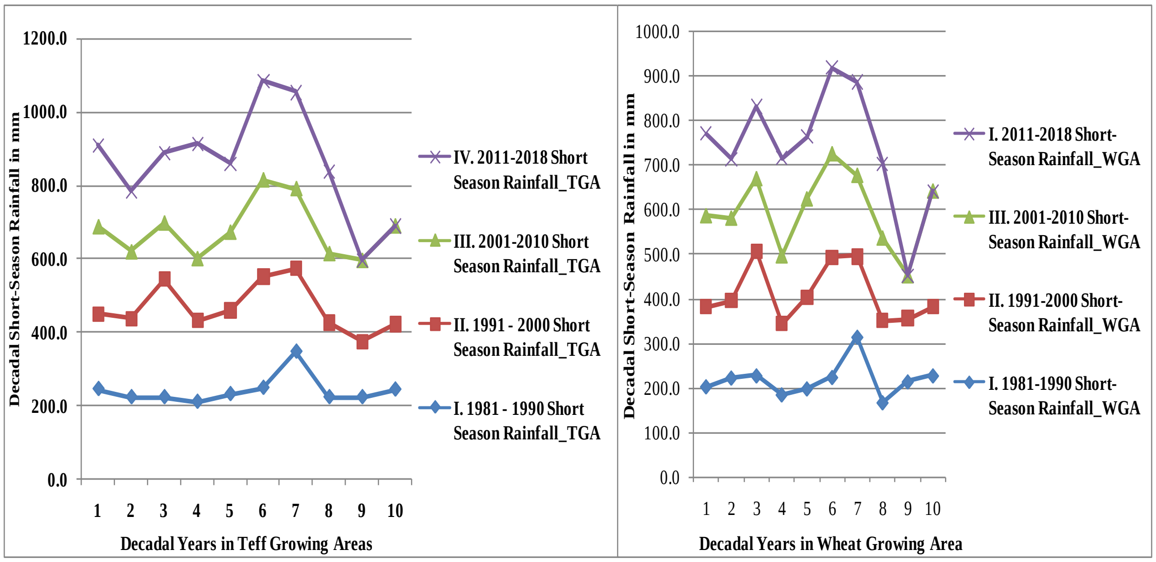


Figure 5.7: Pattern and trend of decadal short- rainfall season in teff and wheat growing areas

Source: Author's Own Analysis of data from NMA, 2019

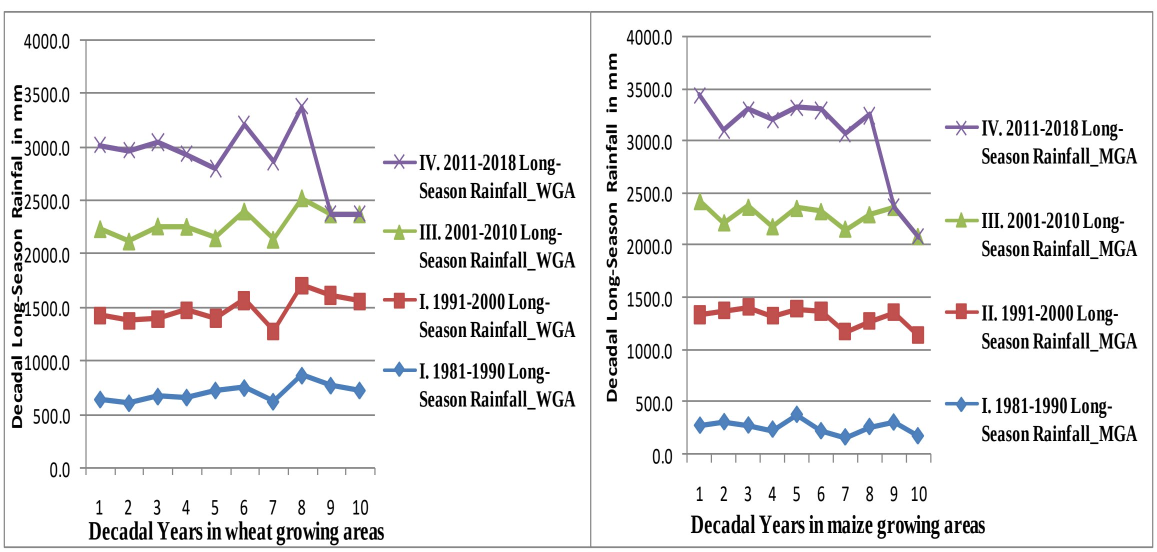


Figure 5.8: Pattern and trend of decadal long- rainfall season in wheat and maize growing areas

Source: Author's Own Analysis of data from NMA, 2019

In conformity with increasing and significant trends of long-season rainfall found over the period of 1981–2018, an increasing (positive) trend has been observed in all decadal categories in teff and wheat growing areas. However, only the trend slope values in the first decade (1981-1990) were statistically significant with a magnitude of 10.05 mm/decade and 16.9 mm/decade for teff and wheat growing areas respectively (see Table 5.3). The long-season rainfall exhibited decreasing trends in all decade categories in maize growing areas, except the third decadal category, between 2001 and 2010; however only the trend slope value in second decade (-10.08) is statistically significant. This long- and short-season rainfall trend analysis in decadal category has also been conducted by some researchers in a similar approach. An instance is the study carried out by Yadav *et al*. (2019). The study analyzed trends of seasonal rainfall in Uttar Pradesh region of India, utilizing data stretching through 1954 to 2013, totaling 60 years, and categorized in decades. The examination ultimately affirmed that the main season or monsoon (JJAS) rainfall demonstrated an increasing trend (0.5mm/year) between 1954 and 1983, while a decreasing trend (-2.09mm/year) was recorded during the period of 1984-2013, evidencing a divergent from the overall period (1954-2013) trend value (-4.143mm/year). Likewise, Naveendrakumar *et al.* (2018) interpreted the seasonal rainfall trends in Sri Lanka using 50-year data, from 1961 to 2010. The 50-year data was subsequently individualized into five decades to ensure vivid interpretation cum comprehensibility. Subsequently, the study avowed that trend slopes of annual rainfall during the last decade (2001–2010) showed an increasing trend (+2.6mm/year) which was significant and a decreasing trend (negative) during the other four decades (1961–1970; 1971–1980; 1981–1990; and 1991-2000).

In general, short-season rainfall trend values revealed pronounced variation along the decadal categories than the long-season rainfall trend values over the study period in crops growing areas.

Table 5.3: Decadal trend of seasonal rainfall data in selected crop growing areas (1981 – 2018)

Season	**Crop Growing Area**	**Decadal Categories**				***1981-2018***
		1981-1990	**1991-2000**	**2001-2010**	**2011-2018**	
Short-season rainfall	Teff	2.520	-7.114	5.538	7.424	-0.472
Long-season rainfall	Teff	10.05*	6.316	3.245	-7.77	2.868**
Short-season rainfall	Wheat	1.658	-4.748	0.508	3.288	-1.954*
Long-season rainfall	Wheat	16.913**	6.953	1.475	-0.505	2.464**
Short-season rainfall	Maize	-8.503	-5.912	-2.227	-5.357	-0.227
Long-season rainfall	Maize	-8.503	(-)10.08*	3.515	-3.339	-1.280

* and ** represents 5% and 10% level of significance, respectively

Source: Researcher's Own Computation of data from NMA, 2019

In summary, it has been found from the above analysis that short-rainfall season showed decreasing pattern in almos all crop growing areas, i.e., teff, wheat and maize growing areas. A linear trend line fitted to short-rainfall equally established a rate of change with magnitude of - 0.473 mm, -1.954 mm, and -0.227 mm for teff, wheat, and maize growing areas respectively; but only slope value for wheat growing areas was found to be statistically significant at 5% and 10% for long- and short season respectively. Conversely, *long-rainfall* season depicted a rising tendency in teff and wheat growing areas while it showed a declining tendency in maize growing areas. The rate of change for the long-season rainfall in teff and wheat growing areas were +2.869mm and +2.464mm, respectively; both values being statistically significant at 1% level. The rate of change for linear trend line fitted to long-season rainfall in maize growing areas was -1.28mm but found statistically insignificant. Analysis of seasonal rainfall pattern and trend in decadal categories also exhibited variations. The short-season rainfall trend values revealed pronounced variation along the decadal categories than the long-season rainfall trend values over the study period in crops growing areas.

5.2.2 Temperature Trend Analysis in Crop Growing Areas

This sub-section presents the analysis of pattern and trend of crop growing period temperature variables (MaxTemp and MinTemp) for teff, wheat and maize growing areas. The temperature data were collected from 20 weather stations as recorded by the NMA of Ethiopia. Table 5.4 presents descriptive data for Maximum and Minimum Temperature in teff, wheat and maize growing areas. The raw data obtained from NMA of Ethiopia represents 20 weather stations; maximum and minimum temperature data of 12 to 13 stations have been aggregated/ pooled for each of the crops under study.

The computed descriptive statistics indicate a mean maximum temperature and minimum temperature of 100^0C and 47^0C respectively in teff growing areas. The mean maximum and minimum temperature in wheat growing areas were 94^0C and 44^0C, respectively. Equally, the mean maximum and minimum temperatures in maize growing areas during crop growing period were found to be 100.4^0C and 47.4^0C, respectively. Thus, the results evince that maximum temperatures in the teff and maize growing areas are almost the same implying that teff and maize crops share similar climatic conditions mostly the mid highland and upper lowland areas. It is also evident that wheat growing areas are located in the midhighland and high altitudes where temperature is normally cool.

Table 5.4: Descriptive Statistics of temperature variables for teff, wheat and maize growing areas

Variables	N	Min	Max	Mean		Std. D	Var	Skewness		Kurtosis	
	Stat	Stat	Stat	Stat	Std. E	Stat	Stat	Stat	Std. Er	Stat	Std. E
MaxTemp_TGA*	38	95	105	100.39	0.366	2.259	5.102	-0.229	0.383	-0.146	0.750
MinTemp_TGA*	38	41	50	46.68	0.386	2.378	5.657	-0.912	0.383	0.396	0.750
MaxTemp_WGA**	38	89	99	94.11	0.395	2.433	5.918	0.084	0.383	-0.418	0.750
MinTemp_WGA**	38	39	48	44.21	0.360	2.222	4.936	-0.432	0.383	-0.129	0.750
MaxTemp_MGA***	38	96	104	100.42	0.370	2.283	5.214	-0.239	0.383	-1.086	0.750
MinTemp_MGA***	38	41	51	47.44	0.419	2.580	6.658	-0.494	0.383	-0.643	0.750

*, ** and *** represents teff growing areas, wheat growing areas, and maize growing areas respectively

Source: Researcher's Own analysis of data from NMA of Ethiopia, 2019

Wheat crops are typically cultivated in the high potential and moist areas of the country while teff and maize are grown in more or less similar agro-ecologies, i.e., in moderately high and average prospective areas and partly damp areas which accounted for the selection of the weather stations used. The data for teff and wheat crops were taken from 12 weather stations, while the data for maize crop were drawn from the records of 13 weather stations.

In order to analyze the pattern and trends of temperature prevailing in crop growing areas, the maximum (MaxTemp) and minimum (MinTemp) temperature data have been collected from 21 weather stations as recorded by NMA of Ethiopia and aggregated/ pooled for each crop. Ordinary linear regression trend line ((OLR) $\hat{y} = \alpha X + \beta$) was adopted to capture correlations; where α represents the rate of change and $\hat{y}$ represent crop growing period temperatures at the given time, t. The gradient of tendencies' line has been calculated using the slope of the linear tendencies expressed in °C per year.

Figure 5.9 presents the pattern and trend of maximum and minimum temperatures in teff growing areas covering the periods between 1981 and 2018. The results of trend analysis of temperatures revealed that both temperature variables (maximum and minimum) showed rising tendency over the observation period. The rate and magnitude of the trend for the maximum and minimum temperatures were 0.13^0C and 0.16^0C, respectively. The trend values estimated for both temperature variables (maximum and minimum) were found statistically significant at 1% level (see Table 5.5 for the significance tests). The result implies that with a change in time there would be an increment in the maximum as well as the minimum temperature variables by 0.13^0C and 0.16^0C, respectively. From this study result, it can be concluded that the trend analysis of mean temperature over the crop growing period for teff growing belts showed positive and significant trend. Thus, the increasing trend in temperature due to climate change and other impacting factors would lead to weather extremes in teff growing areas. The findings of this current research are analogous with the study results of Warwade *et al.*'s (2015) who in their studies have sourced their data in India. They discovered that both temperature variables (maximum and minimum) have showed considerable rising trend over the study period. Further, Hayelom, *et al.*'s (2017) in their study in Northern Ethiopia found an increasing trend in maximum temperatures with the rate of change equivalent to (0.0013). Relatedly, Daba (2018) characterized agro-climates of chosen districts/ woredas in western Oromia of Ethiopia and observed rising tendency in mean temperature variables (minimum and maximum) of Bako area (known for growing maize and teff crops) which was statistically significant. Equally, Tamiru, *et al*, (2015) examined weather factors (precipitation and temperature) variability in Miesso area of eastern Ethiopia from 1990 to 2009. The researchers submitted a consistent increasing trend of long (JJAS) and short (FMAM) season minimum temperature with trend value magnitude of 0.137^{0}C and 0.0124^{0}C, respectively. They also found a reliable rising tendency in mean maximum temperature during the *short-rain season* (FMAM) and a slightly increasing trend in mean maximum temperature during *long-rain season* (JJAS) with a magnitude of 0.1113^{0}C/year and 0.060^{0}C/year, respectively.

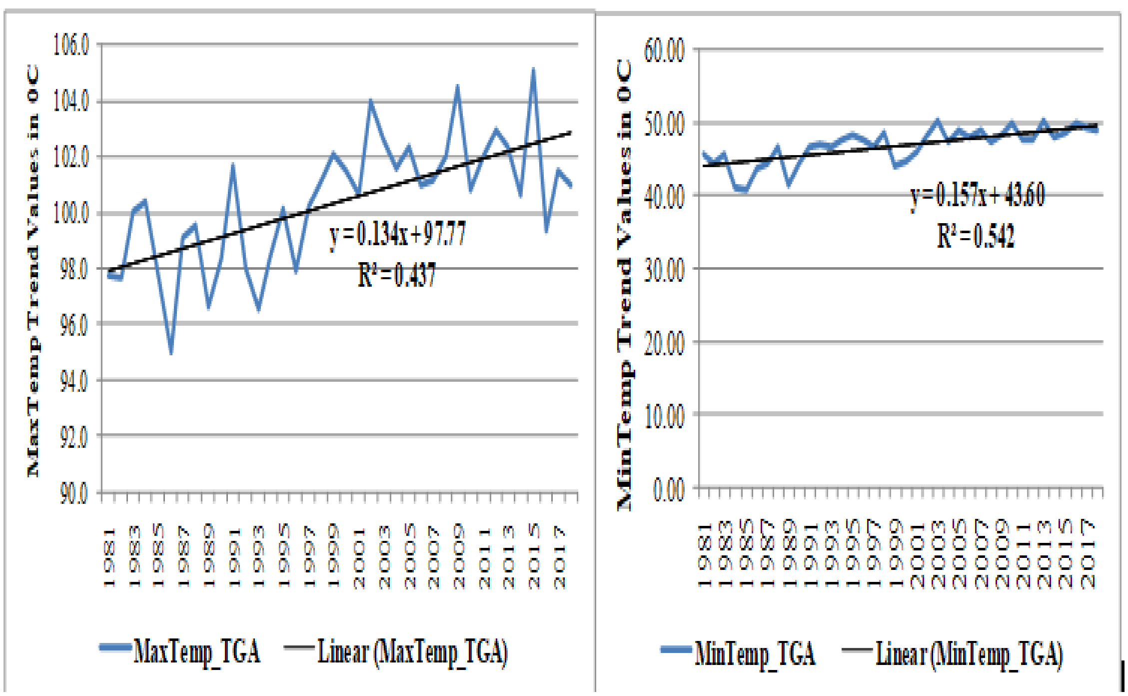


Figure 5.9: Trend of temperature in teff growing areas, 1981 to 2018
Source: Researcher's Own Analysis of from NMA of Ethiopia, 2019

Table 5.5: Temperature trend (slope) test-statistic for teff, wheat and maize growing areas from 1981 - 2018

Variables	β (slope)	St. Error	t-stat	Adjusted R^2	Durbin-Watson	PIF
MaxTemp_TGA	0.134**	0.025	5.290	0.42	1.822	1.000
MinTemp_TGA	0.157**	0.024	6.530	0.53	1.573	1.000
MaxTemp_WGA	0.129**	0.029	4.406	0.33	1.518	1.000
MinTemp_WGA	0.141**	0.024	6.002	0.49	1.495	1.000
MaxTemp_MGA	0.143**	0.025	5.819	0.47	1.151	1.000
MinTemp_MGA	-0.188**	0.024	-7.357	0.59	1.405	1.000

*** indicates 1% level of significance.

Source: Researcher's Own Computation of data obtained from NMA, 2019

Figure 5.10 presents pattern and trends of maximum and minimum temperatures in wheat growing areas. It can be seen from the result that both major temperature indicators such as maximum and minimum portrayed rising tendency in the wheat growing areas over the study period. The trend analysis also revealed that the rates of change in the temperature variables during crop growing period in magnitude were 0.13^0C and 0.14^0C for maximum and minimum temperatures, respectively, both being statistically significant at 1% level (see Table 5.5 for significance levels). It is evident from the results that with change over time, weather variable under the current study (maximum and minimum temperature) would raise by 0.13^0C and 0.14^0C, respectively. This study finding nearly aligns with the results of previous researchers who reported that global surface temperature increased by 0.7^0C during the twentieth century and is projected to cause a further 1 to 2^0C increase during the twenty first century (IPCC, 2007). Again, this study finding harmonizes with the result presented by Warwade, *et al*. (2015). Further, researchers who focused on Indian climate factors found that both the temperature variables under study (maximum and minimum) obviously showed significant rising trend in maximum and minimum temperature. Albeit, Asfaw *et al*. (2018) equally relied on North Central Ethiopia for their data and noted that the temperature variables (maximum and minimum) portrayed a rising tendency, but the increment in the minimum temperature was more pronounced than the maximum temperature. To that end, on the basis of the measured data from NMA, observed temperatures (both minimum and maximum) have revealed an increasing trend which is significant when statistically tested. Congruently, the finding of the current study is additionally aligned with the findings of Tabari and Talaee (2011) and Roy and Das (2013) who in their studies reported higher rising tendency in the minT series than those in the maxT series.

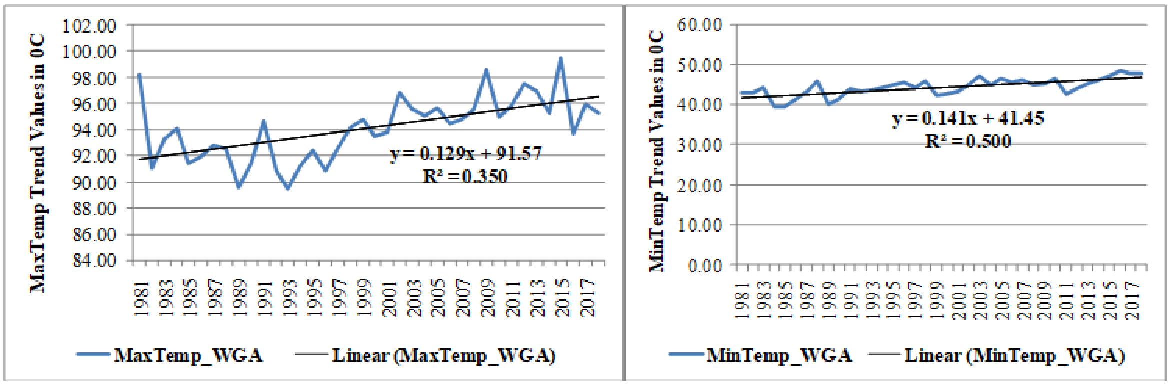


Figure 5.10: Trend of temperature in wheat growing areas, 1981 to 2018

Source: Researcher's Own Analysis of data from NMA of Ethiopia, 2019

The minimum and maximum temperature trend in maize growing areas is presented in Figure 5.11. Thus, it is obvious from the graph that maximum temperature depicted rising tendency while minimum temperature variable displayed a declining tendency in maize growing areas. Correspondingly, the results signify that the speed of alteration in the maximum and minimum temperatures marked out by the gradient of the regression line were about 0.14^0C per 38 years and -0.19^0C per 38 years, respectively. Ergo, both results were found significant at 1% level, as captured in Table 5.5. Given these outcomes, it can be deduced that a significant increase in maximum temperature is the cause for a decrease of both short- and long-season rainfalls over the observation period in maize growing areas. The stance of this research is equally visible in the findings of Panda and Sahu (2019). Their study in India affirmed a rising tendency in maximum temperature and a declining tendency in minimum temperature. The results indicated that the size of change in maximum temperature was 0.002^0C while the rate of change in minimum temperature is -0.038^0C.

Largely, the findings of the variability and trend examination in temperatures reveal that maximum temperature demonstrated considerable rising tendency over the study period in the teff, wheat and maize growing belts. The magnitudes of increase were 0.143^0C, 0.129^0C, and 0.134^0C in teff, wheat and maize growing areas, respectively. From this study result, it can be concluded that the increasing trend in maximum temperature due to changes in climate and other relevant variables can lead weather extremes in relevant crop growing areas. Contrarily, minimum temperature showed increasing trend over the period under study in teff and wheat growing areas and a decreasing trend in maize growing areas with magnitude of 0.16^0C, 0.14^0C and $(-0.\ 19)^0$C respectively.

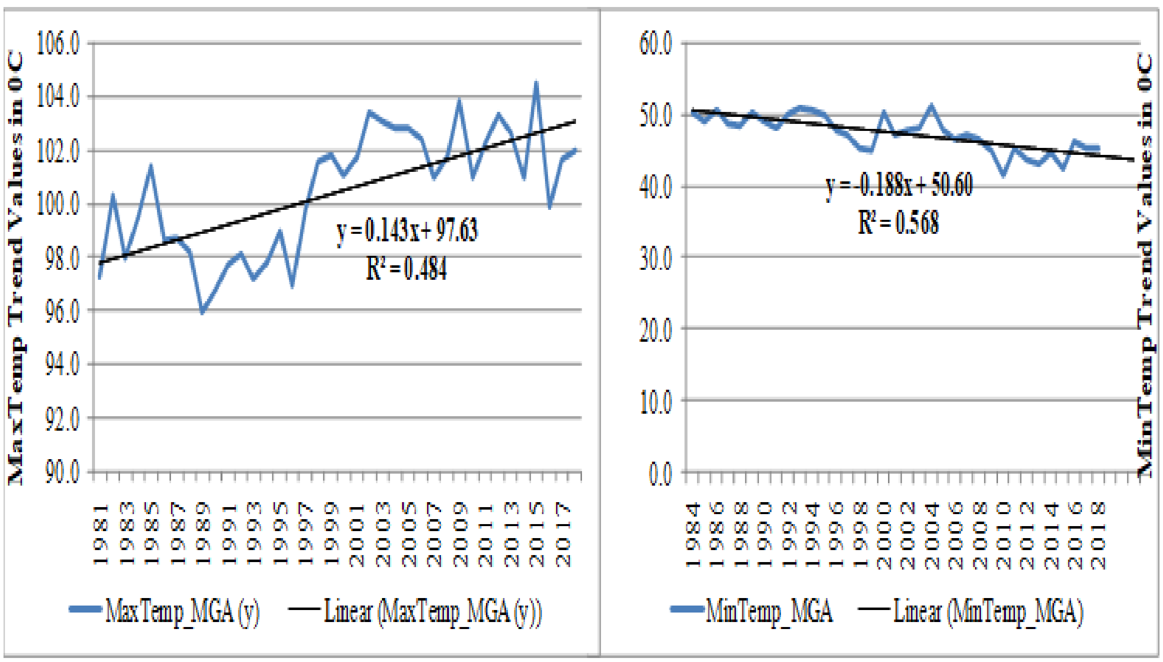


Figure 5.11: Trend of temperature in maize growing areas, 1981 to 2018

Source: Researcher's Own Analysis of data from NMA of Ethiopia, 2019

Thereupon, one can conclude from the preceding examination of temperature variables that increases of maximum temperature in significant comportment in all crop growing areas can function as a stimulant for the decrease of *short-season rainfall* in teff, wheat and maize growing areas as well as a decrease in *long-season rainfall* in some of the study areas.

5.2.3 *Pattern and Trend Analysis of CO_2 from Agriculture Practices*

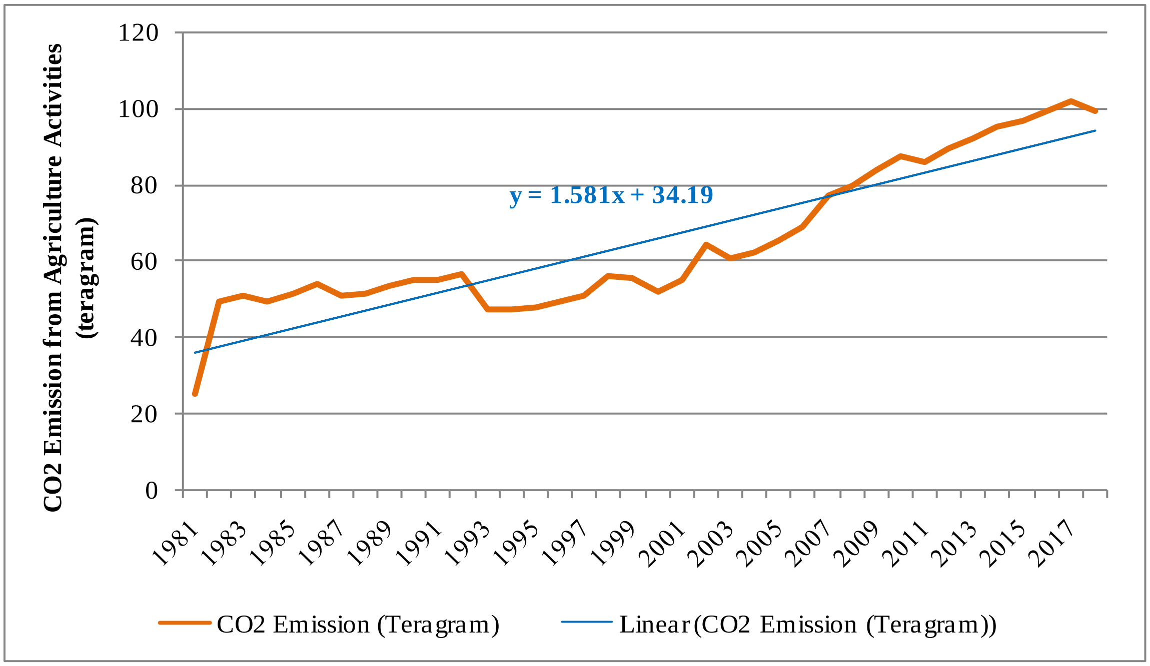
According to Richards, *et al.*, (2015), CO_2 emissions from the agricultural agricultural practices included: enteric fermentation (CH_4), manure management (CH_4 & N_2O), synthetic fertilizers (N_2O), manure applied to soils (N_2O), manure left on pasture (N_2O), crop residues (N_2O), burning crop residues (CH_4 & N_2O), and burning - savanna (CH_4 &N_2O). As can be seen from Table 5.6, the quantity of CO_2 emitted per annum on average was 65.04 teragram over the study period of 1981 to 2018, out of which CH_4 (enteric fermentation) and N_2O (manure left on pasture) accounted for 88.2 percent.

Table 5.6: Average annual CO_2 emitted from agricultural practices, 1981 - 2018

Type of gas emitted	Average Annual Gas Emitted (teragram)	%age share
Enteric Fermentation (CH_4)	33.42	51.4
Manure Management (CH_4 & N_2O)	1.42	2.2
Synthetic Fertilizers (N_2O)	0.53	0.8
Manure applied to Soils (N_2O)	0.49	0.8
Manure left on pasture (N_2O)	23.97	36.8
Crop residues (N_2O)	0.68	1.0
Burning crop residues (CH_4 & N_2O)	0.15	0.2
Burning - Savanna (CH_4 &N_2O)	4.38	6.7
Average annual CO_2 emitted (teragram)	65.04	100.0

Source: Compiled and omputed using raw data from FAOSTAT Data Set, Sept. 2019

In order to analyze the pattern and trends of CO_2 emitted from agricultural practices in Ethiopia, CO_2 data obtained from FAOSTAT data set have been used. Ordinary linear regression trend line ((OLR) $\hat{y} = \alpha X + \beta$) was adopted to capture the relationships; where α represents the rate of change and $\hat{y}$ represent CO_2 emitted at the given time, t. The slope of line tendencies' has been calculated using the slope of the linear trends expressed in °C per year. Figure 5.12 presents trend of CO_2 emitted from the agricultural practices in Ethiopia. As can be observed from the figure, CO_2 exhibited an increasing trend over the period from 1981 to 2018, although a significant sharp increase was from 1996. The magnitude of increase was 1.58 percent. The rate of increase in CO_2 associates with the general increase trend observed in temperature parameter.



Source: Computed using raw data from FAOSTAT data set, Sept. 2019

Figure 5.12: Trend of CO_2 Emitted from Agricultural Practices

5.3 Climate change and variability in Ethiopia

In this study, variability of weather variables (rainfall and temperature) over a given time period was analyzed by calculating the coefficients of variability in the values of these variables for the crop growing areas considered for this study. Towards this effect, the coefficients of variability for *short-rainfall* and *long-rainfall* seasons as well as minimum and maximum temperatures for each crop growing areas were aggregated and calculated. Furthermore, rainfall, temperature and CO_2 deviations from long period means (that is defined as deviations from the 38-year mean rainfall, temperature and CO_2) have been estimated for each season and crop growing period. Additionally, an account of climate change will be presented. Microsoft EXCEL and SPSS softwares were used to manage and analyze the data as well as to produce appropriate graphs for visualization of the trends of the variables.

5.3.1 Variability in Rainfall

In order to analyze and evaluate variability in rainfall, standardized anomaly of rainfall (deviations from long period mean) and coefficient of variation (CV) have been used. In practice, very low rainfall anomaly corresponds to harsh drought prevailing in the country. In line with the results of CV, the degree of variability in rainfall measured by CV is categorized as less variable (if CV<20%), moderately variable (if CV ranges between 20% - 30%), and highly variable (if CV>30%), (NMA, 1996).

Figure 5.13 presents the short- and long- rainfall season anomalies in teff growing areas over a period of 38 years, i.e., 1981-2018. The rainfall anomaly during short-season rainfall in teff growing areas ranged from +2.50 in 1987 to -0.92 in 1984 while it ranged from +1.16 in 1998 to -2.85 in 1982 during long-rainfall season. The result indicates that the average rainfall anomaly in teff growing areas during both short- and long-rainfall seasons over the years, from 1981 to 1987, 1997/98, 2003/04, and 2014/15 were found extremely low and severe. These years coincided with the drought years of 1984/85, 193/94, 2003/04, and 2014/15. As seasonal or annual normalized rainfall anomalies less than negative one (< -1) indicates severe and extreme drought, the years from 1999 to 2006 during short-rainfall season, and the years from 1981 to 1987 during long-rainfall season define severe and extreme droughts in teff growing areas. Differently, the coefficient of variation (CV) witnessed that short-rainfall season to be moderately variable (CV=20%) and less variable during long-rainfall season (CV= 14.4%) in teff growing areas (See Table 5.7).

Therefore, the result noted in this study is underscored in the findings of (Dagne, 2018 and Asfaw *et al*, 2018). For instance, Dagne (2018) studied climate change as well as its variability in Sekota Woreda of Ethiopia. The study stated that there existed a moderately variable long-rainfall season (CV=23.8%) and inter-annual rainfall fluctuation as annual rainfall anomalies (defined as deviations from the 30-year mean rainfall) were not consistent throughout the 30 years. Dagne (2018) added that approximately half of the years within the study periods experienced annual rainfall that was below normal (mean) in the study area. This is equally in accord with Asfaw *et al*. (2018). They researched weather variables (precipitation and temperature) inconsistency and tendency in north central parts of Ethiopia. They submitted that the rainfall anomaly for years 1984, 1987, 1991–1992, 1993–94, 2002, 2009, 2012, 2015/16 were drought years which either correspond or go after El Nino actions. Relatedly, Dandesa, *et al*. (2017) in their assessment of the climate variability in Borena zone of Ethiopia using normalized rainfall anomaly over 32 year period found that the Zone had obtained 7 years moderate to severe damp and 8 years moderate to severe parched condition out of the thirty-two years period. The time series-based normalized rainfall anomalies obviously indicated that drought that prevailed over the periods 1984, 1992, 2000, 2004, 2009 and 2011 frankly connected with nonexistence of long-rainy seasons. The nonexistence of long-rainy seasons would lead to drought years. Sometimes, a drought takes decades to occur again and is very difficult to predict.

Table 5.7: Seasonal mean rainfall and coefficient of variation (CV) by crop growing areas

Season	CV	Mean	St. Dev
1. Teff Growing Areas			
Short-rainfall Season	19.63	223.1	43.80
Long-rainfall Season	14.42	828.2	119.41
2. Wheat growing Areas			
Short-rainfall Season	21.95	194.75	42.75
Long-rainfall Season	9.66	763.80	73.75
3. Maize growing areas			
Short-rainfall Season	18.09	262.0	47.4
Long-rainfall Season	7.22	*988.9*	*71.4*

Source: Researcher's Computation of data from NMA of Ethiopia, 2019

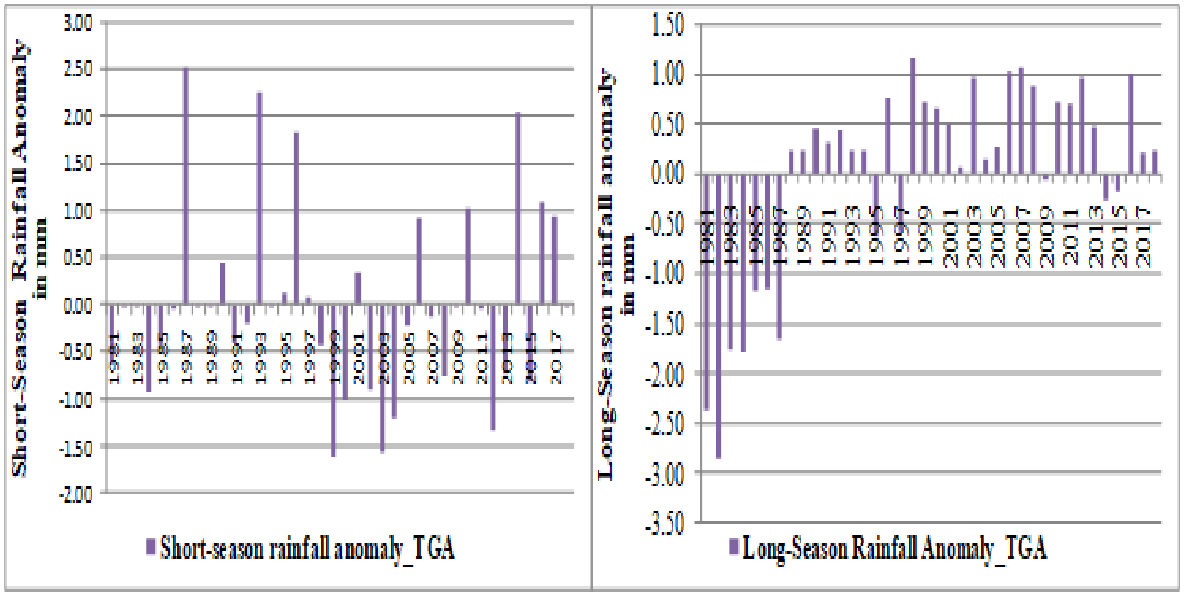


Figure 5.13: Short-Season and Long-Season rainfall anomaly in teff growing areas, 1981-2018

Source: Researcher's Own Sketch of data from NMA of Ethiopia, 2019

The rainfall anomaly during *short-rainfall* season in wheat growing areas, on the other hand, ranged from +2.81in 1987 to -2.29 in 2009 while it ranged from +1.46 in 1988 to -2.02 in 1982 during *long-rainfall* season (see Fig. 5.14). The result evidenced average rainfall anomaly in wheat growing areas during the long-rainfall seasons from 1981 to 1987, and 1990, 1993, 1995, 1997, 2002, 2005, including 2014/15 were found very low and severe. The implication is that those years were fraught with absolute drought. The coefficient of variation (CV) also witnessed short-rainfall season, which can be described as moderately variable (CV=22%) and less variable during long-rainfall season (CV= 10%) in wheat growing areas. These findings are presented in Table 5.7.

The rainfall anomaly for maize growing areas is mostly little and sever during both short-rainfall and long-rainfall seasons (see Fig. 5.15). The rainfall anomaly during short-rainfall season ranged from +2.60 in 1985 to -2.11 in 1996 and from +2.18 in 1996 to -2.09 in 2002. Consequent upon that, it is patent that most of the years under study fall under low rainfall that is severe and laddered with drought. This is because most of the maize growing areas are in relatively medium highland and lowland areas where rainfall is scarce. The coefficient of variation (CV), however, shows less variability for both seasons, i.e., 18% for short-rainfall season and 7.2% for long-rainfall season (Table 5.7).

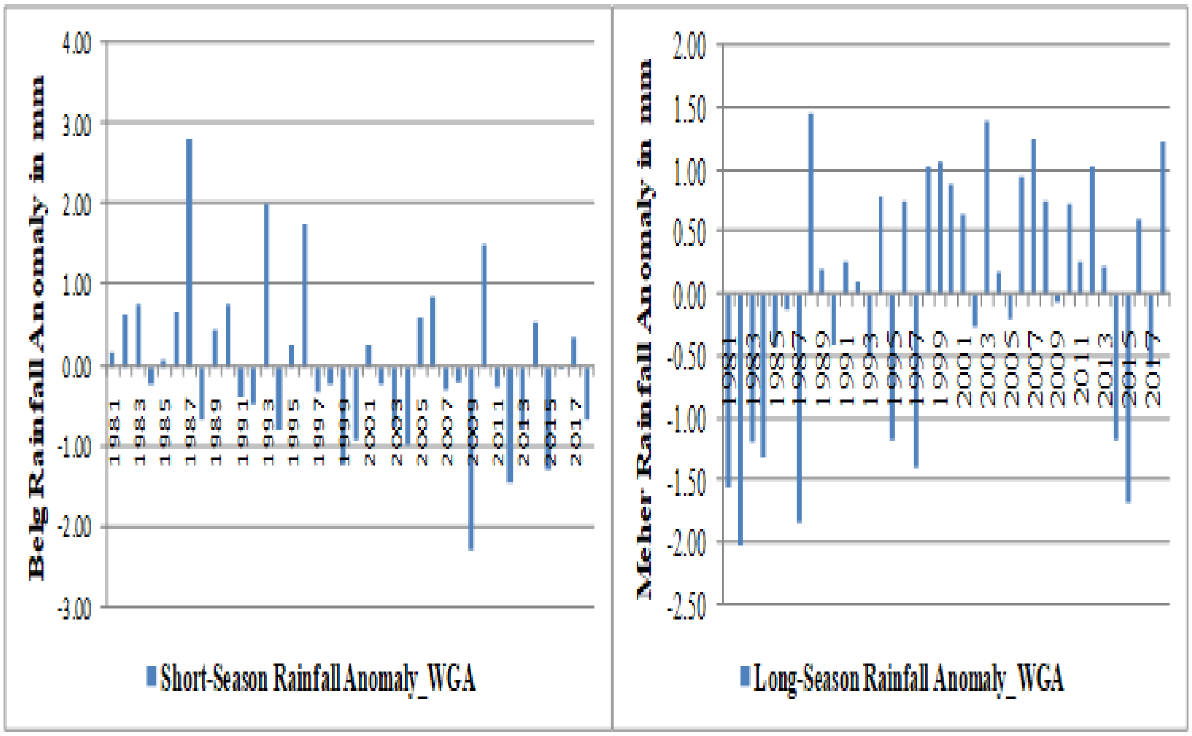


Figure 5.14: Short-rainfall and Long-rainfall Season Anomaly in wheat growing areas, 1981-2018

Source: Researcher's Own Sketch of data from NMA of Ethiopia, 2019

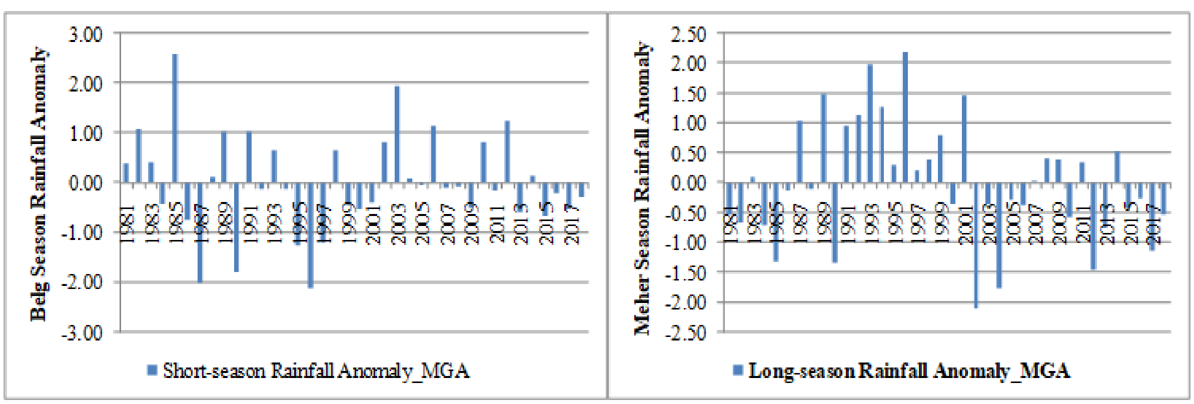


Figure 5.15: Short- and Long-season rainfall anomaly in maize growing areas, 1981-2018

Source: Researcher's Own Sketch of data from NMA of Ethiopia, 2019.

The seasonal rainfalls prevailed over the study period (from 1981 to 2018) have also been analyzed in four decadal categories to facilitate accurate and totalizing investigation, as well as to enhance easy comprehension of the variability in weather parameters over time. Figure 5.16 communicates long-season rainfall anomaly by decadal category in teff and wheat growing areas. Long-season rainfall anomalies in the first (1981-1990) and second (1991-2000) decades in teff growing areas exhibited almost similar results, that is negative (-) values from first to seventh years and positive (+) value during the eighth, ninth and tenth years. The negative values from first to fourth and seventh years in both decades exhibited severe and extremely dry years. In the third and fourth decadal categories, the long-season rainfall anomalies showed more fluctuations than the first and second decadal categories.

In the wheat growing areas, long-season rainfall in all four decadal categories exhibited almost similar pattern as in teff growing areas (Fig. 5.16). In both cases, the long-season rainfall (very detrimental for crop sowing vegetative growth and grain filling) anomalies in all decadal categories decreased up to the fifth year cycle and thereafter on average increasing up to tenth year. The steady decline in long-season rainfall amount may be attributed to disparity in local factors such as orography, warming temperature, moisture build up, etc. It can be seen from the graph (Fig. 5.16) that wet years in both crop growing areas occurred in few years; while *long-season rainfall* exhibited extreme wet events in second, third and fourth decadal categories all at eighth year cycle in both teff and wheat growing areas.

The variability in seasonal rainfall has also been examined based on decadal category of the coefficient of variations (CV) categorized. Table 5.8 verifies that short-season rainfall was moderately variable in the second (23%) and fourth (22%) decadal categories in teff growing areas, also in wheat growing areas it was recorded in second (24%) and third (24%) decadal categories; and just in first decade (25%) in maize growing areas. Short-season rainfalls are less variable in the remaining decadal categories exhibiting a CV ranging from 11.5% to 19%. Contrastingly, long-season rainfall exhibited less variability in all decadal categories and all crop growing areas, which is inline with the overall study period result, that is, from 1981 to 2018.

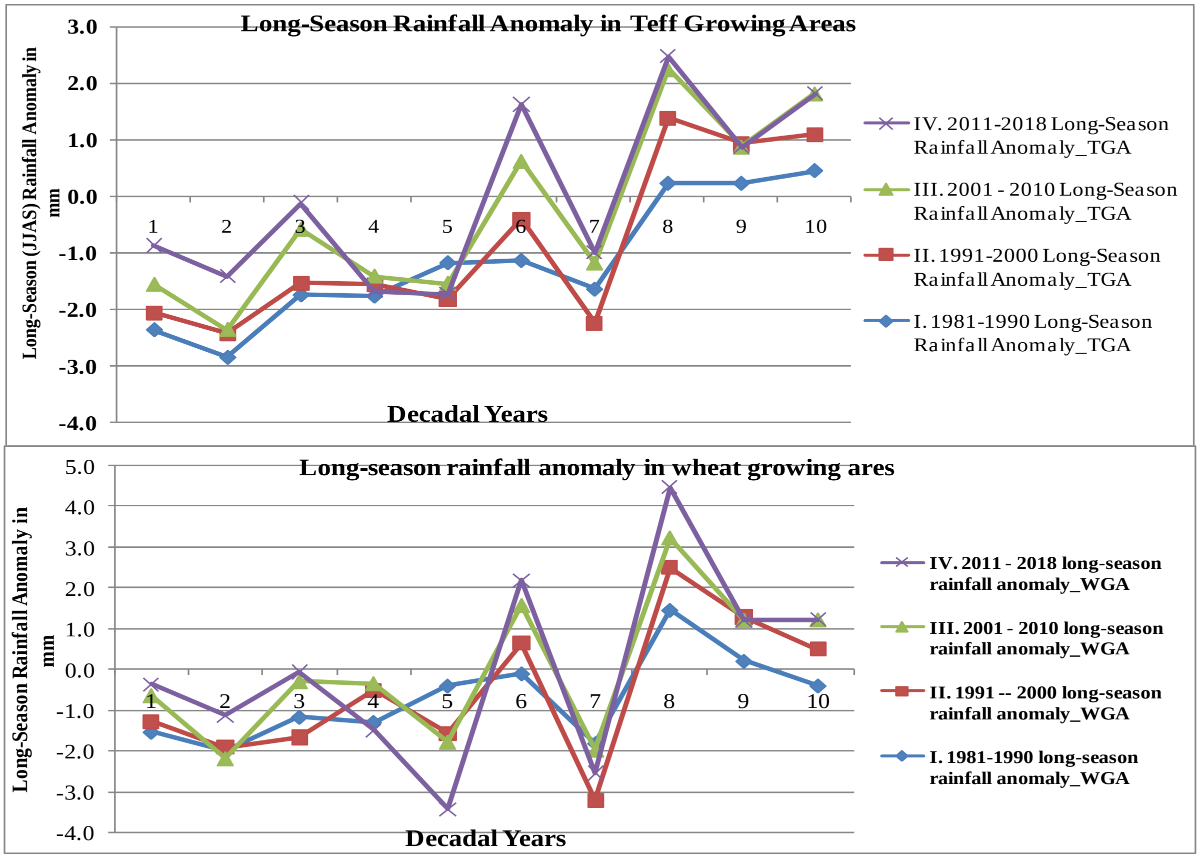


Figure 5.16: Long-season rainfall anomaly by decadal category in teff and wheat growing areas

Source: Researchers Own Sketch of climate data from NMA, 2019

Table 5.8: Decadal coefficient of variation (CV%) for short- and long season rainfalls in crop growing areas, 1981-2018

Seasonal Rainfall Type	**Crop area**	**Coefficient of Variation (%) per decade and overall period**				
		I. 1981-1990	***II. 1991-2000***	***III. 2001-2010***	***IV. 2011 - 2018***	***1981 - 2018***
Short-season rainfall	Teff	16.2	22.8	18.0	21.8	*19.6*
Long Season rainfall	Teff	7.5	7.9	5.7	6.6	*14.4*
Short-season rainfall	Wheat	18.1	24.1	24.1	17.7	*21.9*
Long-season rainfall	Wheat	11.1	8.6	5.4	10.1	*9.7*
Short-season rainfall	Maize	24.8	19.0	13.2	11.5	*18.1*
Long-season rainfall	Maize	6.7	5.4	7.7	5.0	*7.2*

Source: Author's Own Computation of Climate data from NMA, 2019

In general, as verified by coefficient of variation (CV), rainfall was found more variable during short-rainfall season and less variable during long-rainfall season in all crop growing areas under study. The yearly normalized anomaly of rainfall is a clear indication that maize growing areas have more severe rainfall variableness, in addition to experiencing numerous drought years, than teff and wheat growing areas. The standardized seasonal or annual rainfall anomalies less than negative one (< -1) indicates severe and extreme droughts. The standardized rainfall anomalies were found to be coincided with the major drought years documented in the country. These years coincided with the drought years of 1984/85, 193/94, 2003/04, and 2014/15.

5.3.2 Variability in Temperature

Table 5.9 presents descriptive analysis for maximum and minimum temperatures in teff, wheat and maize growing areas. The crop growing season (Feb-Sept) mean maximum temperature during crop growing period was about 100.4^{0}C in both teff and maize growing area, implying that teff and maize share the same agro-ecology in terms of temperature. The mean minimum temperature in teff and maize growing area was also the same, about 47^{0}C. The crop growing season (Feb-Sept) mean maximum temperature for wheat growing areas was 94^{0}C and that mean minimum temperature was 44.2^{0}C, which represents relatively cool agro-ecology. These findings are detailed in Table 5.9 below.

Table 5.9: Descriptive analysis for maximum and minimum temperatures by crop growing areas

	Variables	CV (%)	St.Dev	Mean
1.	***Teff growing area***			
	MaxTemp	2.24	2.25	100.4
	MinTemp	5.10	2.38	46.68
2.	***Wheat growing area***			
	MaxTemp	2.58	2.43	94.11
	MinTemp	5.02	2.22	44.21
3.	***Maize growing area***			
	MaxTemp	2.27	2.28	100.42
	MinTemp	5.44	2.58	47.44

Source: Author’s Own Computation of climate data from NMA of Ethiopia, 2019.

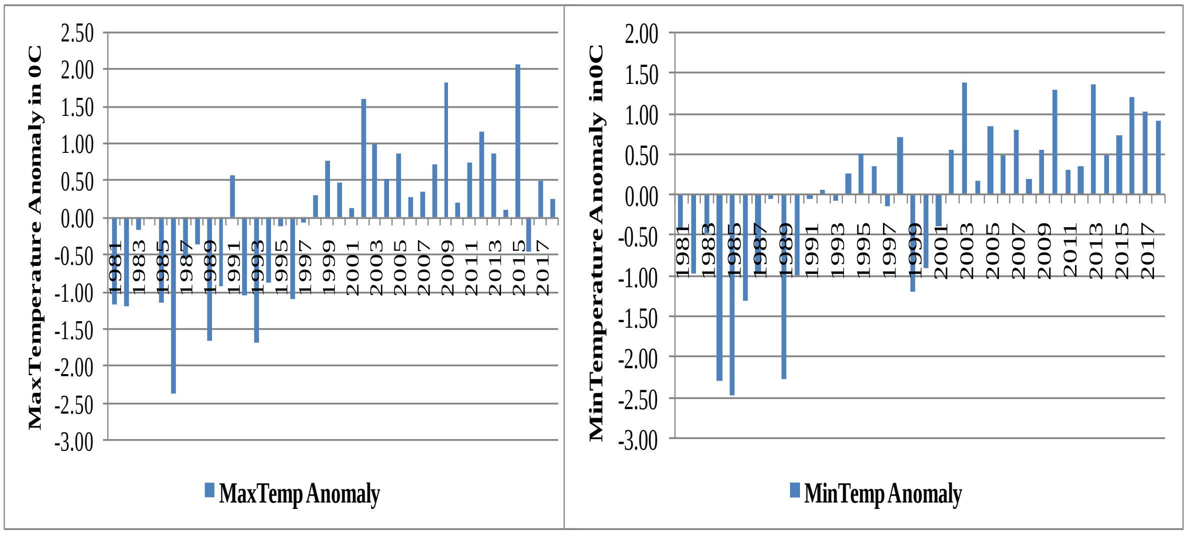


Figure 5.17: Anomalies of maximum and minimum temperature in teff growing areas, 1981–2018
Source: Author's Own Sketch of climate data from NMA of Ethiopia, 2019.

Figures 5.17, 5.18 and 5.19 express anomalies of maximum and minimum temperatures in teff, wheat and maize growing areas respectively, spanning from 1981 to 2018. Appositely, the results showed that maximum temperature anomalies were very low and negative over the period of 1981 to 1997 in the three crops' growing areas. As opposed to that, between 2003 and 2018, the maximum temperature anomalies were positive for all the three crop growing regions. The anomalies of minimum temperature almost followed the same pattern as that of maximum temperature anomalies in teff and wheat growing areas. The anomalies of minimum temperature in maize growing areas were, however, the reverse of those of maximum temperature anomalies, where anomalies of minimum temperature were consecutively positive from 1981-1996 and negative from 2006-2018.

On the other hand, the coefficients of variation (CV) for both maximum and minimum temperatures articulated less variability of temperature in the three crops growing areas. The value of CV ranged from 2.24% to 5.44% for the temperature variables.

Thus, the findings of this study correlate with the submission of Akinsanola and Ogunjobi (2014). Relatedly, they recorded negative anomalies of temperature over the whole country (Nigeria) in the first decade: 1971-1980. However, in the second decade, their analysis showed that some weather stations were found cooler than normal with corresponding negative anomalies while some other stations displayed positive anomalies of temperature. They registered negative anomalies of temperature, while a larger part of the country exhibited positive anomalies of temperature in the third decade that they analyzed, from 1991-2000, which included stations such as Yelwa, Osogbo, Ikeja, Nguru. Dandesa, *et al*. (2017) equally assessed climatic variability in Borena, Southern Ethiopia; and they discovered that minimum temperature was highly variable with an increasing trend during short, dry, and cold (JJA) seasons. They also observed that it had been increasing by about 0.56^{0}C per ten years. The researchers concluded by asserting that the trend line clearly revealed that there has been a warming trend in the annual minimum temperature over the past three decades with the value of about 0.7°C per decade.

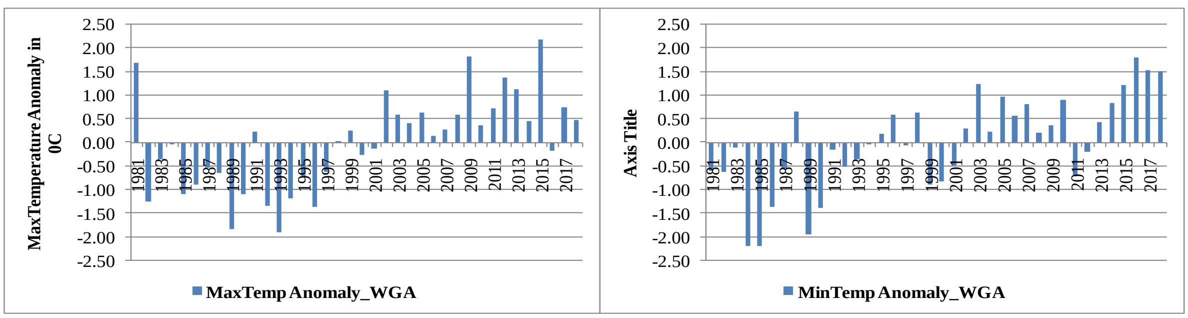


Figure 5.18: Maximum and Minimum temperature anomaly in wheat growing areas, 1981-2018

Source: Researcher's Own Sketch of climate data from NMA of Ethiopia, 2019.

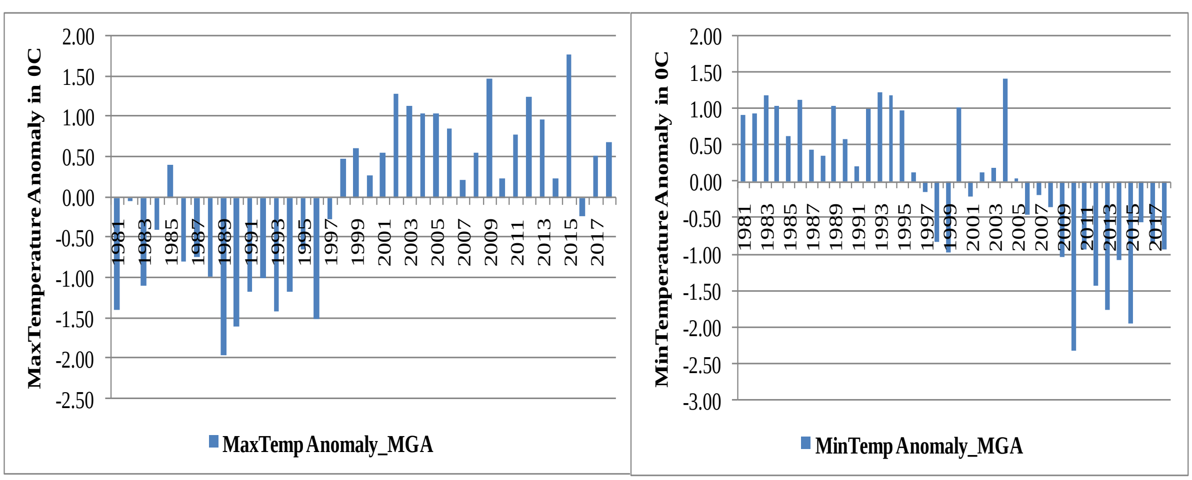


Figure: 5.19: Maximum and minimum temperature anomaly in maize growing areas, 1981-2018

Source: Researcher's Own Sketch of climate data from NMA of Ethiopia, 2019.

Analysis of standardized decadal anomalies of minimum temperature in teff and wheat growing areas is presented in Fig. 5.20. It can be observed that minimum temperatures in most cases have positive anomalies in the first (1981-1990) and second (1991-2000) decades in teff growing areas. During these decades, 6 years (60%) exhibited positive anomalies, consequently denoting warmer temperature than the long period mean. On the other hand, the third decade (2001-2010) exhibited negative anomalies minimum temperatures (60% of decadal years); thus, expressing more of cooler years than normal years. The minimum temperature anomalies and events in wheat growing areas were almost analogous to that of teff growing areas. The result implies that there is pronounced variations in minimum temperature across the decadal categories as well.

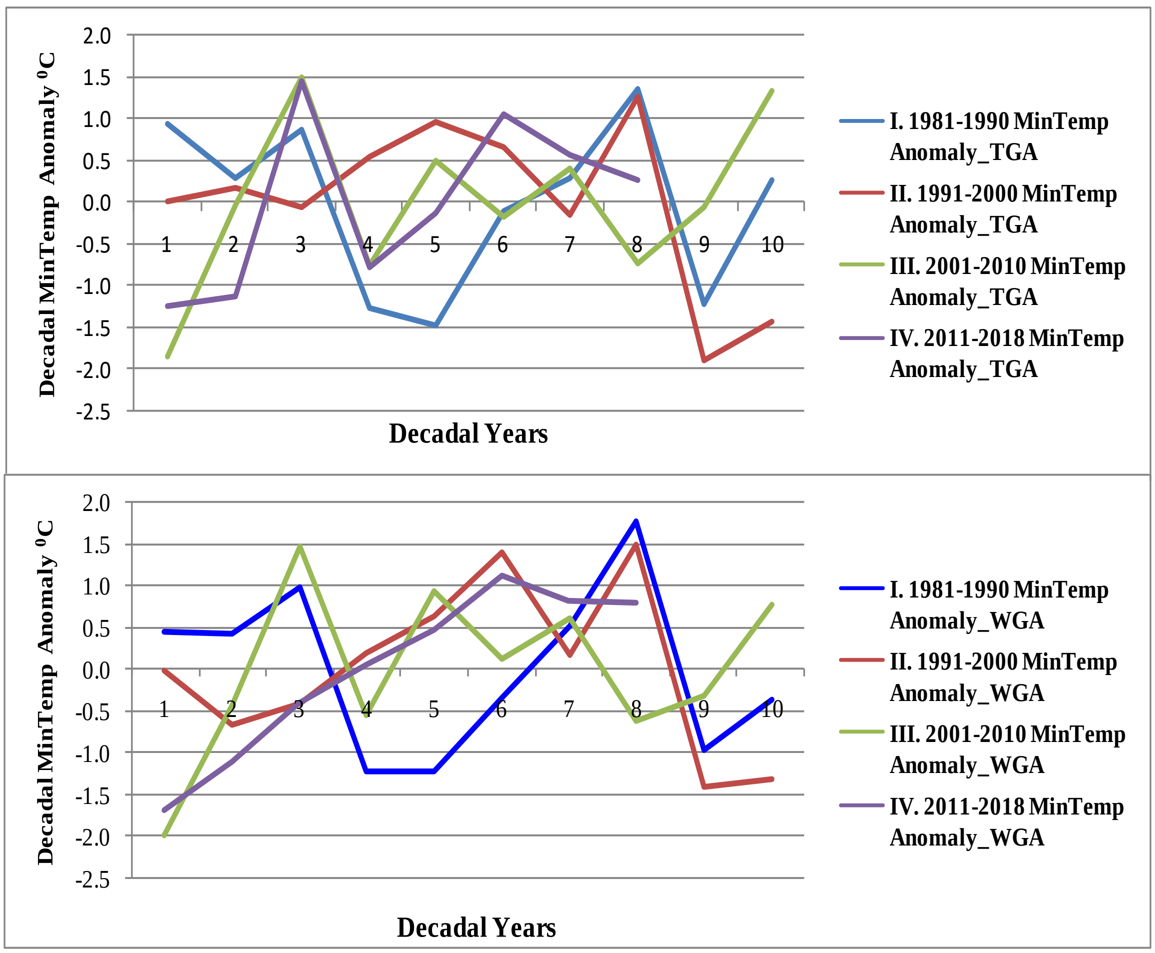


Figure 5.20: Decadal minimum temperature anomalies in teff and wheat growing areas

Source: Author's Own Sketch of climate data from NMA, 2019

Furthermore, the decadal anomalies of maximum temperatures have also been examined to capture the extent of variations in weather variables. The decadal pattern of maximum temperature anomalies in teff growing areas are almost similar to those in maize growing area; the anomalies of maximum temperatures in teff growing areas revealed positive value for five years in the first decade and negative values for six years each in the second (1991-2000) and third (2001-2010) decadal categories, which implies more of cooler years (see Fig. 5.21). Similarly, the anomalies of maximum temperature in maize growing area depicted positive (50%) and negative (50%) values for five years, each in the first (1981-1990), second (1991-2000), and third (2001-2010).

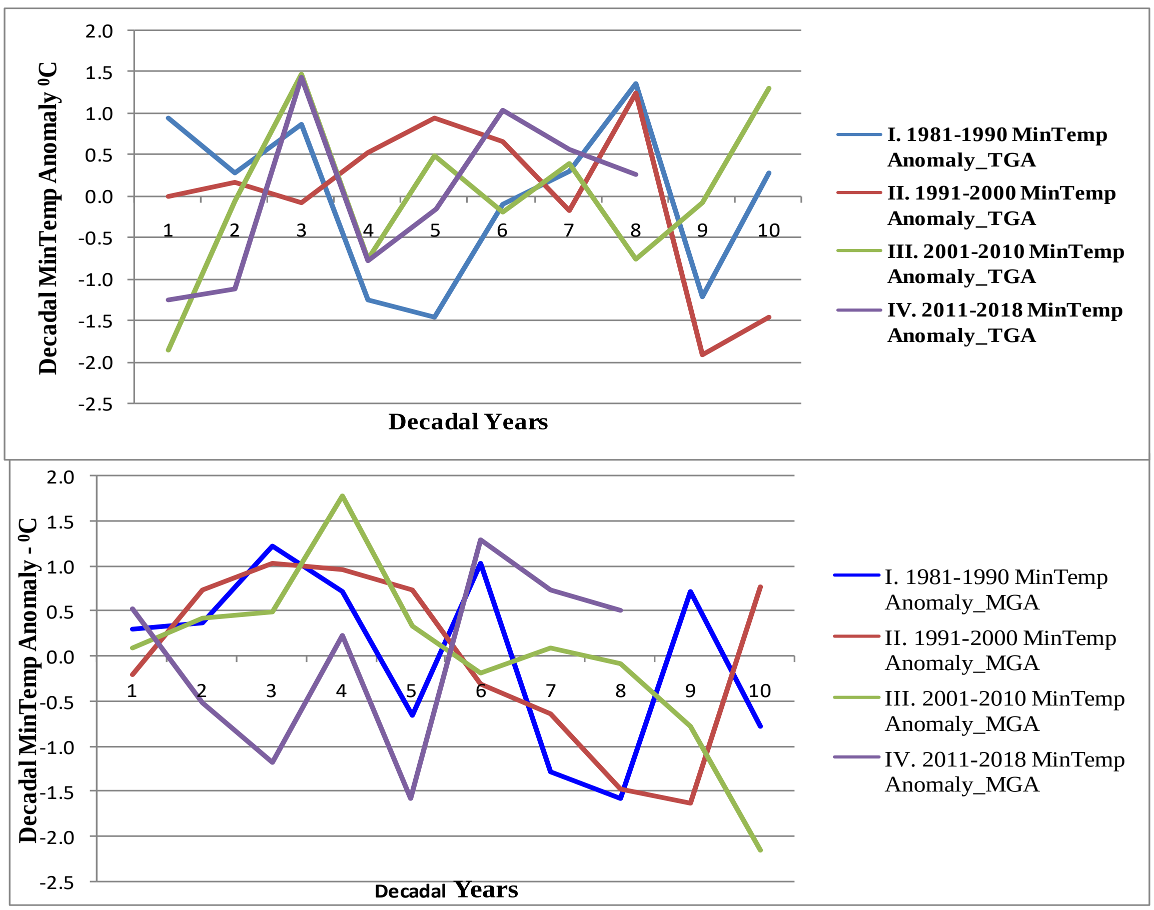
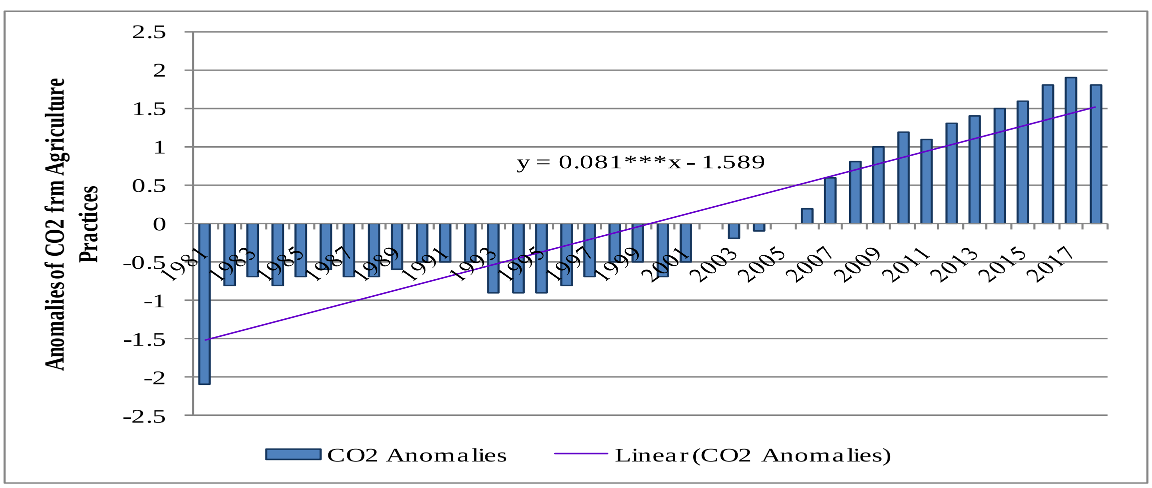


Figure 5.21: Decadal maximum temperature anomalies in teff and maize growing areas

Source: Author’s Own Sketch of climate data from NMA, 2019

5.3.3 *Variability in CO_2*

Similar to other climatic parameters, the variability in CO_2 emission has been assessed using normalized anomalies. Figure 22 presents anomalies of CO_2 emitted from agricultural practices over years 1981 to 2018. The result shows that the anomalies of CO_2 emission from agricultural practices had negative values from 1981 to 2004 and positive values from 2007 to 2018. The negative values show cooler period while the positive values show more of warming events. The result revealed that the variation in CO_2 emission during the period 1982 to 2004 was minimal while the variation in CO_2 from 2007 to 2018 was significant at 1% level. The variation in CO_2 correlates with that of temperature which exhibited minimum variations in all the three crops growing areas. Some studies also confirmed presence of strong correspondence between temperature and the concentration of CO_2 in the atmosphere observed during the glacial cycles of the past several hundred thousand years (NOAA, 2021). They substantiated that ‘‘when CO_2 concentration goes up, temperature goes up. When CO_2 concentration goes down, temperature also goes down’’. Equally, Lia, *et al.* (2010) reported positive as well as negative anomalies in CO_2 arise due to upward (downward) large-scale vertical motions in the lower troposphere associated with the Madden-Julian Oscillation (MJO). These findings can help elucidate how faster processes can organize, transport, and mix CO_2 and provide a robustness test for coupled carbon–climate models.



Source: Computed using raw data from FAOSTAT Data Set, Sept. 2019

Figure 22: Anomalies of CO2 emitted from agricultural practices in Ethiopia

5.3.4 Climate Change

According to United Nations (2022), climate change refers to long-term shifts in temperatures and weather patterns over a long period of time. These shifts may be natural process where temperature, rainfall, wind and other related factors vary over decades or more. But today our glob is experiencing unprecedented rapid warming from human activities, primarily due to burning fossil fuels that generate greenhouse gas emissions. Burning fossil fuels generate greenhouse gas emissions that act like a blanket wrapped around the earth, trapping the sun's heat and raising temperatures. Examples of greenhouse gas emissions that are causing climate change include carbon dioxide (CO_2) and methane (CH_4). These come from using gasoline for driving a car or coal for heating a building, for example. Clearing land and forests can also release CO_2. Landfills for garbage are a major source of methane emissions. Energy, industry, transport, buildings, agriculture and land use are among the main emitters.

Nowadays, climate change is a serious threat to agriculture and to food security. The increase in mean temperature, altered precipitation patterns, and more extreme weather events jeopardize the productivity of cropping systems in many regions. Emissions of greenhouse gases (GHG) are the most important human-induced driver of climate change. Agricultural activities contribute 10%–14% of global anthropogenic GHG emissions, mostly from enteric fermentation (methane), application of synthetic fertilizers (nitrous oxide), and tillage (carbon dioxide) (Smith, et al., 2007).

In this present study, it has been assessed in the preceding sub-sections that temperature was being increasing or becoming worming, seasons and annual rainfall variations were noticed, and CO_2 emissions from agriculture were significant. These climatic parameters show that climate change is already prevailing and pose negative impacts on agricultural production in the country.

5.4 Crop Yield Variability in Crop Growing Areas

This sub-section elucidates the evaluation of area and the yield of crops categorized in relevant intervals of years, and variability of yield of teff, wheat and maize over the study period.

5.4.1 Descriptive Analysis of cultivated area and crop yields

The analysis of cultivated area and yield of crop has been predicated using 38 annual data observations; while the data verifies that between 1981 and 2018 teff output averaged 2.17 million tons with a maximum output of 5.28 million tons and a minimum output of 0.91 million tons. Furthermore, the average land area cultivated under teff production system was approximately 2.0 million hectares, while teff yield ranged from 680 to 1750 kgs per hectare of land area with an average of 1000 kgs per hectare of area. Furthermore, average wheat production was found approximately 1.79 million tons ranging between minimum of 0.64 million tons and a maximum of 4.64 million tons over the period under observation. The average area cultivated under wheat production system was approximately 1.07 million hectares. Regarding yield of wheat, the minimum yield was 0.996 tons and maximum yield was 2.74 tons per hectare of land area with an average of 1.55 tons per hectare of land area.

Furthermore, the average maize production in maize growing belt was 3.08 million tons with a maximum output of 8.4 million tons and a minimum of 0.92 million tons. Average area cultivated under maize within the period under study was found to be more than 1.3 million hectares, but land area annually covered under maize ranged between 0.5 and 2.1 million hectares. Maize yield on the other hand ranged from approximately 1200 kgs to 3944 kgs per hectare of land area with an average of 2145 kgs per hectare of land area. Table 5.10 presents the summary of the statistics of the variables under study in the crop growing belts of the country.

Table 5.10: Summary Statistics on Area, Crop Output, and Yield of Crops

Variables	No. of Obs.	Minimum	Maximum	Mean	Std. Deviation
Teff output (mill. tons)	38	0.912	5.283	2.171	13.028
Area under teff (mill. Ha)	38	1.23	3.02	2.00	0.620
Teff yield (kgs/Ha)	38	678.0	1748.0	1012.0	0.304
Wheat output (mill. tons)	38	0.640	4.640	1.794	1269
Area under wheat (mill. Ha)	38	0.50	1.70	1.07	0.420
Wheat Yield (kgs/Ha)	38	996.0	2736.0	1546.0	4.948
Maize output ((mill. tons)	38	0.920	8.400	3.077	21.773
Area under maize (mill. Ha)	38	0.50	2.10	1.32	0.529
Maize yield (kgs/Ha)	38	1149.0	3944.0	2145.0	4.948

Source: Author's Calculation from NMA Data (2019)

Unlike the assessment of cultivated area and crop yield elicited from 38 annual observations; quite differently, the evaluation of area under crops and yield of crops hinged on a five-year interval categorization. Table 5.11 summarizes the analysis of average area and yield of teff, wheat and maize crops in category of five years interval. The tabling evidenced the fact that the average area and teff yield in the first (1981-1985), second (1986-1990), and third (1991-1995) five-year categories are lower in magnitude than those in sixth (2006-2010), seventh (2011-2015) and eighth (2016-2018) five-year categories. The averaged area and yield of teff in the last three categories in terms of magnitude are almost double of the first three categories, and even more than the overall period study period averages (2 million hectare and 1657 kgs). The same pattern discovered in teff crop is recorded in the average area and yield of wheat and maize. Ergo, from the foregoing evaluations, it can be concluded from the empirical average values in the table that average yields of teff, wheat and maize have consecutively increased over the last four to five years interval categories. The increase can be attributed to limited area expansion and use of improved inputs such as fertilizer, improved seed and irrigation.

Table 5.11: Average area and yield of teff, wheat and maize crops in categories of five years interval over the period of 1981 -2018

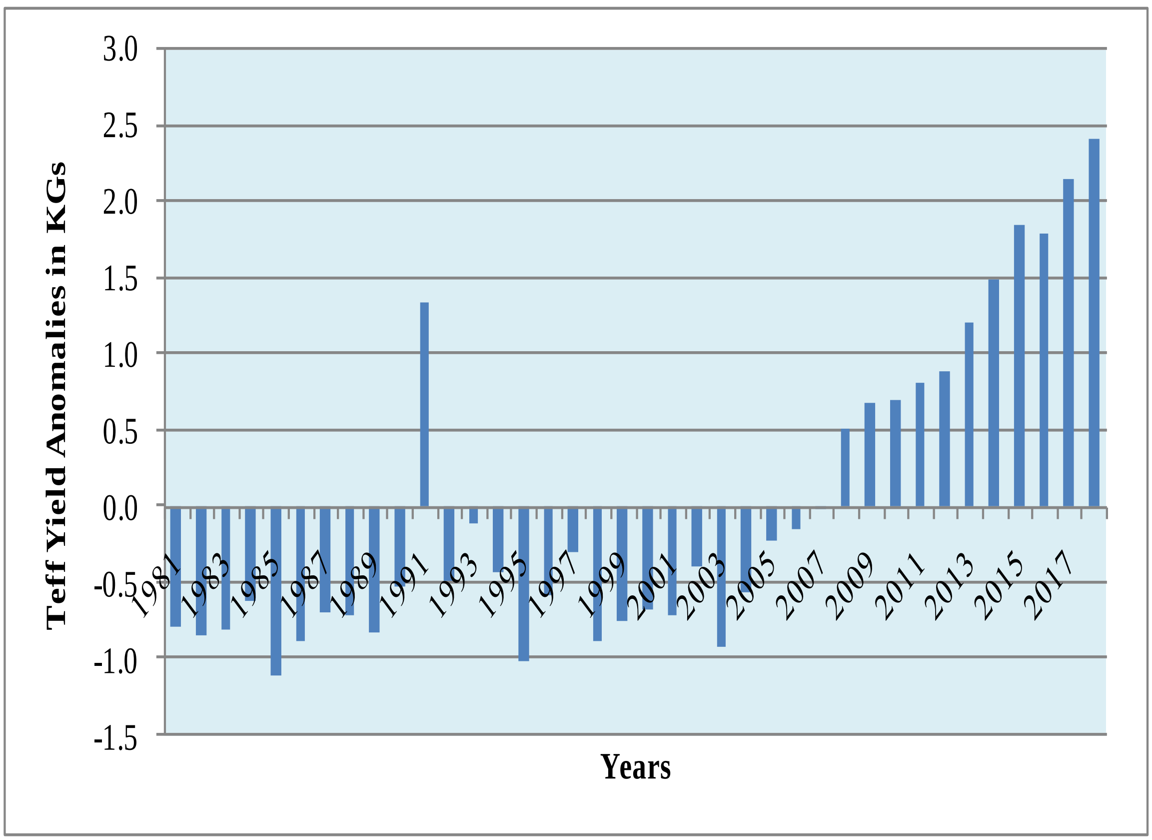
Categories of Years	Years of Ob-ser.	Teff		Wheat		Maize	
		Area (mil-lion ha)	Yield (kgs/ha)	Area (mil-lion ha)	Yield (kgs/ha)	Area (mil-lion ha)	Yield (ton/ha)
I. 1981-1985	*5*	1.31	761.9	0.66	1046.2	0.74	1707.2
II. 1986-1990	*5*	1.31	793.2	0.63	1046.2	0.68	1897.5
III. 1991-1995	*5*	1.46	969.4	0.63	1423.2	0.96	1588.1
IV. 1996-2000	*5*	2.05	820.3	0.89	1246.7	1.28	1861.4
V. 2001-2005	*5*	2.01	843.5	1.13	1383.2	1.40	1861.4
VI. 2006-2010	*5*	2.46	1119.5	1.50	1677.7	1.71	1804.2
VII. 2011-2015	*5*	2.85	1392.3	1.58	2193.1	2.03	3047.1
VIII. 2016-2018	*3*	2.97	1657.1	1.69	2648.8	2.13	3668.3
1981-2018	***38***	***2.00***	***1012.4***	***1.06***	***1546.5***	***1.32***	***2144.5***

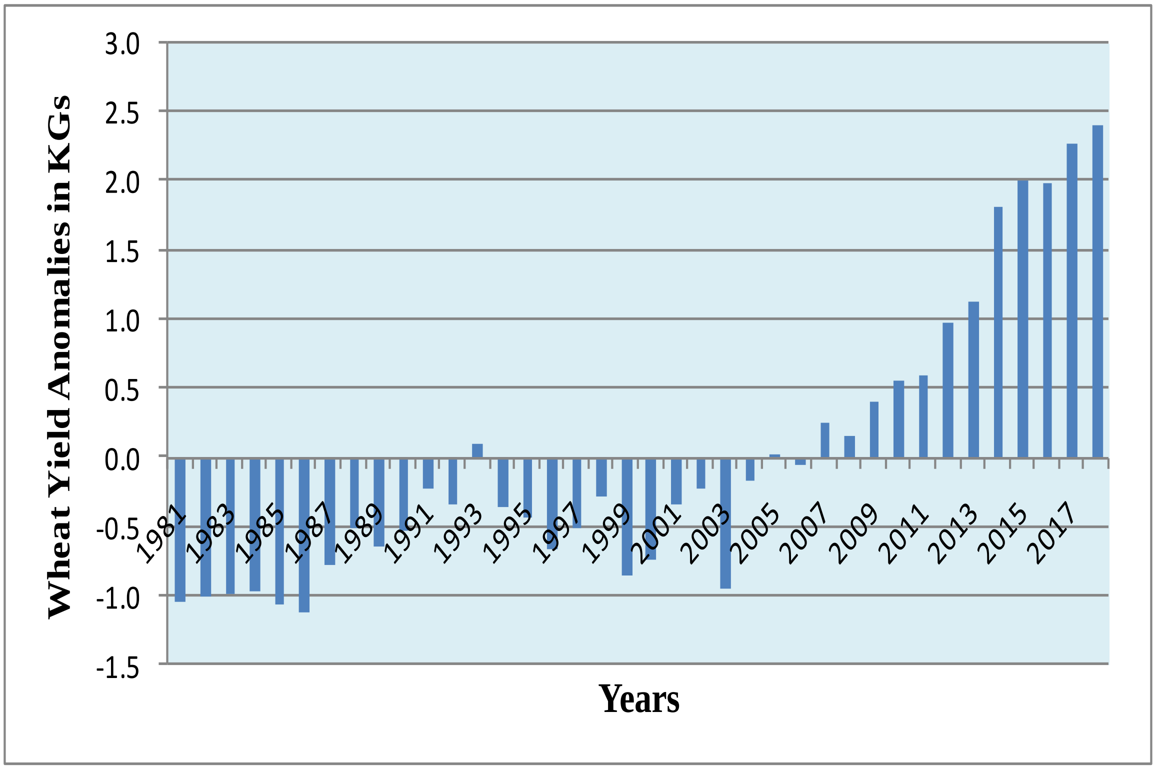
Source: Researcher's Own Computation of data from CSA, Various Bulletins

5.4.2 Variability of Crop Yields

In order to measure the degree of variability in cereal crops yield, crop yield anomalies and coefficient of variation (CV) have been employed. Figure 5.23 presents the yearly sequence of crop yield anomalies for teff, wheat and maize crops over the study period, that is, 1981-2018. The yearly sequencing of teff yield anomalies depicted negative values from 1981 to 2006, except in 1991 where fluctuations were noted, where as positive values were observed in 2008 to 2018 with an increasing trend. Evenly, in wheat growing areas, the wheat yield anomalies have portrayed negative values, and positive value in an increasing trend from 1981 to 2006, excepting during 1993 and 2005. Furthermore, the maize yield anomalies have negative values from 1981 to 2005, except during 1988, and with more fluctuations. It portrayed positive values from 2006 to 2018, but with more of increasing trend from 2011 to 2018.

The positive values in the preceding analysis represent a positive impact on crop yield anomalies while the negative values indicate negative impact on yield anomalies. In other words, a positive yield anomaly shows that data is above the mean (long-term mean), while negative yield anomaly signifies negative impact of the climate or weather and vice versa (Omoyo *et al.*, 2015). The figures lucidly explicate that all the three crops under study (teff, wheat and maize), have showed yield variability (negative value) in a similar fashion during the first two and a half (2½) decades, and a positive and increasing yield anomalies over the last decade (2007 to 2018). The findings of this study corroborate with the results of Panda *et al.* (2019) who investigated climate and crop yield variability in three districts of Odisha, India. They observed negative crop yield (maize and rice) anomalies, impacted due to rainfall deficit related to climate variations.





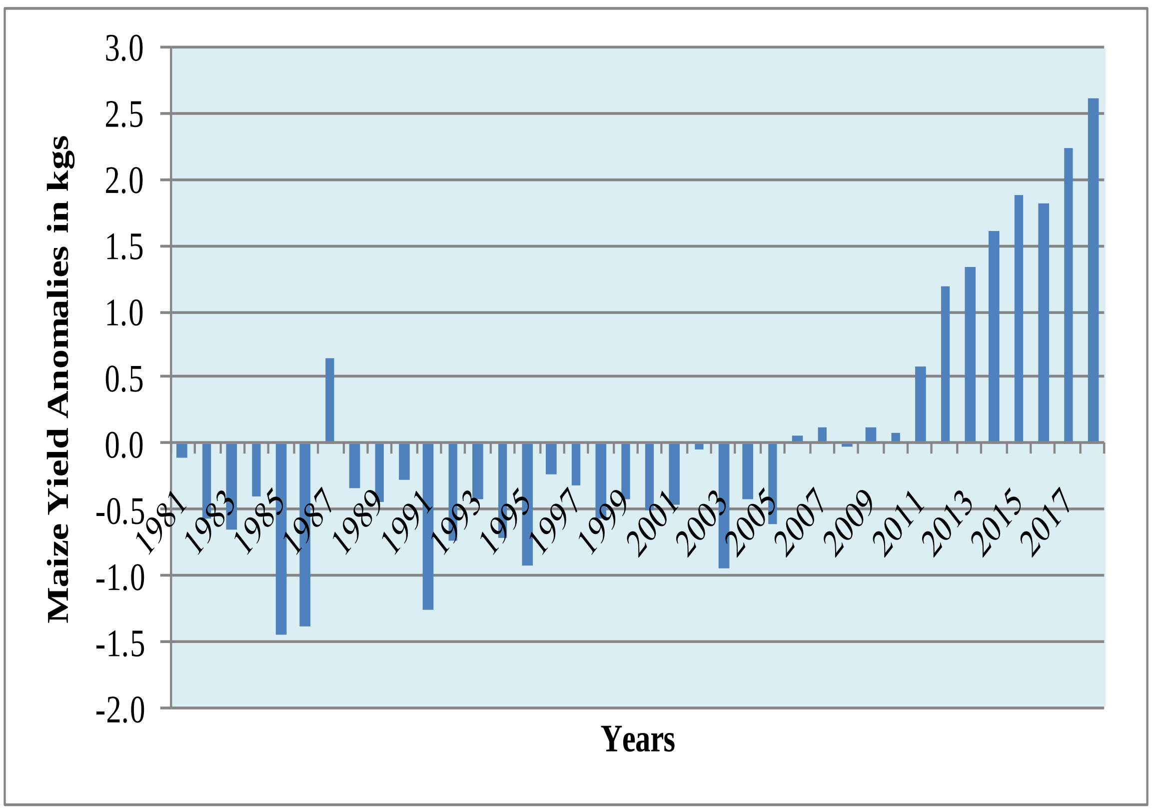


Figure 5.23: Year to year yield anomalies of teff, wheat and maize crops
Source: Researcher's Own Calculation and Sketch of data from NMA, 2019

The coefficient of variation computed for the yield of crops under study confirmed variability of crop yields in the crop growing areas over the observation period. Table 5.12 presents the coefficient of variations (CVs) for teff, wheat and maize over the period of 1981–2018. The coefficient of variations (CVs) exhibited high variability in yield of wheat and maize with magnitude of 32% and 31% respectively, which undoubtedly implies instability in yield of crops. The CV also portrayed that the yield of teff is moderately variable with a magnitude of 30%.

Table 5.12: Coefficient of variation (CV) for teff, wheat and maize yields over the period: 1981 - 2018

Crop	No of Observations	CV (%)	Mean (kgs)	St. Deviation	Variability
Teff	38	30.0	1012.4	303.8	Moderately variable
Wheat	38	32.0	1546.5	494.8	Highly variable
Maize	38	31.9	2144.5	683.9	Highly variable

Source: Researcher's Own Computation of data from CSA, Consecutive Bulletins

5.5 Summary

Chapter V has presented a comprehensive analysis of the characterization of rainfall, temperature, and crop yield in Ethiopia. In this chapter, assessment of trends of climate, changes in weather variables and their variability, and crop yield variability have been done in crop growing areas, all in Ethiopia. To this end, this present study discovered that short-rainfall showed decreasing pattern in all the three crops growing area, i.e., teff, wheat and maize growing areas. Additionally, a linear trend line fitted to short-rainfall manifested a rate of change which are estimated to be:- 0.474 mm, -1.26 mm, and -0.189mmfor teff, wheat, and maize growing areas, respectively. On the other hand, long-rainfall season depicted a rising tendency in teff and wheat growing areas and a declining tendency in maize growing areas. The rate of change for the long-rainfall season rainfall fitted line were +2.72mm, +2.37mm, -1.287mm for teff, wheat and maize growing areas, respectively.

Overall, the results of trend analysis of temperatures reveal that both maximum and minimum temperatures showed increasing trend over the period under study in teff and wheat growing areas. The rate of increment was 0.13^0C of maximum temperature and 0.15^0C of minimum temperature in teff growing area. The rates of change in wheat growing areas was 0.724^0C for maximum temperature and 0.136^0C for minimum temperature, which shows that the increment is more pronouncing for maximum temperature than minimum temperature. Furthermore, minimum temperature portrayed a decreasing tendency with magnitude of (-0.376) while maximum temperature showed increasing trend (+0.139) in maize growing areas.

Likewise, the examination of climate change and variability, as verified by coefficient of variation (CV), the variableness of rainfall was more during *short-season rainfall*, and less variable during long-rainfall season in all crop growing areas under study. Besides, the year to year anomaly of rainfall indicated that maize growing areas undergo more severe anomalies, in addition to experiencing drought years than teff and wheat growing areas. The rainfall standardized seasonal or annual anomalies less than negative one (<-1), denoting severe and extreme droughts. The rainfall anomalies were found to coincide with the major drought years documented in the country. These years coincided with the drought years of 1984/85, 193/94, 2003/04, and 2014/15.

Equally, the analysis of crop yield variability in crop growing areas signified that the coefficients of variation (CV) for maximum and minimum temperatures manifested less variability of temperature in all the three crops growing areas with the values ranged from 2.24% to 5.44% respectively. Besides, the examination evidenced that maximum temperature anomalies were extremely low and negative over the years from 1981 to 1997 while maximum temperature anomalies were positive from years 2003 to 2018 in all crops growing areas. The anomalies of minimum temperature almost followed the same pattern as that of maximum temperature anomalies in teff and wheat growing areas. The anomaly of minimum temperature in maize growing areas were, however, the reverse of those of maximum temperature anomalies, where anomalies of minimum temperature were consecutively positive from 1981 to 1996 and negative from 2006 to 2018.

Furthermore, regarding the yield anomalies and coefficient of variation (CV), the yield anomalies for the three crops under study (teff, wheat and maize) showed pronounced yield variability (both negative and positive values) over the study period of 1981 to 2018. The coefficient of variations (CVs) also witnessed crop yield variability among crops studied. The study exhibited high variability in yield of wheat and maize with magnitude of 32% and 31% respectively, demonstrating instability in yield of the crops. The CV also portrayed that the yield of teff was moderately variable with magnitude of 30%.

Consequently, in view of pronounced variability in yield of studied crops induced by changes and variations in climate variables in the country, the association between yield of crops and climatic factors should be studied in-depth, which would be the main theme of the next chapter.

CHAPTER VI

ECONOMETRIC MODELLING AND ANALYSIS

6.1 Introduction

This chapter presents the second part of the findings based on regression estimations and analyses. The first section articulates the outcomes of tests on time series properties as well as diagnostic tests on estimated models. This is followed by the findings and discussions on the effects of changing climate conditions on yields of teff, wheat and maize crops. Lastly, employing the models selected and estimated, the findings of the effect of changing climate variables on yields and output supply of teff, wheat and maize have been discussed.

6.2 Time Series Properties

Before estimating and testing appropriate models that are suited to examine the effect of climate change on yield and output of crops, test for stationarity of time series data needs to be conducted. In testing the time series properties, if all variables are of unit root, a co-integration test is further embarked upon. The next section examines the stationary properties of the variables

6.2.1 Unit Root Tests

Test for stationarity, as a prerequisite, is being conducted to determine the stationarity as well as otherwise of a series of variables and the appropriateness of the specified models. In the process of the tests, both ADF and PP tests have been applied to each of the data series to test the presence of a unit root. The details of the approaches, procedures, and steps followed in the testing processes have been presented in section 4.7 of this thesis. Furthermore, the results of the tests on unit root to identify presence or non-presence of stationarity are in Appendix 6.1.

It has been found from the outcome of the unit root test that the following variables have exhibited existence of stationary (I(0)) in the data series: log mean temperature in teff growing areas, log *short-rainfall* and *long-rainfall*s in teff growing areas, log CO_2, log fertilizer quantity used in wheat growing areas, log mean temperature in wheat growing areas, log short-rainfall and long-rainfall in wheat growing areas; log mean temperature in maize growing areas, log short-rainfall and long-rainfall in maize growing areas; log improved teff seed, log fertilizer quantity used in teff growing areas, log irrigated area under teff; log mean temperature in teff yield data series, minimum temperature in teff yield data series, maximum temperature in teff yield data series; log wheat yield, log improved wheat seed, log fertilizer quantity used in wheat growing areas; mean rain in wheat growing areas, minimum and maximum temperature in wheat growing areas; log fertilizer quantity used in maize production; mean rain in maize growing areas; and minimum and maximum temperature in maize growing belts.

Equally, the following climatic and socio-economic variables exhibited an integration of order 1 in the data series: log teff output; log area under teff; log fertilizer quantity used in teff production; log wheat output; log price of wheat; log area under wheat; log fertilizer used in wheat production; log maize output; log price of maize; log area under maize production; log fertilizer used in maize production; log teff yield; log area in teff yield data series; log improved teff seed, log fertilizer quantity in teff yield data series; log irrigated teff area; log minimum temperature in teff growing areas; log maximum temperature in teff growing areas; log wheat yield; log area under wheat; log improved wheat seed; log fertilizer used in wheat production; log irrigated area under wheat crop; the minimum and maximum temperature in wheat growing areas; log maize yield; log area under maize; log fertilizer used in maize production; log irrigated maize area; and log minimum and maximum temperature in the maize growing belts. The unit root test has demonstrated a mixture of I(0) and I(1) for the climatic and socio-economic variables that have been included in the current study. In view of these results, both ARDL and Cobb-Douglas Models can be applied to estimate the selected models as the researchers and econometricians (Ssekuma., 2011) suggested the application of ARDL model to time series that exhibit mixture of I(0) and I(1). Bounds test of integration should be also conducted in this case so as to certify the stability of the model. Variance error correction model (VECM) can be used in case the variables of interest are integrated of the same order (Sharma and Singh, 2019). Shamsher (2017), also advised that an ARDL approach should be utilized when variables display different orders of integration. However, before applying ARDL, two conditions must be met. First, the dependent variable cannot be an I(0); second, none of the variables have to be an I(2). Some literatures indicate that the dependent variable has to be I(1), while the independent variables can be a mix of I(0) and I(1) variables (Granger, *et al.*, 1997). Likewise, Cobb-Douglas production model can also be suited to mixture of I(0) and I(1) in as much as similar tests are conducted as ARDL model (Dushko, *et al.*, 2011). In addition to unit root tests, cointegration and VECM, Cobb-Douglas model further needs VAR stability test, serial correlation (LM), multicollinearity test, Heteroscedasticity, Wald F-statistic, stability and RESET Test.

Hence, it is necessary to carry out cointegration tests on the integrated variables as well as other diagnostic tests.

6.2.2 Cointegration Analysis

According to Hatanaka (1996), the cointegration relation must involve at least two I(1) variables. Consequently, I(0) variables may equally be incorporated in the cointegrating equation. The test for cointegration needs to do with running a regression of log teff output, log wheat output and log maize output on the climate and socio-economic variables. Oppositely, residual series were obtained from the estimated equations and tested to identify the presence of unit root. Framing hypothesis in this process, existence of unit root is presented by the null hypothesis, (i.e. H_o: $\gamma = 0$) which implied absence of cointegration, which can be rejected at 5 percent significance level for each of the estimated residuals. The cointegration tests outcomes are presented in Table 6.1 below. The outcomes ascertained that the linear combination of the variables incorporated in each of the model were stationary. Moreover, the results of the cointegration tests denoted the existence of long-run association among the variables included in each of the selected models.

Table 6.1: Estimation of Cointegrating Equations

Dependent Variable	Type of Test	Test Statistic	Critical Values	Conclusion
Teff output response	Wald Test	-5.1689**	4.130	Long run cointegration exists
Wheat output response	Wald Test	-5.3689**	4.130	Long run Cointegration exists
Maize output response	Wald Test	4.4477**	4.145	Long run Cointegration exists

** implies significant at 5 % level

6.3 Diagnostic and Stability Tests

In the current study, the estimated models were tested using different diagnostic and stability tests. The outcomes of such test have been presented and discussed in sections 6.3.1, 6.3.2 and 6.3.3 below.

6.3.1 Normality, Serial Correlation and Heteroscedasticity Tests

In this study, t**ests** have been carried out on the serial correlation, heteroskedasticity, and the misspecification of the functional form, etc using Eviews 9 software. In addition, normality and robust covariace tests have been conducted. Whenever the disturbance terms from various time periods become interrelated or correlated, it can be said that the disturbance or error term is serially correlated. Serial correlation may occur in time-series data whenever the errors associated with the observations in a given time period have been carried over into future time periods. Serial correlation supposedly breaks one of the major assumptions of linear regression that the residuals are independent. This implies that the statistical significance of the regression coefficients will not be entirely reliable. The first-order serial correlations, disturbance errors in one time period are associated directly with the errors in the resultant time period; second-order serial correlation occurs where an error affects data over two time periods later. Orders higher than second-order can happen, but they are rare.

The Durbin-Watson (DW) test is often used to test for positive or negative, first-order, serial correlation. Furthermore, LM test has been carried out for each equation to test for absence of autoregressive conditional heteroscedasticity (ARCH). When heteroscedasticity exists, the OLS estimators (β) and the regression estimate remains unbiased and consistent. If the p value related with calculated test statistic is >0.05, the formulated null hypothesis of homoscedasticity, could not be rejected at 5% significance level.

Further, normality test has been conducted, which are used to test and determine if data set is well-modeled by normal distribution. The tests for normality conducted for this study shown in the histogram exhibit probability values of Jarque-Bera statistic are found greater than 0.05 so that the null hypothesis stating standardized residuals are normally distributed and could not be rejected at 5% level of significance. The results of the tests are presented in Appendix 6.2.

6.3.2 RESET and Parameter Constancy Tests

The RAMSEY RESET test is a statistical tool used in statistics and econometrics to test the omitted variables or misspecification of explanatory variables. In practical terms, it tests whether the non-linear combinations of the fitted values of the model has appropriate explanatory variables. It also tests whether the model accounted for the association among the explanatory and response variables.

In order to test the above circumstances, Ramsey (1969) has developed a regression error specification test (RESET). RESET is a popular test, routinely applied to detect omitted variables and the mistaken functional form during the process of linear regression model specification. Appendix 6.3 captures the outcomes of the tests that were conducted in this study. The findings of the test depict that the p-values calculated are greater than 0.05 in which the researcher was unable to reject the null hypothesis revealing that the powers of the dependent variable under study have zero coefficients, highlighting that the models selected are correctly specified.

Equally, in order to test parameters for change in time series models, CUSUM tests were conducted for each of crop supply response equations. These tests are easy for implementing and are applied to substantiate the stability of ARDL model. The outcome of the test in this study has been depicted in graphical form. Further, the detailed test results are presented in Figures 6.1 – 6.3 of appendix 6.3. It can be observed from the figures that the CUSUM and CUSUMSQ lines are overtly in between the critical bound of 5% significance level over time. The output of CUSUM and CUSUMSQ shows that the model is stable.

6.4 The Impact of Climatic and Agro-Economic Factors on Yield of Teff, Wheat, and Maize

In order to examine and achieve the ***second objective*** of the current study, Cobb-Douglas Production Function with OLS technique was employed to determine the causal relationships existing between the yield of each crop and climatic variables (temperature and rainfall) as well as non-climatic variable (area under crop, quantity of seed and improved seed used). Since the unit root tests above demonstrated a mixture of I(0) and I(1) for climatic and non-climatic variables included in the model, a first difference model was estimated for each of the crop yield model specification, for which Cobb-Douglas model best suits the data.

Before running the Cobb Douglas production function model, the time series data were tested for serial correlation and multicollinearity. The tests exhibited existence of no serial correlation in the regression models since the Durbin Watson statistic was almost close to 2 in most cases. The multicollinearity test at the initial test denotes presence of multicollinearity due to inclusion of improved seed quantity and short season rainfall in teff yield model. Thus, the variable has been dropped from the models and again tested for the same. After dropping and testing for the remaining variables the effect of multicollinearity was minimized and resolved as the values of VIF are less than 10 for teff and wheat crop yield models. The variables included in maize yield model have not revealed problem of multicollinearity.

Details of the estimates of climatic and non-climatic variables along with corresponding standard errors and t-ratios from each of the crop yield models have been presented in the following sub-sections by type of crop.

6.4.1 Impacts of Climatic and Agroeconomic Factors on Yield of Teff

In this study, OLS technique has been employed to establish the causal relationships existing between yield of teff and relevant climatic variables, namely temperature and precipitation for teff growing areas in Ethiopia. Contribution of climatic variables to production of teff crop in the country has been represented by variables such as crop season mean rainfall (CGSRF), *long-season rainfall* (main season rainfall), mean minimum and maximum temperatures, and CO_2 during crop growing season, i.e., February to September. In addition, non-climatic variables such as area cultivated under teff and quantity of fertilizer consumed for teff crop production were added to the model. Area of land irrigated under teff and improved seed consumed have been tried to include into the model, but irrigated areas are already part of total area allocated for teff production and highly correlated with teff yield, cropped area and fertilizer quantitu used. Improved teff seed showed insignificant and minimal contribution to teff production system, therefore, the two variables were dropped from inclusion to the model. A simple correlation matix of the final variables included in the model has been examined. The result of simple correlation coefficient shows that there exists correlation between LnTAr and LnTYi; LnFertQ and LnTYI; and LnFertQ and LnTAr. Smoothing the LnTAr, LnFertQ, and LnTYI data through moving average method has reduced the correlation between these variable to some extent, although not at levels with climate variables. Since analysis without land area and fertilizer consumed would not give sense, the two variables were included in the analysis (see Table 2.2 for details).

Table 6.2: Simple Correlation matrix of Variables included in Teff Yield Model

Variable	LnTYi	LnTAr	LnFertQ	LnCGSRF	lnSSRF	lnLSRF	LnMinTemp	LnMaxTemp
LnTAr	0.750							
LnFertQ	0.820	0.965						
LnCGSRF	0.216	0.330	0.303					
lnSSRF	0.087	-0.148	-0.038	0.275				
lnLSRF	0.213	0.448	0.345	0.734	-0.309			
LnMinTemp	0.569	0.715	0.674	0.328	-0.036	0.377		
LnMaxTemp	0.429	0.667	0.551	-0.027	-0.517	0.275	0.519	
lnCO2	0.814	0.850	0.859	0.331	-0.082	0.359	0.551	0.546

Source: Author's Coputation using raw data from CSA and NMA, 2019

The estimated coefficients of the Cobb Douglas functional model are presented in Table 6.3. The F-test value for the estimated model depicts good fitness of the overall regression model to the present data. In this context, the adjusted R^2 values of 0.7502 in teff yield function implies that 75% of the variations in teff yield are explained by climate variables, fertilizer consumed, and area cultivated under teff crop.

The elasticity coefficient estimates obtained from teff yield regression model revealed that among the rainfall variables included in the study lnCGSRF (Feb-Sept) had negative and significant impact on yield of teff. The result indicated that a 1% increase/ change in CGSRF would lead to a decrease of teff yield by 1.76%. This result implies that increases in rainfall during the *long-rain season* will highly affect production and yield of teff crop if it exceeds the optimum level. In practice and theory, as rainfall increases beyond the optimum level, extreme events like flooding, landslide, crop lodging, and erosion of top soil would be contributing to reduction of yield and production of teff crop. Agronomically, such negative events would damage crop, in addition to leading to crop failure posed by overflooding of teff fields, lodging of crops, and favored weeding and pests, which leads to decline in teff yield.

Table 6.3: Estimates of Cobb-Douglas Production Function from teff yield model

Explanatory Variables	Coefficients	Std Errors	T-Ratio	P-Value	VIF
(Constant)	-9.3290				
LnTAr	-1.0816**	0.4344	-2.490	0.0188	34.200
LnFertSM	0.6216***	0.2009	3.095	0.0043	26.455
LnCGSRF	-1.7580*	0.9707	-1.811	0.0805	5.719
lnSSRainfall	0.4704**	0.2264	2.078	0.0467	3.588
lnLSRainfall	1.2149*	0.7085	1.715	0.0971	6.542
LnMinTemp	0.7003	0.6485	1.080	0.2890	2.253
LnMaxTemp	2.4278	1.8903	1.284	0.2092	3.705
lnCO2	0.4931***	0.1556	3.169	0.0036	4.260

Sample size	38
Coefficient of determination R^2	0.8042
R^2-adjusted	0.7502
Multiple correlation coefficient	0.8968
Residual standard deviation	0.1376
D'Agostino-Pearson test for Normal distribution – Proposed to accept normality	P=0.0002)

***, ** and * indicates 1%, 5% and 10% significance level, respectively

Source: Author’s computation

Conversely, short-season rainfall and long-season rainfall exhibited positive and significant impact on teff yield. This implies that, a 1% increase in volume of short-season rainfall and *long- season rainfall* would increase the yield of teff by 0.47% and 1.22% respectively. In practice and normal cases, teff crop needs *high and optimum* amount of rainfall during the *long-rainy season*, the period when seedbed preparation, seed sowing, weeding, as well as crop vegetative growth takes place. It is the long-season rainfall that is important for growing of teff crop as all the agronomic practices take place during this season. For teff, land preparations take place in the month of June, seed sowing and first fertilization from July to mid-August, second fertilization and weeding from mid-August to September, and harvesting and threshing operations from October to December.

This finding corroborates with theory that suggests an increase in rainfall during crop development phase will reduce the yield and production of crop under consideration. The results of this study correspond with the study results of Ademe (2017), Menya (2011), Mahmood *et al.* (2012) and Singh (2017). Ademe (2017) assessed the impact of variability in climate variables on yield of cereal crops in Ethiopia and found that crop growing season precipitation has negative and considerable effect on yield of wheat. The result revealed that a 1% increase in the crop growing season rainfall reduces wheat yield by 0.124%. Similarly, Menya (2011) studied rainfall variation due to climate change in Ethiopia. The investigation reported negative and significant effect of the long-season rainfall on crop yield. Essentially, the result of the study portrayed that a 10% increase in long-season rainfall also reduces crop yield by 0.01%. Equally, Mahmood *et al.* (2012) recorded negative and significant coefficient of rainfall variable and further observed that a rise in rainfall during months of crop reproductive and harvesting period decreases crop yield. Correspondingly, Singh (2017) found that the regression coefficient estimate for crop growing season rainfall has negative, but insignificant impact on yield of wheat during Rabi season in Gujarat, India.

On the other hand, temperature parameters had positive signs, although the coefficients of both variables are statistically insignificant. Consequently, the elasticity coefficient of CO_2 had positive and significant (10% and 5% level respectively) impact on the yield of teff in the study areas. The result signifies that a 10% raise in CO_2 emission concentration would increase teff output by 4.9%.

The findings of this study is found similar to the submission of Ademe (2017), who in their study on impacts of variability in climate on the cereal crops in Ethiopia reported that crop growing period temperature revealed positive and significant (at 1% level) impact on yields of wheat and barley. The result actually indicated that a 1% increase in crop growing season temperature increases wheat and barley yield by 0.984% and 0.564%, respectively. Mahmood *et al.*'s (2012) carried out a study in Pakistan and discovered that average minimum temperature during crop growing period was positively associated with the yield of rice crop. Joshi, *et al*. (2011) also examined the impact of weather variables (temperature) on yield of major food-crops in Nepal; subsequently they avowed that the coefficients of temperature for summer season were positive.

Regarding agro-economic variables, the elasticity estimates of area cultivated under teff crop showed negative and significant impact on yield of teff crop. The result evinces that a 1% increase in area allocated for teff crop decreases teff yield by 1.1%. The result implies that allocation of new and marginal land under teff cultivation will reduce teff yield, although it will increase the volume of total production. This finding is in contrast with the study results of Byishimo (2017) on the impacts of climate change on crop yields in Rwanda. Byishimo (2017) asserted that area harvested under teff crop has positive and significant impact on teff yield, denoting that a 10% increase in area harvested under teff crop increases yield of teff by 3.31%.

On the contrary, the results showed that the quantity of fertilizer applied on teff farms has positive and significant (at 1% level) impact on yield of teff. It follows that a 10% increase in quantity of fertilizer used increase teff yield by 6.2%. Therefore, it means that any increase in quantity of fertilizer used under teff cultivated area will lead to an increase in the yield of teff, which consequently necessitates the use of fertilizer only up to optimum level. This result is in contrast with the results submitted by Issahaku (2014), who studied the impact of climate change on productivity of agriculture and poverty in Ghana. The results showed a negative effect of fertilizer on productivity of Cassava, but statistically insignificant.

The elasticities estimated for the explanatory variables included in the Cobb-Douglas production model for teff yield totaled to 3.0885, and this affirms an *increasing return to scale*. This implies that there is an increasing return to scale in teff production business.

6.4.2 Impacts of Climatic and Agro-economic Variables on Wheat Yield

The explanatory variables considered in the wheat yield model estimation were climatic variables (*short-season* rainfall, *long-season* rainfall, mean minimum and maximum temperatures) and other *economic variables* (land area cultivated under wheat cropping system, quantity of fertilizer and improved seed used and irrigated area under wheat cropping system). The wheat yield model has been estimated by employing OLS technique. The F-value of the estimated elasticity coefficients for the Cobb Douglas functional model was found significant and has good fitness to the present data used in the regression modeling. The adjusted R^2 values of 0.78 (see Table 6.4) in the estimated wheat yield model denotes that 78% of the variations in wheat yield model are elucidated by weather variables (short- and long-rainfall seasons, mean minimum and maximum temperatures) and socioeconomic factors (fertilizer and improved seed consumed, area cultivated under wheat crop and irrigated area under wheat cropping system). This indicates that 22 percent of the variations in the yields of wheat are to be explained by other variables that were not included in the model.

The results of estimates of elasticity coefficients of wheat yield regression model are exhibited in Table 6.3. The results affirm that short-season rainfall (Feb. – May), *long-season rainfall* (June - September) and *maximum temperature* variables during crop growing period (February - September) are negatively associated with yield of wheat crop. However, only long- season rainfalls as well as maximum temperature elasticity coefficients were found to be statistically significant at 10% level. This implies that a 1% rise in maximum temperature during crop growing period and a 1% rise in *long-rainfall season* would reduce wheat crop yield by 2.81% and 0.5%, respectively. Here, the crop growing period refers to both *short-rainfall* and *long-rainfall* seasons. The short-rainfall (*Belg*) season is the period when most of the land preparation tasks are performed and the long-rainfall (*Kiremt*) season is the period when the planting, weeding, and related activities are performed. The long-rainfall season is also the period when crop vegetative and reproductive growth process takes place.

Table 6.4 Estimates of Cobb-Douglas Production Function from wheat yield model

Explanatory Variables	Coefficients	Std Errors	T-Ratio	P-Value	VIF
(Constant)	9.1192				
lnWhAr	-0.3542*	0.1955	-1.812	0.0803	12.653
lnFertWh_	0.269***	0.0952	2.828	0.0084	10.458
lnImSWh_	0.1849***	0.06731	2.747	0.0102	3.354
lnIrrgArWh	0.1529**	0.06745	2.268	0.0310	3.068
ln*Short-season rainfall*	-0.08814	0.1434	-0.615	0.5435	2.018
ln*Long-season rainfall*	-0.498*	0.2888	-1.725	0.3252	1.625
lnMinTemp _	0.9149	0.6452	1.418	0.1669	2.134
lnMaxTemp _	-2.8099*	1.6121	-1.743	0.6192	3.331
Coefficient of determination R^2		0.825			
R^2-adjusted		0.777			
F-ratio		17.17***			
Multiple correlation coefficient		0.9085			
Residual standard deviation		0.1372			
Sample Size		38			

*** Significant at 1%, ** significant at 5% and * Significant at 10%
Source: Author's computation

The above result corroborates with the findings of presented under Chapter V which portrayed increasing and significant trend in mean maximum temperature during the long-rainfall season. It has also been found in Chapter V that the rainfall occurred during *long-rain season* in wheat growing areas portrayed an increasing trend which lead to an extreme weather conditions such as flooding, landslide and soil erosion. The long-season rainfall mean amount of 764mm estimated for wheat growing belts also exceeds the rainwater requirement of wheat crop that in maximum requires 650mm rainwater. Furthermore, the findings of the current study on the association among crop growing period maximum temperature and yield of wheat crop aligns with theory proposition that states a rising temperature may result in reduced agricultural productivity.

The findings of this study align with the study findings of Byishimo (2017), Singh *et al*. (2017), Shumetie, *et al*. (2017), and Ajay and Pritee, (2013). Byishimo (2017) studied the effect of changes in climate on yield of Irish potato and found that maximum temperature had negative and significant impact on Irish Potato yield. The estimated elasticity of maximum temperature indicates that a 1% increase in maximum temperature reduces yield of Irish Potato by 0.32%. Equally, Amin *et al*, (2015) in their study on the impacts changes in climate variables on yield of main cereal crops in Bangladesh. They confirmed that weather variables (maximum and minimum temperature and precipitation) that increase beyond their optimum requirement would devastate the yield of Aman rice. Shumetie, *et al* (2017) in their study in Ethiopia also found that the elasticity coefficient estimate for *wheat growing season* mean rainfall was negative and significant at 10% level. Singh *et al*. (2017) stated that maximum temperature and rainfall depicted negative and significant effect on wheat yield in Punjab; they identified that wheat crop needs cool, dry and clear climate with an optimum temperature ranging from 14-20°C. They further observed that excessive heat eventuates into declined number of grain, besides lessening length of the grain filling period in wheat, obviously and eventually affects yield of wheat crop. By the same token, Shumetie *et al*. (2017) focused their research on Ethiopia; at the end of the examination they discovered that the coefficient estimate for *wheat growing season* rainfall was negative and significant at 10 percent level. Meanwhile, according to Ajay and Pritee (2013), an increase in maximum temperature depicted a negative and significant impact on yield of wheat. The researchers were of the opinion that a rise in maximum temperature by 1% would negatively influence the yield of wheat by 2.63%. However, the study results of Ajay and Pritee is in contrast to this study in the sense that the productivity of wheat is negatively impacted due to a rise in minimum temperature; the regression coefficient estimated for minimum temperature being significant at 1% level, denoting that a 1% increase in minimum temperature would negatively affects productivity of wheat by 1.73%.

Furthermore, the estimated elasticity coefficients of non-climatic factors like the quantity of fertilizer, improved seeds and irrigated area under wheat crop production showed positive and significant impact on wheat yield. The results imply that use of these inputs; fertilizer, improved seed and irrigated area have vital role in increasing the yields of wheat crop. The result showed that a 10% increase in quantity of fertilizer used, quantity of improved seed used and irrigated area under wheat crop would definitely increase yield of wheat by 2.69%, 1.85%, and 1.53%, respectively. The findings of this study also imply that a 10% raise in land area under wheat crop diminishes wheat yield by 3.54%. The study results of input usage on wheat production are consistent with the findings of other researchers (Birthal *et al.,* 2014; Ajay and Pritee, 2013). Ajay and Pritee (2013) in their study on the effect of variations in climate on the productivity of agricultural crops in rural India found that any fertilizer usage increment could enhance wheat, maize, barley and sorghum productivity as well as augmented use of irrigated area on wheat crop is important to boost productivity of wheat crop, which was a finding corroborated with the above modeled result for cereal crops. Birthal, *et al.* (2014) in their study found that irrigation has significant impact on wheat yield; the coefficient of irrigated area has been found significant and had the anticipated signs in wheat cropping system, implying that irrigation is an important input to counterbalance the harmful effects of climate change on wheat crop. Furthermore, Shumetie *et al.* (2017) observed that chemical fertilizers have had positive and significant impact on yield of wheat and barley crops under study; it means that small unit increment in its application has the capacity of enhancing yield significantly. Sibiko, *et al.* (2013) had similar report regarding the utilization of fertilizer on bean productivity. Likewise, any fertilizer usage increment has the probability of boosting wheat, maize, barley and sorghum productivity, in addition to augmenting the irrigated area, which is very crucial factor needed for increment in the production of wheat (Ajay and Pritee, 2013). In the same vein, these researchers' findings tallied with the above model result for all cereal crops. Relatedly, Birthal, *et al.* (2014) noted that irrigation had significant impact on wheat yield; the coefficient of irrigated area was found significant and had the estimated signs in wheat cropping system. This consequently substantiates and underlined the central role of irrigation in counterbalancing the harmful effects of climate change on wheat crop.

Conversely, the land area cultivated under wheat has portrayed negative and significant impact on yield of wheat crop. The result indicates that a 10 percent increase in the area cultivated under wheat crop will decrease yield of wheat crop by 3.54%/Ha of land area. This implies that any further increase in land area cultivated area under wheat crop beyond its optimum level would diminish the yield of wheat crop.

When the elasticities of all the explanatory variables included in the model are summed up, the result is -2.228. This shows the existence of *decreasing returns to scale* in wheat production business.

6.4.3 Impacts of Climatic and Socioeconomic Variables on Yield of Maize

In this current study on supply responsiveness of maize output to changes in explanatory variables (climate and socioeconomic), the explanatory variables incorporated in the model are transformed into their log form so as to provide convenient socio-economic interpretation of the elasticities thereby minimize the heterogeneity of the variance. In the process of estimating the Cobb-Douglas functional model, mean rainfall of the crop growing season (F-S), *short-rainfall* season, *long-rainfall* season, mean minimum and maximum temperatures (Feb-Sept), and CO_2 emission were incorporated in the model. From the non-climatic variables, quantity of fertilizer and improved seed used and land area and irrigated area under maize cropping system were included in the maize yield model. The quadratic form climate variables were also considered for inclusion into the yield model but excluded because of multicollinearity ($VIF>10^4$).

In this study, the maize yield model has been estimated by employing ordinary least square technique. The estimated coefficients of the Cobb Douglas production function model was significant as the F-value indicated that the overall regression model was well fitted and followed normal distribution for the present data. The adjusted R^2 values of 0.775 in the estimated maize yield model implies that 77.5% of the variations in the maize yield model are explained by climate variables (mean rainfall: Feb-Sept, *short-season rainfall* and *long-season-rainfall*, mean minimum and maximum temperatures), fertilizer and improved maize seed consumed, and land area and irrigated area under maize cropping system. This indicates that only 22.5 percent of the variations in the maize yield are explained by other variables not included in the yield model.

The results of the elasticity coefficient estimates of the maize yield regression model are presented in Table 6.5. The elasticity coefficients estimated show that climatic variables that were included in the model, except minimum temperature and CO_2, have expressed negative relationship with yield of maize. The elasticity coefficient of maximum temperature during crop growing period (February to September) was negative and significant at 10% level. This implies that a 1% increase in maximum temperature, during the crop growing period diminishes yield of maize by 3.68%, which is in line with the theory proposition. In practice, an increase in temperature above the optimum level during crop development phase will reduce the growth of shoots and roots of maize plant. High temperature also affects the flowerering and grain filling process of crops, particularly maize crop. From this, it can be concluded that maize crop is very sensitive to high temperatures that are beyond optimum level as well as to the shortages in rainfall during the crop development process. The result of this study maintains a parallel with the results articulated in Chowdhury and Khan's (2015) study. They researched the association of changes in climate variables on yield of rice in Bangladesh and realized that maximum temperature had negative (-4.95) and significant (10% level) impact on yield of rice. Similarly, Kumar, *et al*. (2015) in their study on the impacts of changes in the climate variables on productivity of cereal crops also reported negative influence of average rainfall (-0.0212) and average maximum temperature (-0.224) on the yield of potato crop, but only average rainfall was significant at 1% level. They further reported that the mean minimum temperature have negative (-0.756) and significant (at 5% level) impact on cotton yield.

Table 6.5: Estimates of Cobb-Douglas Production Function from maize yield model

Explanatory Variables	Coefficients	Std Errors	T-Ratio	P-Value	VIF
(Constant)	15.7269				
lnMzAr	-0.5233***	0.1604	-3.263	0.0030	9.251
lnFertMz	0.2974***	0.07196	4.133	0.0003	9.995
lnMzIS	0.1576**	0.07209	2.187	0.0376	4.384
lnIrrigMzAr	-0.0759	0.1081	-0.702	0.4885	3.878
lnCGSRain	-3.5250***	0.4735	-7.4446	0.4630	1.483
lnShort-Season Rainfall	-0.4292**	0.1607	-2.670	0.0127	1.688
lnLong-Season Rainfall	-0.2729	0.4084	-0.668	0.5097	1.595
lnMinTemp_Feb-Sept	1.5199**	0.7430	2.046	0.0507	3.034
lnMaxTemp_Feb-Sept	-3.6811*	2.1439	-1.717	0.4398	4.581
lnCO2	0.1944	0.1677	1.159	0.2565	4.709
Coefficient of determination R^2		0.834			
R^2-adjusted		0.775			
F-ratio		13.742***			
Multiple correlation coeff.		0.9142			
Residual standard deviation		0.1411			
Sample Size		38			

*** Significant at 1%, ** significant at 5% and * Significant at 10%
Source: Author's computation

In this study, the elasticity coefficients of mean rainfall (F-S) over crop growing period, *short-season rainfall* (F-M), and *long-season rainfall* (J-S) were all found negative, but only the elasticity coefficients for crop growing season rainfall and short- rainfall season are found significant at 1% and 5% levels, respectively. Apparently, the result signifies that a 1% increase in crop growing rainfall and short-season rainfall reduce maize yield by 3.53% and 0.43%, respectively. The result of this present research is in conformity with the outcome of the research carried out on the association among climate change and yield of rice by Chowdhury and Khan (2015). They have examined the effect of changes in climate on yield of rice in Bangladesh and reported that the crop season rainfall demonstrated negative and significant (at 10% level) impact on rice yield. As such, the result patently evinces that a 10% increase in crop season rainfall reduces rice yield by 1.83%.

Oppositely, the elasticity coefficients of quantity of fertilizer and improved seed used in maize production established positive and significant (at 1% and 5% respectively) impact on maize yield. Accordingly, the result implies that a 10% increase in fertilizer and improved seed increases maize yield by 2.97% and 1.58%, respectively. Furthermore, the elasticity estimate of area cultivated under maize and irrigated area under maize cultivation have negative impact on maize yield, but only cultivated area under maize crop is statistically significant at 1% level. The result also signifies that a 10% increase in area cultivated under maize crop reduces maize yield by 5.23%.

Summing up all the elasticity coefficients of the explanatory variables included in the maize yield Cobb-Douglas model, the result becomes (-6.356), which shows existence of *decreasing returns to scale* in maize crop production business.

6.4.4 Forecast of Future Impacts of Climate Change on Yields Selected Crops

Previous researchers used various models to assess and forecast future impacts of changes in climate variables on crop yields. Many researchers have adopted a statistical approach to estimate future climate change impact on crop yields (e.g., Lobell, *et al.*, 2011; Zhang, *et al*., 2008), among which Cobb-Douglas Production Functional model is considered as well-known one.

The Cobb-Douglas functional approach elucidates an empirical relations between various inputs in the production process;it can be utilized because it is utile, besides it effectively fit to the actual production to a greater degree (Yuan *et al.*, 2009). Nonetheless, the modified Cobb-Douglas production function is a special and sui generis form of double-log regression model, whereby there is a natural logarithmic association between independent and dependent variables. Accordingly, it is evident that that Cobb-Douglas functional model has intrinsic and valuable fundamental principles, coupled with distinctive benefits in resolving forecasting difficulties, in addition to possessing the additional utility and pragmatic significance in comparison to other general multivariate non-linear regression models (Dong, *et al.,* 2018). Thus, from the foregoing and a scrutiny of related and valuable studies that have been reviewed, it is irrefutable that the biggest contribution of the model is to provide researchers with an effective and relatively simple model that might reflect and statistically measure the "input-output" relationship.

In this forecasting exercise, elasticity coefficients from Cobb-Douglas Functional model estimated in section 6.4 has been utilized. The elasticity coefficients estimated for maximum temperature, minimum temperature, short-season rainfall, and long-season rainfall on yields of creal crops selected for this study (teff, wheat and maize) were taken from the model estimates presented in Tables 6.3, 6.4 and 6.5, respectively. These elasticity coefficients were estimated at average crop yield level by multiplying the coefficients of weather variables (minimum and maximum temperature as well as short- and long-season rainfall) by the mean climate variables and breaking up the result into the average yield (as cited by Chen, *et al*. 2004).

Table 6.6 presents the elasticity coefficients of average crop yield to a change in climate estimated under Cobb-Douglas models described above. Using the estimated elasticity coefficients of climate variables at average crop yield, the effects of future scenarios of climate variation on crop yield can be estimated (IPCC, 2013). In this forecasting presentation, the variations in climate for three time-slices (Scenarios) viz. 2045, 2065 and 2080 have been selected and adopted.

The predicted impacts of climate change on crop yields are given in Table 6.7. As can be seen from the table, by 2080, the crop growing season mean temperature may rise from -4.85^{0}C to 0.195^{0}C in teff growing areas while the changes in crop growing season rainfall by the same period are expected to be within the range of -0.32mm to -1.58mm in teff growing belt. In wheat growing belt, the changes in temperature are expected to be within the range of 1.7^0C to -0.95^0C by 2080 while the change in crop growing season rainfalls are expected to range from -0.58mm to -1.3mm in the same area. In maize growing areas, the changes in temperatures have been projected to be in the range of 0.18^0C to -0.91^0C by 2080. Similarly, the changes in crop growing seasons' rainfalls are projected to be in the range of -0.05mm to -0.17mm by 2080 in the maize growing areas.

Table 6.6: Elasticity of Climate Variables at Average Crop Yield

Crop	**MinTemp**	**MaxTemp**	**SSRain**	**LSRain**
Teff	-0.003	0.037*	-0.000022	-0.299***
	(0.0995)	(0.2176)	(0.1023)	(0.0679)
Wheat	0.452	-0.354*	-0.0273	-0.200*
	(0.6452)	(1.6121)	(0.1434)	(0.2888)
Maize	0.175**	-0.1124*	-0.0095**	-0.0128
	(0.7430)	(2.1439)	(0.1607)	(0.4084)

*** Significant at 1%, ** significant at 5% and * Significant at 10%
Note: Numbers in parentheses are standard errors
Source: Author's computation

By 2065, the increase in crop growing period mean temperature is expected to vary from -2.77^0C to 0.11^0C; 0.97^0C to -3.42^0C; and 0.10^0C to -0.52^0C in teff, wheat and maize growing areas respectively. The crop growing season rainfall is predicted to range from -0.18mm to -0.90mm; -0.33mm to -0.74mm; and -0.03mm to -0.10mm in teff, wheat and maize growing belts respectively by 2065. The variations in the temperature and rainfall towards 2045 are not so significant. For example, the crop growing season temperature is predicted to augment by -1.59°C to 0.06°C and crop season rainfall range is expected to be between -0.1mm and -0.5mm in teff growing areas. Similar patterns have been observed in wheat and maize growing areas by 2045.

The forecasted change in temperature towards the selected scenario showed that changes in maximum temperature has increasing trend in teff growing belt and a decreasing trend in wheat and maize growing belts. On the other hand, the forecasted change in rainfall (both short- and long-season rainfalls) revealed a decreasing trend in all crop growing belts over the selected scenarios of period. This will have impact on the yield of the crops under study.

Table 6.7: Forecast of Changes in Temperature and Rainfall by 2045, 2065 and 2080

Crop Belts	Scenarios	Temperature (^{0}C)		Rainfall (mm)	
		MinTemp Δ	MaxTem Δ	SSRainfall Δ	LSRainfall Δ
Teff	Baseline (1981 – 2018)	-0.92	0.037	-0.06	-0,30
	2045	-1.59	0.064	-0.104	-0.519
	2065	-2.77	0.111	-0.181	-0.903
	2080	-4.85	0.195	-0.316	-1.581
Wheat	Baseline (1981 – 2018)	0.284	-1.13	-0.111	-0.246
	2045	0.558	-1.955	-0.192	-0.426
	2065	0.971	-3.402	-0.334	-0.741
	2080	1.699	-5.954	-0.585	-1.296
Maize	Baseline (1981 – 2018)	0.034	-0.172	-0.010	-0.032
	2045	0.059	-0.298	-0.017	-0.055
	2065	0.102	-0.518	-0.030	-0.096
	2080	0.179	-0.906	-0.053	-0.169

Source: Authors Calculation from Cobb-Douglas Model estimates and mean climate and yield variables

Future mean crop yields have been forecasted using the elasticity coefficients of climate variables estimated at average crop yield and forecasted changes in temperature and rainfall variables. As can be seen from Table 6.8, the future impacts of variations in climate on yields of wheat, maize and teff are minimal as the projection showed an increase in yield of all crops over the selected scenarios (periods). By the year 2080, with a significant change in climate variables, particularly a decrease in rainfall, the increase in yield of wheat will be significant (237%). As wheat is a cool temperature crop mostly grown in the highlands and mid-highlands, the effect of changes in weather factors is on aggregate minimal. Conversely, the yield of teff and maize showed an increase of 48% and 10% respectively by 2080. In the short-run scenario of 2045, the change in yield of all three crops compared to the baseline scenario is minimal. However, the change in the yield of maize is marginal showing that maize yield is more affected by changes in the climate variables.

Table 6.8: Projected mean crop yield by 2045, 2065 and 2080 (percent)

Crop	Baseline		2045		2065		2080	
	Minim.	**Maxim.**	**Minim.**	**Maxim.**	**Minim.**	**Maxim.**	**Minim.**	**Maxim.**
	∆T & ∆R	**∆T & ∆R**	**∆T & ∆R**	**∆T & ∆R**	**∆T & ∆R**	**∆T & ∆R**	**∆T & ∆R**	**∆& ∆R**
Teff	0.3	0.2	3.6	15.8	0.8	27.4	1.5	48.0
Wheat	13.1	44.9	25.7	77.7	44.8	135.3	78.4	236.7
Maize	0.6	2.0	1.0	3.4	1.8	5.9	3.2	10.4

Source: Author's Calculation from elasticities and projected changes in climate

In summary, projected change in crop growing season mean temperature in teff growing belts showed an increasing trend (rise from -4.85^{0}C to 0.195^{0}C) while it has shown a decreasing trend in wheat (drop from -1.3^{0}C to -5.94^{0}C) and maize (-0.172^{o}C to -0.906^{0}C) growing areas. Furthermore, the forecasted change in rainfall (both short- and long-season rainfalls) revealed a decreasing trend in all crop growing belts over the selected scenarios of period, i.e. from -0.06mm to -1.58mm in teff growing belt, from -0.11mm to -1.3mm in wheat growing belt, and from -0.01mm to -0.17mm in maize growing areas. This will have negative impact on the yield of crops under study.

The future impacts of variations in climate on the yields of wheat, maize and teff are found minimal as the future projection showed an increase in yield of all crops over the selected scenarios (periods). By 2080, the forecasted future mean yield of wheat showed significant increase (237%) while that of teff and maize showed an increase of 48% and 10% respectively. In the short-run scenario of 2045, the change in yield of all three crops compared to the baseline scenario is minimal. However, the change in yield of maize is marginal showing that maize yield is more susceptible to changes in climate variables.

6.5 Supply Response of Teff, Wheat, and Maize Output to Changes in Climate and Socio-economic Explanatory Variables

Under this section, the investigator has employed and estimated three ARDL crop output response equations so as to test and validate the *third objective* of this study. Before the estimation of the supply responses of teff, wheat and maize output, the researcher have had determined the most favorable lag lengths for each of the crop model. Accordingly, depending on the lag-order selection criteria, i.e. AIC, SIC, and HQC, an optimum lag-order of 2 has been selected for teff and wheat supply response models and an optimum lag-order of 1 has been selected for maize supply response model. The detailed results obtained in this regard are presented in Appendix 6.4.

The regression coefficient estimates along with the corresponding standard errors as well as the long-run coefficient estimates for respective crop output supply response ARDL models are briefly described and presented under sub-sections 6.5.1, 6.5.2, and 6.5.3.

The estimated regression models yielded an adjusted R-squared with relatively moderate and high values. The values for adjusted R^2 were 0.46, 0.97 and 0.74 for teff, wheat and maize output supply functions, respectively. This result implies that 46%, 97% and 74% of the variations in the teff, wheat and maize output respectively, are elucidated by the climate and non- climatic variables included in the models. The remaining 54%, 3%, and 26% of the variation in teff, wheat and maize, respectively, are explained by the variables not included in the models. Detailed description of the model estimates for each model and their coefficient estimates has been presented under the sub-sections that follow.

6.5.1 Supply Response of Teff Output to Climatic and Socioeconomic Variables

This current study was sought to assess the supply responses of teff output to climatic (rainfall, temperature, CO_2) and socioeconomic (area under teff, fertilizer quantity used, and price of teff output) variables. To this end, an ARDL model has been estimated and tested for goodness of fit.

The ARDL regression model for teff output supply produced adjusted R-squared with relatively moderate value. The value of adjusted R^2 of 0.46 in the teff output functional model implies that 46% of the variations in teff output are explained by climatic and non-climatic variables while the remaining 54% are elucidated by factors not included in the modelling process. To this end, futher study should be conducted to assess additional real factors impacting teff output production in the future. Furthere, the Durban-Watson statistics on the other hand showed no evidence of serial Autocorrelation. Durban-watson statistics test was conducted for models by running first-order, second-order or higher-orders on the observed data series. P-values greater than 0.05 indicates non-existence of serial correlation (autocorrelation) in the observed data series.

The coefficient estimates of teff crop output supply model is presented in Table 6.9. The coefficient estimates for *short- rainfall* season with first order difference showed negative sign, but statistically insignificant. However, the coefficients of *short-rainfall* season have manifested positive sign and insignificant impact in its first lag and zero and second order differences. Thus, the findings evidenced that the amount of rainfall from February to May does not influence the output level of teff crop over the study areas. This result of *short- rainfall season* is justified with a fact that the larger proportion of teff output was supplied during the *long- rainfall season* (main crop season) including land preparation which normally starts in the middle of June.

Besides, the estimated teff output supply response model to changes in climate revealed that the coefficient estimate of rainfall amount during *long-rainfall* season (J-S) in zero order difference and *first lag* order are negative, although statistically insignificant. The result also manifested positive and insignificant relationship with teff output in the first and second order differences during the same season (*long-rainfall).* The result implies that the supply response of teff output to changes in *long-season* rainfall is negligible in their lag and difference orders.

Table 6.9: Coefficient Estimates of Teff Crop Output Supply Response Equation

Variables	Coefficient	Std. Error	t-Statistic	Prob.
Cons	75.4193	70.6885	1.066925	0.3642
LNTO(-1)	1.3280	1.8328	0.724580	0.5211
LNPRIT(-1)	-1.3053	0.9782	-1.334387	0.2743
LNART(-1)	-1.2920	1.6274	-0.793954	0.4852
LNFERT(-1)	-0.6421	0.9230	-0.695675	0.5367
LNTEMP(-1)	-15.6151	15.1795	-1.028703	0.3793
LNRAINBEL(-1)	0.5886	1.9056	0.308904	0.7776
LNRAINMEH(-1)	-4.2238	4.7589	-0.887569	0.4402
LNCO2(-1)	4.7598**	2.1223	2.242836	0.1107
D(LNTO(-1))	-1.8685	1.9956	-0.936296	0.4182
D(LNTO(-2))	-1.0405	1.2671	-0.821213	0.4717
D(LNPRIT)	-1.6236*	0.8846	-1.835267	0.1638
D(LNPRIT(-1))	0.4345	0.3108	1.398033	0.2565
D(LNPRIT(-2))	-0.5166	0.4919	-1.050153	0.3708
D(LNART)	5.1456**	2.4631	2.089064	0.1279
D(LNART(-1))	8.8713	6.7201	1.320108	0.2785
D(LNART(-2))	6.1242	4.7757	1.282371	0.2898
D(LNFERT)	-1.4620	0.9410	-1.553721	0.2181
D(LNFERT(-1))	-1.1748	1.2348	-0.951353	0.4116
D(LNFERT(-2))	-0.7179	0.8174	-0.878252	0.4445
D(LNTEMP)	10.1147	7.3622	1.373880	0.2631
D(LNTEMP(-1))	21.1479	19.8137	1.067335	0.3641
D(LNTEMP(-2))	9.6066	10.6797	0.899521	0.4347
D(LNRAINBEL)	0.7533	0.8568	0.879181	0.4440
D(LNRAINBEL(-1))	-0.0620	0.9845	-0.062950	0.9538

Variables	Coefficient	Std. Error	t-Statistic	Prob.
D(LNRAINBEL(-2))	0.7824	0.5209	1.502061	0.2301
D(LNRAINMEH)	-0.0770	0.7704	-0.099930	0.9267
D(LNRAINMEH(-1))	2.3426	2.9280	0.800053	0.4822
D(LNRAINMEH(-2))	0.6042	1.0250	0.589483	0.5970
D(LNCO2)	7.7268	5.7982	1.332621	0.2748
D(LNCO2(-1))	1.1990	3.6002	0.333029	0.7610
D(LNCO2(-2))	1.2220	0.7858	1.555043	0.2178
R-squared	0.9525			
Adjusted R-squared	0.4615			
S.E. of regression	0.1299			
F-statistic	1.9400			
Prob(F-statistic)	0.3253			
Durbin-Watson stat	3.0768			

*, **, and *** Significant at 10%, 5%, and 1% respectively.
Source: Author's computation.

As regards to temperature variables, the coefficient estimates over crop growing period (F-S) mean temperature in its first lag order portrayed negative sign, but non-significant. Oppositely, the coefficient estimates of mean temperature over the crop growing period turned to be positive in the first and second lag order differences, but found statistically non-significant. The result also implies that teff ouput response to the temperature factor is not important in its first lag and first and second order differences.

Relatedly, the coefficient estimates of CO_2 emission from the agriculture sector depicted positive sign in all first lag orders and first and second order differences. However, the coefficient estimate of CO_2 emission is significant in its first lag order only. The study result reveals that a 1% increase in CO_2 emission leads to respective increment of teff output by 4.8%. From the current study results, it can be concluded that CO_2 emission from agriculture sector is beneficial for teff crop production and supply in the teff growing belts of the country. However, an excessive CO_2 concentration beyond the optimum required level would adversely affct the supply response of teff output. The finding of the current study is analogous with the study findings of Janjua *et al*. (2013). Correspondingly, their study evinced that the coefficient estimate of CO_2 turned to be positive and significant in the short-run. Meanwhile, the research result submitted by Amponsah *et al.* (2015) is in contrast with the result of this present study. They carried out a research on the impact of CO_2 emission on the yield of selected cereal crops in Ghana and observed that the coefficient estimate of CO_2 concentration is negative and found significant (at 10% level) on yields of selected cereal crops in the long run. As a result, the results indicated that a rise in CO_2 emissions by 1% will lead to a decline in yields of cereal crops by about 54.7%.

Additionally, the present research examined the socio-economic variables such as price of teff, land area cultivated under teff, and fertilizer quantity consumed. Subsequently, the regression coefficient estimates of these variables in the first lag order showed negative sign. The results are, however, statistically not significant. The coefficient estimates for the producer price of teff in the first lag, zero order difference and the second lag order difference showed negative impact on teff output supply. However, the coefficient for teff farm gate price is found negative and significant at zero order difference only. The negative sign of the coefficient estimate for producer price of teff points out that a rise in the producer price of teff directs to a decrease in teff output supply. The result shows that a 1% increase in the zero order producer prices of teff is expected to decrease teff output supply by 1.6% (significant at 10% level).

Conversely, the coefficient estimate for area harvested under teff crop showed negative sign during first lag order; whereas the coefficient estimates of area under teff crop turned to be positive in zero order, first and second lag order differences, and significant at 5 percent level in the zero order difference. It follows that the result in the zero order difference evidenced that an increase in area put under teff crop production results in an increase of teff output supply. In view of this, the result signifies that a 1% increase in area under teff crop would further increase teff output in zero order difference by 5.15% (significant at 5% level). The current study result is congruous with the study results of Janjua, *et al.* (2013) who in their studies on climate change and wheat production in Pakistan observed that the regression coefficient of area cultivated under wheat production in the short-run turned positive and significant at 5% level. They concluded that area cultivated under wheat crop in the short-run would play significant role in increasing output of wheat crop. To that end, the results demonstrated that a 1% increase in area cultivated under wheat could increase the production of wheat by 0.39%.

Furthermore, the coefficient estimates of fertilizer quantity consumed on teff production in first lag, zero and first and second lag differences revealed negative sign. However, the result was statistically insignificant. Ergo, the result ascertained that an increase quantity of fertilizer on teff production would reduce the output supply of teff.

Moreover, long-run elasticity coefficients have also been estimated based on ARDL model. Table 6.10 presents the long-run elasticity coefficients estimated for an ARDL having lag length of 2 (1, 1, 0, 0, 0, 0, 0). The outcome portrayed that log of rain during *long-rainfall* season (*lnRainmeh*) had negative relationship, but insignificant, with teff output in the long-run. The result implies that a rise in long-season rainfall by 100 mm decreases teff output by 20.78 percent. The inverse relationship between long-season rainfall and output of teff could be drawn to extreme rainfall during main season that may lead soil erosion and leaching, which is the case in many teff growing areas. The findings of this study are in alignment with the conclusions of Igwe *et al.* (2013) who reported that an opposite association prevailed between rainfall and output of maize crop. Their result suggests that a 1% change in rainfall variable leads to a 1.23% decline in yield of maize. Also, findings from these studies align with the submission of Idumah *et al.* (2016) who in their studies reported inverse relationship between precipitation variable and agricultural crop output. They concluded that the direct association among variables such as temperature and maize output supply could be connected to the expediency of temperature during the maize crop growth period/ stage although it may lead to a phase where rise in temperature becomes harmful to maize plants.

Table 6.10: Estimated Long-run elasticities of teff crop output with respect to climatic and non-climatic variables

Variable	Elasticity	Std. Error	T-Ratio	P-value
Constant	-9.149	6.7090	-1.3637	0.1839
lnPrit	0.04697	0.1377	0.3411	0.7356
lnArT	0.2139	0.1414	1.5128	0.1420
lnFert	0.6404**	0.2335	2.7431	0.0107
lnTemp	0.0494	0.1237	0.3993	0.6928
lnRainbel	2.1241	1.4699	1.4450	0.1600
lnRainmeh	-0.2078	0.1767	-1.1760	0.2499
lnCO2	0.10597	0.3790	0.2796	0.7819
R-squared	0.960194	Mean dependent variable		2.938919
Adjusted R-squared	0.946926	S.D. dependent variable		0.547513
S.E. of regression	0.126135	Akaike info criterion		-1.077466
Sum squared resid	0.429572	Schwarz criterion		-0.642083
Log likelihood	29.93313	Hannan-Quinn criteria.		-0.923973
F-statistic	72.36635	Durbin-Watson stat		2.319672
Prob(F-statistic)	0.000000			

*, ** and *** implies that the estimates are significant at 1%, 5% and 10% respectively
Source: Author's computation

In contrast to that, temperature, *short-season rainfall,* and CO_2 showed positive relationship with teff output, but statistically insignificant in the long run. This indicates that teff output increase as temperature, *short-season rainfall* and CO_2 variables increase. This means as temperature, *short-season rainfall* and CO_2 concentration increase by 10%, teff output increases by 0.49%, 21.24% and 1.06% respectively.

On a similar note, the results of non-climatic factors showed positive relationship with teff output, but all are statistically insignificant except quantity of fertilizer consumed in the long-run. In this current study, the elasticity of quantity of fertilizer consumed on teff production showed positive and significant (at 5% level) effect on teff output supply in the long-run. It follows that a 1% rise in the quantity of fertilizer consumed on teff crop production increases teff output by 0.64% in the long run. This finding shows a parallel with the study findings of Endale (2010) and Fufa and Hassen (2005), who found comparable results on fertilizer consumption. In particular, Fufa and Hassan (2005) in their study in Ethiopia posted that the use of fertilizer is significant with an elasticity values of 0.03% for sorghum crop output, and 0.08% for maize crop output supply in two woredas of East Hararghe Zone of Ethiopia in the long-run.

Furthermore, the short-run elasticity coefficients have been estimated from the previous ARDL (1, 1, 0, 0, 0, 0, 0) model using short-run dynamic ECT Model. The short-run elasticities of climatic variables were positive, except log of short-season rainfall which showed negative relationship with teff output supply in the short run. However, the short run estimates of elasticity coefficients for climatic variables were statistically insignificant. This means that the impact of the climatic variables on teff output in the shot-run is minimal.

The elasticity coefficients of agro-economic variables in the short run are all positive, but statistically insignificant, apart from area harvested under teff crop. The estimated elasticity coefficient of log of area harvested under teff crop is found significant at 1% level. This implies that a 1% rise in area harvested under teff crop increases teff output by 0.54

kg in the short-run operation. The short-run estimated elasticity coefficients of dynamic ECT model are exhibited in Table 6.11 below.

Table 6.11: Short-Run elasticity coefficients from dynamic ECT Model

Variables	**Elasticities**	**Std. Error**	**t-Statistic**	**Prob.**
C	-2.61044	5.73066	-0.45552	0.6521
ECT_{t-1}	**-0.72129***	**0.16162**	**-4.46296**	**0.0001**
D(lnprit)	0.03967	0.11652	0.34042	0.7362
D(lnart)	0.54087*	0.19426	2.78418	0.0097
D(lnfert)	0.04172	0.10730	0.38883	0.7004
D(lntemp)	1.79385	1.29704	1.38303	0.1780
D(lnrainbel)	-0.17546	0.13728	-1.27815	0.2121
D(lnrainmeh)	0.08950	0.32101	0.27880	0.7825
D(lnCO2)	0.35394	0.33075	1.07011	0.2940

*, ** and *** implies that theestimates are significant at1%, 5% and 10% respectively

Source: Authors' computation using Eviews 9

6.5.2 Supply Response of Wheat Output to Climatic and SocioeconomicVariables

To determine the response of wheat output supply to climatic (rainfall, temperature, CO2) and non-climatic (area under wheat, fertilizer quantity used, and price of wheat output) variables, an ARDL model has been estimated and tested for fitness.

The ARDL regression model for wheat output supply exhibited best fit to the data series with high adjusted R squared. The adjusted R^2 of 0.97 in wheat output function imply that 97% of the variations in wheat output supply system are explained by variables of climatic and socio-economic factors included in the model. It can be concluded that the explanatory variables included in the study have the best fit to the formulated model. The Durban-Watson test on the other hand showed no evidence of serial autocorrelation.

The coefficient estimates of wheat crop output supply model is presented in Table 6.12. In this study, the coefficient estimates for temperature and *short*-season rainfall with first and second lag order differences showed negative relationship with the wheat output. However, only the estimates for temperature in the first and second lag orders showed negative and significant response at 5% level. Consequent upon that, a 1% increase in mean temperature during crop growing period leads to a respective decrease of 2.88% and 1.7% in wheat output supply in the first and second lag orders, respectively; which aligns with the theory that states an increase in temperature would lead to a decrease in crop output supply. Furthermore, the result implies that wheat crop output is negatively responsive to the high temperatures recorded in previous years. The result presented by Waqas *et al.* (2019) and Zhai *et al.* (2017) cohere with the findings of this present research. For instance, Waqas, *et al.* (2019) has found that maximum temperature showed negative impact on wheat production in Pakistan, although statistically insignificant. Similarly, Zhai *et al.* (2017) in their investigation on the effects of changes in climate on wheat production in China reported that the maximum temperature included in the model had negative effect on wheat production, although the result is statistically insignificant. Despite that similarity, there was a contrast regarding the result of temperature variables in teff growing areas where temperature in the first lag and zero difference orders showed positive and significant (at 1% level) relationship with teff output.

Furthermore, the present work noted that coefficient estimates of *short-* season *rainfall* (F-M) showed negative sign in its first and second difference orders, although the finding was significant at 1% level in the first difference order only. On account of that, then it can be deduced that a 10% increase in *short- season* rainfall results in decline of wheat output by 4.5% in the first difference order (i.e. previous year). However, the coefficient estimate for short-season rainfall in the first lag (previous year) has portrayed positive and significant (at 1% level) on wheat crop output. This implies that wheat crop is highly responsive to last year's short-season rainfall. This means, producers are encouraged to produce more wheat crop by allocating more land, inputs and labour looking into the favorable short-season rainfall prevailed last year. This current study finding was equally underpinned in Chisasa's (2014) research; which confirmed that the coefficient estimate for rainfall was negative and significant in South Africa. Thus, Chisasa's (2014) study signifies that a 10% rise in the amount of rainfall will result into a decline of crop crop output by 3%.

Nevertheless, the coefficient estimates for *long-season rainfall* (J-S) in zero and all lag order differences portrayed positive relationship with wheat output. The results for the first and second difference orders were positive and significant at 1% level. As such, on that ground, a 10% rise in long-season rainfall will lead to a boost of wheat output by 5% and 7.2% in the first and second difference orders, respectively. The result is not surprising since wheat needs sufficient water during *long-rainy* season (season when crop planting, vegetative growth and flowering phases takes place). In Chapter V, it has been ascertained that *long-rainfall* season has exhibited positive and significan increasing trend in the wheat growing belts; the result of which corroborates with the positive and significant impact on wheat output supply response recorded in this chapter. Accordingly, the results of this study are equivalent to the ones in Ali (2018). The study explored the influence of precipitation on maize and rice in Northern Togo; subsequently Ali (2018) avowed that it had positive and significant impact on the maize (at 1% level) and rice outputs. The study further added that a unit increase in precipitation over crop growing season increased maize yield by 0.13 metric tons and rice yield by 0.32 metric tons. On the same account, the analysis of Waqas, *et al.* (2019) in Pakistan affirmed that rainfall variables have had a positive and significant effect on rain-fed wheat crop output. Also, Muchpondawa (2009) centered his research on the supply response of the Zimbabwean agriculture, and thereafter submitted that the regression coefficients for rainfall exhibited positive and significant nature both in the short and long runs. Apropos, the result evinced that a 1% rise in precipitation eventuated into a further mount in crop output by 0.43% and 0.43% in the short-run and long-run, respectively. Additionally, Muchpondawa (2009) asserted that precipitationn is considered as key input determining the supply of agricultural crop output in the long-run. Fahimifard, *et al.* (2011) also divulged that the occurrence of precipitation in early months of the season had brought positive and considerable impact on wheat output in the long-run. The analysis established that a 1% augment in precipitation will rise the wheat output equal to 4.76%.

In this study, the coefficient estimates of CO_2 showed positive relationship with wheat output in all orders, i.e., first lag and zero, first second difference orders. The result is, however, significant for the zero and first difference orders at 1% level. The result in this regard indicates that a 1% rise in CO_2 emission will increase wheat output by 2.88% and 2.26% in zero and first difference orders, respectively. It can be deduced from this study finding that an elevated CO_2 during crop growing period would increase wheat output, provided that its concentration did not exceed the required optimum level. The outcomes of this current study corroborated with the study findings of Janjua *et al.* (2017). They have reported that CO_2 emission had positive association with wheat output in Pakistan, but statistically insignificant. Assessing the results, they argued that the response of wheat production to CO_2 in the long-run is minimal since it manifested insignificant result, and as such there was no perceptible or momentous major change in wheat production due to changes in climate. Even though, the methodical researches, contrastingly signified that the effect of CO_2 on wheat output supply is positive, but the degree of its positivity is yet to be ascertained.

Table 6.12: Wheat output supply response equation coefficient estimates

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-50.82249***	9.25369	-5.49213	0.0119
LNWHO(-1)	-0.132436	0.21639	-0.61202	0.5838
LNPRIWH(-1)	0.21650***	0.06594	3.28340	0.0463
LNARWH(-1)	-0.5967***	0.13046	-4.57380	0.0196
LNFERTWH(-1)	-0.3958***	0.12191	-3.24676	0.0476
LNTEMP(-1)	10.5696***	2.26351	4.66957	0.0185
LNRAINBEL(-1)	0.65086***	0.18675	3.48511	0.0399
LNRAINMEH(-1)	-0.07685	0.12666	-0.60677	0.5868
LNCO2(-1)	0.53194*	0.28463	1.86890	0.1584
D(LNWHO(-1))	-0.77625***	0.15775	-4.92082	0.0161
D(LNWHO(-2))	-0.04690	0.09553	-0.49096	0.6571
D(LNPRIWH)	-0.28917***	0.09044	-3.19737	0.0494
D(LNPRIWH(-1))	-0.00620	0.05667	-0.10937	0.9198

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LNPRIWH(-2))	-0.24505***	0.07343	-3.33736	0.0445
D(LNARWH)	0.69874***	0.12711	5.49732	0.0118
D(LNARWH(-1))	1.09914***	0.15578	7.05548	0.0059
D(LNARWH(-2))	0.76266***	0.09926	7.68346	0.0046
D(LNFERTWH)	0.00051	0.05259	0.00964	0.9929
D(LNFERTWH(-1))	0.07349	0.07168	1.02524	0.3807
D(LNFERTWH(-2))	-0.2992***	0.04692	-6.37614	0.0078
D(LNTEMP)	2.96426***	0.57614	5.14500	0.0142
D(LNTEMP(-1))	-2.87678**	1.16740	-2.46426	0.0905
D(LNTEMP(-2))	-1.70949**	0.66268	-2.57965	0.0818
D(LNRAINBEL)	0.04485	0.05163	0.86856	0.4490
D(LNRAINBEL(-1))	-0.4533***	0.10669	-4.24884	0.0239
D(LNRAINBEL(-2))	-0.05641	0.05211	-1.08251	0.3583
D(LNRAINMEH)	0.06245	0.16006	0.39016	0.7225
D(LNRAINMEH(-1))	0.50158***	0.16602	3.02123	0.0567
D(LNRAINMEH(-2))	0.71936***	0.10864	6.62133	0.0070
D(LNCO2)	2.8789***	0.28533	10.0899	0.0021
D(LNCO2(-1))	2.25559***	0.31965	7.05649	0.0059
D(CO2(-2))	0.00282	0.00355	0.79446	0.4850

R-squared	0.997	Mean dependent var	0.053086
Adjusted R-squared	0.974	S.D. dependent var	0.143579
S.E. of regression	0.0232	Akaike info criterion	-5.315521
Sum squared resid	0.00162	Schwarz criterion	-3.893489
F-statistic	41.82731	Hannan-Quinn criteria	-4.824636
Prob(F-statistic)	0.005110	Durbin-Watson statistics	2.432468

*, **, and *** implies significant at 10%, 5%, and 1% respectively.
Source: Author’s computation using Eviews 9.

Furthermore, economic variables such as price of wheat, area cultivated under wheat crop and fertilizer quantity consumed on wheat production were included in the wheat output response model, where they generated mixed results. Subsequently, the coefficient estimate of wheat producer price showed positive and significant impact at 1% level in the first lag order. Based on that, the result apparently underlined a 10% increase in producer price of wheat in the first lag order, consequently substantiating an increase in wheat output by 2.16%. This upshot is found consistent with the theory of supply response that suggests crop output supply positively responds to changes in own prices (wheat crop in this case). This implies that as price rises, farm households are confident to augment wheat crop production by putting more area and modern inputs on wheat production. A confirmation is registered in the work of some researchers as well. For example, Fahimifard and Saboui (2011) interrogated the supply response of cereals to changes in climate in Iran and noted that guaranteed prices of wheat crop have positive response with the wheat output function, although statistically insignificant in the long run. The obvious indication illustrated in the result points to the fact that wheat farmers show minimal response to wheat guaranteed prices in the long-run supply response function. Per se, that evidenced a similarity in the estimates obtained by Boansi (2017) who focused his area of study on Nigeria, and subsequently recorded a short run coefficient of 0.600, denoting that a unit increase in the producer price of rice give rise to 0.6% increase in rice yield.

However, the coefficient of wheat price in zero and second lag order differences showed negative impact and significant at 1% level. This specifies that a 10% rise in wheat price in zero and second lag differences reduces wheat output by 2.89% and 2.45% respectively. This result is synonymous with the investigation of Iqbal (2017). In this, the research examined global crop supply response to price and found that the coefficient estimate of the wheat price was negative and significant at 5% level. The result indicates that a 10% rise in wheat price will diminish wheat output by 1.8%.

The coefficient estimates of fertilizer consumed in wheat cultivation showed negative and significant (at 1% level) relationship with wheat output in the first lag and second order difference. Accordingly, the signification is that a 1% increase in quantity of fertilizer used in wheat production during first lag and second order difference will decrease wheat output by 0.396% and 0.299% respectively. However, the coefficient estimates for quantity of fertilizer used on wheat production showed positive relationship with wheat output in the zero order and first order differences, although the result is statistically insignificant.

Conversely, the coefficient estimates of log area cultivated under wheat production showed positive and significant effect on wheat output in zero, first and second lag order differences. The results indicate that a 1% increase in area under wheat crop production increases wheat output by 0.7%, 1.1% and 0.76% in the zero, first and second lag order differences, respectively. The result implies that wheat output is highly responsive to changes in area allocated for wheat crop production. The finding of this study is consistent with the study findings of Chandio et al. (2019) who their study discovered positive and exceedingly significant impact of area cultivated under wheat crop on wheat output supply. Their finding implies that a 1% in area cultivated under wheat production raises 0.87% wheat output supply. Nevertheless, land area allocated under wheat cultivation during the first lag order showed negative and significant (at 1% level) impact on wheat output. The result implies that a 1% increase in land allocated for wheat cultivation will decrease wheat output by 0.597%. As land allocated under wheat production during first lag order (last year) will be marginal lands, its contribution to output will be minimal and negative. This finding shows a parallel with the study of Zhai *et al.* (2017). They noted negative relationship of area under wheat production with wheat output in Henan, China, although the result was not significant. The result indicates that a 10% increase in area under wheat will decrease wheat output by 0.38%.

Based on ARDL approach and selected lag length of (1, 1, 0, 0, 0, 0.0.0) model, log run elasticities of wheat output with respect to climatic and non-climatic variables have been estimated. Table 6.13 presents the estimated elasticities of wheat with respect to climatic and non-climatic variables. The predicted elasticity coefficients show that all the climatic variables showed positive association with wheat output in the long run. However, only log CO_2 was statistically significant. Given this result, evidently a 1% rise in the concentration of CO_2 signals an increase in the output of wheat by 0.58% in the long run. This finding implies that an optimum level of CO_2 emission from agriculture sector is beneficial to boost wheat crop output in wheat growing areas. In consequence, this upshot coheres with the results submitted by Janjua *et al.* (2014). The researchers stated that the predicted elasticity coefficient for CO_2 was positive, but non-significant in the long-run. The signification of their premise is that no significant shift is registered in wheat output supply due to climate change in the long-run.

Table 6.13: Estimated long-run elasticities of wheat output with respect to climatic and non-climatic variables

Variable	**Elasticity**	**Std. Error**	**T-Ratio**	**P-value**
Constant	-9.55289*	5.50035	-1.73678	0.0938
lnPriWh	0.17070**	0.07593	2.24807	0.0329
lnArWh	0.52473***	0.16153	3.24847	0.0031
lnFertWh	0.18901**	0.07968	2.37200	0.0251
lnTemp	1.98947	1.26591	1.57157	0.1277
lnRainbel	0.01749	0.09387	0.18628	0.8536
lnRainmeh	0.09343	0.23313	0.40074	0.6918
lnCO2	0.58011**	0.27751	2.09043	0.0461
R-squared	0.982848	Mean dependent variable		2.68240
Adjusted R-squared	0.977130	S.D. dependent variable		0.66353
S.E. of regression	0.100344	Akaike info criterion		-1.53497
Sum squared resid	0.271858	Schwarz criterion		-1.09959
Log likelihood	38.39702	Hannan-Quinn criteria		-1.38148
F-statistic	171.9039	Durbin-Watson stat		2.18081

*, ** and *** implies 10%, 5% and 1% significance levels, respectively.

Source: Authors Computation using Eviews 9.

Similarly, the estimated elasticity coefficients of all socioeconomic variables are positive and have significant effect on wheat crop output supply. As such, it can be affirmed that a

10% increase in producer price of wheat, area covered under wheat crop, and fertilizer used in wheat production system will distinctly result into an increase in wheat output by 1.7%, 5.2% and 1.89% respectively. The offshoot is that wheat crop output is very highly responsive to its own price, area cultivated under wheat as well as the amount of fertilizer consumed on wheat farming in the long-run. Thus, it is obvious that fertilizers have double effect in this case: (1) fertilizers enhance land fertility, and (2) fertilizers augment plant growth. Hence, chemical fertilizers in the long-run would augment the land fertility and increase productivity of agricultural businesses. Producer farmers in the wheat crop growing belts/ areas normally use natural as well as inorganic fertilizers to increase the fertility of their land. Hence, for the crop belts/areas under consideration fertilizers may play important role in increasing productivity and production of wheat. The result of this study is alignment with the study results of Chandio, *et al.* (2019) who in their study in Pakistan found that all the economic variables included in their study have positive and significant impact on wheat output supply in the long-run. They further reported that the impact of land area cultivated under wheat crop on output supply of wheat crop was positive and highly significant in the long-run. One percentage increase in area cultivated under wheat production system will boost wheat production by 0.78%. Likewise, the support price in favour of wheat crop was found to be positively and significantly connected with wheat crop output supply. In addition, the examination showed that 1 percent increase in support price would elicit 0.12 percent wheat production increase. Similarly, wheat production would be enhanced by 0.19 percent due to a 1 percent increase in fertilizer consumption in the long run. Correspondingly, Janjua *et al.* (2013) observed that area's long-run result was positive and insignificant. They opined further that area under wheat cultivation was substantially significant in comparison to other major crops. Ipso facto, they do visualize the occurrence of any perceptible input of area cultivated under wheat crop towards enhancing production of wheat crop in the long-run. Thus, in the long-run fertilizer was considered as the major changeable input that significantly boosts production of wheat crop. Moreover, after re-parameterization of the coefficient of fertilizers became 0.2007. Consequent upon that, they hypothesized that there might be a likelihood of rise in wheat production by 0.20%, on the supposition that there was 1% increase in consumption of fertilizers.

The short-run elasticities for wheat crop supply model have also been estimated through the application of the ARDL approach Dynamic Error Correction Term model. Table 6.13 articulates the analysis. The estimation of the short-run results illustrate that the elasticities of log area under wheat cultivation in zero order, log price of wheat in first lag order, and log fertilizer quantity used in zero order have positive and highly significant effect on wheat production. Hence, the results point to the fact that a 1% raise in the area cultivated under wheat crop, lagged price of wheat, and quantity of fertilizer consumed on wheat production would raise wheat production by 0.45%, 0.18% and 0.16% respectively. The result of this study is in consonance with the study findings of Chandio, Jiang and Rehman (2019), who explicated the association among support price of wheat and wheat production in Pakistan. They have discovered that incentive price of wheat, area allocated under wheat crop cultivation, and quantities of fertilizers consumed on wheat production have positive and highly significant effect on production of wheat in the short-run. Thus, the upshot of the e empirical result signifies that a 1% raise in area cultivated under wheat crop raises wheat output supply by 0.87%. Similarly, a 1% raise in support price of wheat augments wheat output supply by 0.13%, while a 1% raise in the quantity of fertilizer consumed would improve wheat output supply by 0.21%.

By the same fashion, the elasticities for all climatic variables included in the model showed positive association with wheat production in the short run. However, the estimated elasticities are statistically insignificant, except CO_2. The elasticity estimated for the CO_2 variable in zero order difference has positive and significant effect on production of wheat. This result indicates that a 1% rise in CO_2 concentration increases wheat output supply by 0.5% in the short run. This finding is in harmony with the study result of Onour (2019), who in his study on effect of CO_2 concentration on yield of cereal crop in Sudan found that changes in CO_2 has a positive and significant effect on yield of cereal crop in the short run. The result indicates that a 1% increase in carbon dioxide increases cereal yield by 3% in the short run.

Table 6.14: Short-Run Wheat Dynamic ECT Model

Variables	Elasticities	Std. Error	t-Statistic	Prob.
C	-8.23183*	4.76654	-1.72700	0.0956
ECT_{t-1}	-0.86171***	0.16050	-5.36891	0.0000
D(LNWHO(-1))	0.13829	0.16050	0.86161	0.3965
D(LNPRIWH)	-0.03318	0.09214	-0.36008	0.7216
D(LNPRIWH(-1))	0.18027**	0.08515	2.117212	0.0436
D(LNARWH)	0.45216***	0.13643	3.314142	0.0026
D(LNFERTWH)	0.16287**	0.08022	2.030173	0.0523
D(LNTEMP)	1.714348	1.07260	1.598311	0.1216
D(LNRAINBEL)	0.015068	0.08104	0.185939	0.8539
D(LNRAINMEH)	0.080506	0.20140	0.399730	0.6925
D(LNCO2)	0.499884*	0.28105	1.778625	0.0866

*, **, and *** implies significant at 10%, 5%, and 1% level.

Source: Authors' Computation using Eviews 9

6.5.3 Supply Response of Maize Output to Climatic and Agro-economic Variables

Just like teff and wheat output response analysis elaborated above, this study sought to determine the response of maize production to climatic and socioeconomic variables. To this end, the ARDL model estimated included climatic variables (crop growing season mean temperature, *short*- season *rainfall*, and *long*- season *rainfall*) and agro-economic variables (lagged maize output, producer price of maize, area cultivated under maize, and quantity of fertilizer used in maize covered area). CO_2 concentration from climate and irrigated area from socioeconomic variables were tried for inclusion into the model but dropped due to existence of high serial correlation and multicollinearity with other variables included in the model.

The ARDL regression model for maize output supply has good fitness to the data series with moderate values of adjusted R squared. The adjusted R^2 values of 0.74 in the maize output model imply that 74% of the variations in maize output are explained by climatic and non-climatic variables included in the model. The Durban-Watson test on the other hand showed no evidence of serial autocorrelation in the series. As stated above, the variables of CO_2 and irrigated area under maize cultivation were dropped from the model as they revealed serial autocorrelation. The model becomes viable and fit at lag length 1 and first order difference only, lag length 2 and second order difference were tried but revealed high serial autocorrelation.

The coefficient estimates of maize crop output supply model is presented in Table 6.15. In this current study, the coefficient estimates of temperature depicted mixed results. The coefficient estimates of mean temperature during crop growing period in its zero order difference manifested a demonstrable negative and significant impact on the production of maize. As such, the deduction is that a 1% raise in temperature accounted for a decline of maize output by 6.15%. This can be justified by the fact that a temperature variable elevated than a threshold may be harmful for the growth of crops by affecting the crop growing degree days (GDD). The GDD is an evaluator of warmth accretion used to forecast plant and pest growth rates such as date on which the crop reaches maturity. The finding of this study equals that of Miao, *et al.* (2015) and Mendelsohn and Wang (2017) postulations. Miao, *et al.* (2015) examined the responsiveness of crop yield to climate in the U.S, and subsequently submitted that temperature during June to August evidenced negative and significant effect on corn yield, which were robust across two models, in addition to beingin line with expectations. The magnitude of the coefficients of temperature variable in maize yield model I are nearer to those in model II, i.e., the coefficients of GDD are 0.027 and 0.026 in models I and II, respectively. Congruently, Mendelsohn and Wang (2017) surveyed the effect changes in climate on agriculture in China, and they also found that higher summer and winter temperatures have negative and significant impact on maize production in China. In view of that, they opined that crop grown in a place that is too wet (dry) or too hot (cold) would as a matter of fact have negative marginal effect. Liu *et al*. (2014) further observed that temperature is an essential variable influencing maize yield, and evenly penned that a rise in temperature during crop growing period can result into yield decline in China.

Equally, an evaluation of the result of this current study ascertained that the coefficient of first lag order difference of mean temperature has positive impact on maize output, but statistically insignificant. The result ultimately signifies that maize output is moderately responsive to first lag order temperature variables, which also underscores the fact that a 1% rise in first lag temperature increases maize yield by 1.87%.

Consequently, the coefficient estimates for *short*- season *rainfall* in the zero and first lag order differences displayed negative and significant impact on maize production. The finding surmises that a 1% increase in *short-season rainfall* will necessarily reduce maize output by 0.47% and 0.35% in zero and first lag order differences, respectively. In this case, it is pertinent to note the sensitivity of maize crop to rainfall variable, and as such, any shortage in rainfall during *short-rainfall* season is bound to reduce maize output. In Ethiopia, it cannot be gainsaid that maize is a long cycle crop, and on account of that fact all land preparation and planting/ sowing works are performed during the *short-rainfall* season. Therefore, shortage of rainfall during this season would greatly affect production of maize crop; hence it is not unexpected that farmers are obliged to replant burnt young maize plants. This evaluative result is in concordant with the outcome of Mendelsohn and Wang's (2017) research, as well as Akanni and Okeowo's (2011) work. The elucidation of Mendelsohn and Wang's (2017) study in China detailed that the coefficient estimates for fall precipitation and winter precipitation exhibited negative and significant impact on maize production. Their finding markedly demonstrates that a 100% increase in fall and winter rain stimulates a reduction of maize output by 0.04% and 4.6% respectively. With respect to Akanni and Okeowo's (2011) evaluation, their study certified that the amount of rainfall in Nigeria have negative and significant impact on maize output. Subsequently, the inference drawn from the survey indicates that a 10% increase in quantity of rainfall eventuates into a reduction in the output of maize by 1.65%.

Estimation of regression coefficient has also been carried out for zero order and first lags order differences of *long-season rainfall* (main crop season). The study results reveal that coefficient estimates have negative and significant (at 1% level) impact on maize output in zero order difference. This might be justified in actuality that any change in *long-season rainfall* in zero difference (current year), be it is shortage or above normal, would patently affect maize output. This season is critical crop growing period when maize crops' vegetative and reproductive growths including flowering take place. In contrast, the coefficient estimate for first lag order difference of *long*-season *rainfall* portrayed positive and significant (at 5% level) impact on maize output supply. The result implies that a 1% increase in *long*-season *rainfall* in first lag difference order would increase maize output by 1.04%. The finding reveals that maize output is more responsive to the changes in the *long-season rainfall* of previous year (first lag of *long-season rainfall*), although the result for zero order difference (current year) is more pronouncing. These study results are in alignment with the study findings of Blanc (2011) and Byishimo (2017). Correspondingly, Blanc (2011) explored the effect of changes in weather factors on cereal crop production in SSA; subsequently, the study ascertained that previous year rainfall had a positive impact on cassava cropping decisions in non-LFAC countries in SSA, Sudano-Sahel and East Africa. Accordingly, Blanc (2011) opined that the positive impact signified that farmers' preference for cassava increase as precipitation and yield increase. Byishimo (2017) in his research on impacts changes in climate variables on crop yields in Rwanda found that lagged annual rainfall, a denotation for previous year rainfall has a positive and significant effect on maize yields. On the basis of that, it was estimated that a 100% increase in previous year annual rainfall will increase maize yield by 0.04%.

Apart from climatic variables, the responsiveness of maize output to the socioeconomic variables such as lagged price of maize, area cultivated under maize, and quantity of fertilizer used on maize production has been estimated. Accordingly, the coefficient estimate of first lag price (previous year) showed negative impact on maize output, but statistically insignificant. Furthermore, the coefficient estimate of producer price of maize in zero and first lag order differences demonstrated positive relationship with maize output, but are statistically insignificant, implying that the responsiveness of maize output to price changes both in zero order (current) and first lag order (previous year) is not a significant variable to explain changes in maize output. The findings of this study are similar to the findings of Akanni and Okeowo (2011). Akanni and Okeowo (2011) in their study on the responsiveness of maize output supply to the changes in its own producer prices in Nigeria have reported positive and significant impact with the coefficient of 0.986%.

Maize crop output responsiveness to area cultivated under maize crop in maize growing belt has also been estimated. Accordingly, the regression coefficient estimate of the area cultivated under maize crop production in zero order difference and first lag order showed positive and significant impact on maize output supply. The result presupposes that 10% increase in area cultivated under maize production tantamount to an increment in maize output by 5.7% and 7.1% in zero order difference and first lag order, respectively. It follows that maize output is highly responsive to both first lag (previous year) and zero order difference (current year) of area cultivated under maize production. However, the regression coefficient estimate for area cultivated under maize crop in the first lag difference showed negative impact on maize output, but statistically non-significant. Following these, the findings of this study is coherent with the postulation in of Riaz *et al.* (2014). They averred that lagged (previous year) area under maize cultivation showed positive and significant impact on maize output in their analysis on acreage response of the maize growers in Pakistan. Taking this into account, then if lag area is increased by 1%, on the average, it will lead to an increase of about 0.72% in current maize output. Thus, the analysis showed that area under maize in lagged year functioned as an important variable directing farmer's decision on acreage allocation. Akanni and Okeowo (2011) noted that the coefficient of land area cultivated under maize crop production match to *a priori* as they have positive and significant effect on maize output in Nigeria. This result reveals that a unit rise in land area cultivated under maize crop will convey about equivalent bump up in the maize output.

Table 6.15: Maize output supply response equation coefficient estimates

Variables	Coefficient	Std. Error	t-Statistic	Prob.
C	57.53080	22.18096	2.59370	0.0204
LNMZO(-1)	-0.6809**	0.33762	-2.01678	0.0620
LNPRIMZ(-1)	-0.10171	0.13508	-0.75301	0.4631
LNARMZ(-1)	0.70756**	0.26697	2.65033	0.0182
LNFERTMZ(-1)	0.23352	0.14973	1.55965	0.1397
LNTEMP(-1)	-10.7016**	4.53893	-2.35773	0.0324
LNRAINBEL(-1)	-0.29544	0.39354	-0.75071	0.4644
LNRAINMEH(-1)	-1.03033	0.87630	-1.17577	0.2580
D(LNMZO(-1))	-0.27845	0.22837	-1.21931	0.2416
D(LNPRIMZ)	0.09318	0.12764	0.73005	0.4766
D(LNPRIMZ(-1))	0.04633	0.11346	0.40836	0.6888
D(LNARMZ)	0.56912**	0.25273	2.25185	0.0397
D(LNARMZ(-1))	-0.07010	0.26916	-0.26046	0.7981
D(LNFERTMZ)	0.10177	0.13878	0.73327	0.4747
D(LNFERTMZ(-1))	-0.05975	0.11627	-0.51388	0.6148
D(LNTEMP)	-6.1496**	3.05482	-2.01309	0.0624
D(LNTEMP(-1))	1.86684	2.34716	0.79536	0.4388
D(LNRAINBEL)	-0.47024***	0.14857	-3.16500	0.0064
D(LNRAINBEL(-1))	-0.35255*	0.20826	-1.6978	0.1112
D(LNRAINMEH)	-0.13900	0.47635	-0.29179	0.7744
D(LNRAINMEH(-1))	1.03806**	0.45765	2.26824	0.0385
R-squared	0.88696	Mean dependent variable		0.05611
Adjusted R-squared	0.73624	S.D. dependent variable		0.25102
S.E. of regression	0.12892	Akaike info criterion		-0.96805

Variables	Coefficient	Std. Error	t-Statistic	Prob.
Log likelihood	38.42499	Schwarz criterion		-0.044335
F-statistic	5.884820	Hannan-Quinn criteria.		-0.645652
Prob(F-statistic)	0.000521	Durbin-Watson stat		2.404029

*, ** and *** implies significant at 10%, 5% and 1% significance level

Source: Author's computation using Eviews 9.

On the other hand, the coefficient estimates for quantity of fertilizer used in zero order difference (current) and first lag order (previous year) have positive relationship with the maize output, but statistically insignificant. This study finding is related to the regression coefficient estimate submitted by Kollurmath *et al.* (2008). They have examined the supply response of rice and maize in Karnataka, India and discovered that the regression coefficient of lagged quantity of fertilizer utilized were positive, but non-significant. Thus, the analysis designates that the yield of maize is dependent on lagged quantity of fertilizer used on maize production. In the same vein, Huong and Yorobe (2016) studied the response of maize supply in Vietnam; they found that the coefficient estimate for lagged quantity of fertilizer utilized on the maize production has positive and significant impact on maize output. Based on that fact, it is a pointer that an increase by 10% in lagged quantity of fertilizer used results in an increase of 0.39% in maize production in the same period.

In accordance with the ARDL model approach, long-run elasticity coefficients have been estimated for the maize output model. The long run elasticity coefficients of ARDL (1, 0, 0, 0, 0, 0, 0) for maize with respect to weather variables and socio-economic variables are presented in Table 6.16. The weather and socio-economic explanatory variables that were considered in the model after dropping serially autocorrelated variables include: climatic variables (log mean temperature over crop growing period, log short- season rainfall and log long- season rainfall) and socio-economic variables (log producer price of maize, log area cultivated under maize crop, and log quantity of fertilizer consumed in maize production). The estimated elasticity coefficients affirm that all climatic variables included in the model showed negative relationship with maize output supply in the long run. However, the elasticity coefficient for temperature is statistically insignificant while the elasticity coefficients estimated for *short-rainfall* and *long-rainfall* seasons exhibited significant impact on maize output supply. In this study, the elasticity coefficients show that temperature over crop growing period is negatively related to maize output in the long-run, implying that a 1% rise in temperature over crop growth period will result in reduction of maize output by 4.79%. This finding alignes with the theory that states increase in temperature will decline the yield and production of crops. The finding of this study in relation to temperature is comparable with the results of Idumah, *et al.* (2015); who carried out a study on the relationship between changes in climate and food production in Nigeria. Subsequently, they reported that log temperature in first lag order is negatively related to agriculture crop output. The result indicated that a 1% change in previous year temperature leads to a reduction of agriculture crop output by 30.8% in the long-run.

Table 6.16: Estimated long run elasticities of maize output with respect to climatic and non- climatic variables

Variable	**Elasticity**	**Std. Error**	**T-Ratio**	**P-value**
Constant	34.85323	15.35902	2.269235	0.0309
lnPriMz	0.073229	0.090148	0.812315	0.4232
lnArMz	0.517254**	0.213822	2.419084	0.0221
lnFertMz	0.364263***	0.084292	4.321418	0.0002
lnTemp	-4.793830	3.166014	-1.514153	0.1408
lnRainbel	-0.776387**	0.287140	-2.703857	0.0113
lnRainmeh	-0.991452*	0.540569	-1.834091	0.0769
R-squared	0.9635	Mean dependent var		3.2211
Adjusted R-squared	0.9547	S.D. dependent var.		0.6693
S.E. of regression	0.1424	Akaike info criterion		-0.8709
Sum squared resid.	0.5884	Schwarz criterion		-0.5226
Log likelihood	24.1128	Hannan-Quinn criterion		-0.7482
F-statistic	109.4001	Durbin-Watson stat		2.3519

*, ** and *** implies significant 10%, 5% and 1% significance level

Source: Author’s Computation using Eviews 9

Intrinsically, the elasticity coefficient of both *short-rainfall* and *long-rainfall* seasons in this study showed negative and significant association with maize output supply in the long run. The result indicates that a 10% increase in *short-rainfall* and *long-rainfall* is responsible for a decrease of maize output supply by 7.76% and 9.9% respectively. The result can be justified with the fact that maize crop is overly sensitive to the extremes of rainfall situation both shortage at initial growing period and excessive rain at vegetative and grain filling stage. The findings of this study cohere with the evaluation postulated by Siahi, *et al*. (2018). They appraised the impact of changes in weather factors on maize productivity and production in Kenya and reported that the elasticity coefficient estimate of rainfall was negatively related to maize production in the long run, though statistically insignificant. Thus, the result indicates that a 1% change in rainfall will decrease maize output supply by 1.64% in the long run.

The elasticity coefficients estimated for non-climatic variables such as log producer price of maize, log area cultivated under maize, and log quantity of fertilizer used have showed positive relationship with maize output. The elasticity coefficients of the area cultivated under maize and quantity of fertilizer employed had significant impact on maize output while that of producer price of maize was statistically insignificant. Therefore, the result indicates that a 10% increase in area cultivated under maize and quantity of fertilizer used increases maize output by 5.17% and 3.64% respectively in the long run. The study result implies that maize output is highly responsive to changes in area cultivated and quantity of fertilizer used in maize production, which alignes with the theory. Additionally, the finding of this study is in consonance with the results of some researchers. An instance of the equivalent finding is observed in Chandio, Jiang, and Rehman (2019). They studied the nexus between support price and wheat production in Pakistan, and they perceived that the impact of area under cultivation and fertilizer consumed on wheat production was positive and highly significant. Thus, the results indicated that a 1% increase in area under cultivation and fertilizer consumption will improve wheat production by 0.78% and 0.19%, respectively. Relatedly, Huong and Yorobe (2016) found that the coefficient of area planted under maize and fertilizer used in Vietnam showed positive and significant impact on maize production in the long run. Their finding evinced that a 10% augement in area planted under maize, and fertilizer quantity used on maize farming will increase maize output by 13.2% and 0.39%, respectively. Similarly, Tchereni and Tchereni (2013) found that the elasticity coefficients of hectarage under maize and fertilizer used as an input in maize production portrayed positive and significant impact on maize production in Malawi. The results affirmed that a 10% increase in hectarage under maize and fertilizer consumed increase maize output by 3.75% and 0.40% respectively in the long run. The findings of all the researchers reviewed show that maize output is highly responsive to changes in area cultivated and quantity of fertilizer consumed in producing maize crop.

Once a long-run association among the climatic and socio-economic variables has been established, the ECM has been estimated to attain short-run vibrant coefficient estimates connected with long-run co-integration associations. Table 6.17 presents estimates of the short-run elasticity coefficients of ARDL (1, 0, 0, 0, 0, 0, 0). The results showed that weather factors (temperature and precipitation) considered in the ARDL model exhibited negative effect on the output of maize crop in the short-run. The coefficients of both short- and long-season rainfall had significant impact on maize output, while the elasticity coefficient for temperature was statistically insignificant. The results indicated that a 10% increase in *short-rainfall* season and *long-rainfall* season leads to a reduction of maize output supply by 5.48% and 7.0%, respectively in the short run. Conversely, the association that prevails among precipitation and maize output variables could be due to heavy precipitation that causes storm, flooding, soil erosion, and soil leaching. The negative coefficient of ECM (-1) for the maize output supply verifies the existence of long-run association among variables in maize crop output supply model. ECM measures the speed at which endogenous variables adjust themselves to alterations in the explanatory variables before the endogenous variables converge to the stability level. The findings of this study aligne with the findings of Ayinde *et al*. (2011) who in their studies reported negative and significant influence of precipitation on the production and productivity of agricultural crops.

Equally, the elasticity coefficients of non-climatic variables such as producer price of maize, area cultivated under maize and quantity of fertilizer used on maize production showed positive relationship with maize output supply in the short-run. The estimated regression coefficient of area cultivated, and quantity of fertilizer utilized have significant impact on maize output, while the coefficient of producer price is statistically insignificant. The results indicate that a 10% increase in area cultivated under maize, quantity of fertilizer used and producer price of maize leads to increase in maize output by 3.65%, 2.75% and 0.52% respectively in the short run. The result signifies that maize output is highly responsive to changes in area cultivated and quantity of fertilizer used in maize production in the short run as well.

Table 6.17: Short-Run Elasticities of Maize Dynamic ECT Model

Variables	**Elasticities**	**Std. Error**	**t-Statistic**	**Prob.**
C	24.62264	11.95495	2.05962	0.0485
ECT_{t-1}	-0.70647***	0.12361	-5.71514	0.0000
LNPRIMZ	0.05173	0.06467	0.79999	0.4302
LNARMZ	0.36542**	0.15701	2.32744	0.0271
LNFERTMZ	0.25734***	0.07381	3.48639	0.0016
LNTEMP	-3.38668	2.41366	-1.40313	0.1712
LNRAINBEL	-0.54849***	0.14601	-3.75651	0.0008
LNRAINMEH	-0.70043*	0.39719	-1.76344	0.0884
R-squared	0.96351	Mean dependent var		3.22108
Adjusted R^2	0.95471	S.D. dependent var		0.66929
S.E. of regression	0.14244	Akaike info criterion		-0.87096
Sum squared resid	0.58840	Schwarz criterion		-0.52265
Log likelihood	24.1128	Hannan-Quinn criter.		-0.74817
F-statistic	109.400	Durbin-Watson stat		2.35188

*, ** and *** implies significant at 10%, 5% and 1% level respectively

Source: Authors' Computation using Eviews 9.

CHAPTER VII

SUMMARY, CONCLUSION, AND POLICY IMPLICATIONS

7.1 Introduction

In this chapter, summary of the results of the study on the impact of changes in weather factors on selected cereal crops are presented. In addition the chapter presents the main conclusions induced from the study findings. Also included in this chapter are the policy implications of the findings and the contribution of the study to existing knowledge as well as areas of further research.

7.2 Summary

Among agricultural production, crop production forms significant basis for ensuring food security. Crop production also contributes to the livelihood of a larger percentage of the rural based people of the country. However, production of crop is largely dependent on climate conditions that change over time making it very susceptible to variability in the climate. In recent years, changes in climate have significantly impacted on the important economic sectors, which in particular included the agricultural sector. The impacts changes in weather variables can arise and influence production factors and their productivity as well as prices and international trade patterns. The appraisal of various investigations encompassing a broad array of regions and crops authenticates the fact that negative effects of climate change on yields of crops greatly surpass the positive impacts (IPCC, 2014).

Congruently, in the Ethiopian agricultural sector, yields of cereal crops could be reduced considerably due to the contrary impacts of changes in climate variables, which as a matter of cause result in drastic consequences upon food production and availability. This necessitates in-depth studies to analyze and explore the possibility of taking adaptation measures to changes in climate in the country. In addition, socioeconomic factors such as limited use of chemical fertilizers, improved seeds, poor access to irrigation facilities, etc. also have contributed to low level of crop yield in Ethiopia. Studies on how change in climate factors affects agricultural production and how agriculture in return responds to a changing climate as well as socio-economic factors becomes very important research agenda, as agriculture invariably influences food supply and security efforts of agrarian economies.

Studies on the association between variability in climatic variables and food crops supply in general and the productivity of agricultural crops in particular are scarce in Ethiopia (Deressa 2007; Mideksa 2010). Some researchers have conducted researches on the likely effects of changes in climate conditions on agriculture in general and on output and yield response of selected crops in particular in Ethiopia. However, these studies are limited to some regions and local areas and did not cover the analysis aggregately at national level. In order to bridge this gap, the current investigation has been carried out to examine the effect of changes in climate factors on yield and output supply response of selected cereal crops aggregately at national level. Studies on supply response of cereal crops become very important to best understand the supply mechanisms and relationships between factors of production and output production.

Towards this end, this study has focused on three important cereal crops, viz. teff, wheat and maize so as to provide sufficient information on the influences of changes and variability in climate factors on cereal crop productivity and production in Ethiopia. Moreover, inorder to present a comprehensive and clear-cut examination on the subject, the study was based on three crucial and plausible objectives; i.e. the *first objective* dealt with the characterization of the trend and variability of climatic variables and variation in crop yields, i.e., seasonal rainfall and crop growing period mean temperature variables over the period 1981 to 2019. The *second objective* presented an examination of the influence of changes in climate variables on the yield of selected cereal crops using augemented log-linear econometric model. The *third objective* examined the likely effects of climate and socio-economic variables on the response of cereal crop output supply using linear econometric models appropriate for measuring impacts of climate and socio-economic factors.

The study can be considered different from previous studies conducted in Ethiopia in several ways. First, this study employs crop production and climatic variables aggregately at national level, thereby analyzing and identifying the influences of variability in climatic factors on both smallholder and large-scale farmers at macro-level. Secondly, this study employed time series approach to study impact of changes in climate, which helps to examine how changes in climatic variables are associated with agricultural production over time, as changes in climate takes place over time. Third, apart from precipitation and temperature, this study incorporated CO_2 emissions from agriculture to capture the impact of CO_2 concentration on crop yield and output supply. In order to model supply response of crop outputs, an ARDL model approach has been employed in this study.

In Ethiopia, the production of teff, wheat and maize plays vital role in achieving food self-sufficiency given that these crops are considered as key staple foods. However, the production levels of these cereal crops were being seriously affected by the changes and variability in climate as has been exemplified and elucidated in this study. This calls for taking commendable strategies and actions to boost crop production especially in the midst of growing population and climate change and its variability in the country.

This study follows the theory of production and profit maximization behavior of farmer households, which lays down groundwork for modeling aggregated supply responses of the crops under consideration. Each of the crop output models encompassed variables that included seasonal rainfall (short- and long-rainfall seasons), crop growing period mean temperatures (minimum and maximum), CO_2 emission from agriculture sector, and the socio-economic variables as regressors. The socio-economic variables considered in this study included: crop output prices, quantity of fertilizer used, quantity of improved seed used, area cultivated under specific crop, and irrigated area under each crop.

To examine the impacts of changes in weather variables and their respective irregularity on yield of cereal crops, augmented Cobb-Douglas production function model has been specified and fitted for each of the crops under consideration. The production functional models specification included log-linear form of seasonal rainfall and crop growing period mean temperature variables. This was to examine whether an excess rain or extreme temperature variables have affected yield of cereal crops. Data on the climatic variables were taken from the NMA of Ethiopia; time series data on crop output, yield and area under crops selected were obtained from CSA Survey and Statistical Abstracts. Data on other variables were obtained from published sources, which include Ethiopian Grain Trade Enterprise (EGTE), FAOSTAT website, and World Bank website. All the data gathered and compiled covered the period from 1981 to 2018 (38 years).

In order to examine the impacts of changes in weather and socio-economic variables on crop output supply, an ARDL model has been specified and predicted employing an OLS approach and the related elasticities were calculated for the crops under study.

In an effort to the analysis of trend and characterization of the variability of weather such as precipitation, temperature and CO_2 variables, it was found that short-season rainfall showed decreasing pattern in all the three crops growing belts: i.e. teff, wheat and maize growing belts. Furthermore, *long*- season *rainfall* showed a rising trend in teff and wheat growing belts and a declining trend in maize growing belts. As has been perceived by coefficient of variation (CV) rainfall was found more variable during *short-rainfall* season and less variable during *long-rainfall* season in all crop growing areas under study. The year to year/yearly anomaly of rainfall indicates that maize growing areas were more severe and experienced drought years than teff and wheat growing areas. The rainfall anomalies were found to coincide with the major drought years documented in the country. These years coincided with the drought years of 1984/85, 193/94, 2003/04, and 2014/15.

The results of trend analysis of temperature variables revealed that both maximum and minimum temperatures demonstrated a rising trend over the observation period in teff and wheat growing areas. In contrast, minimum temperature showed a decreasing trend whereas the maximum temperature variable showed a rising trend in maize growing areas. The coefficients of variation (CV) for maximum and minimum temperatures showed less variability of temperature in all the three crops growing areas. The findings of the study demonstrated that maximum temperature anomalies were very low and negative over the years, from 1981 to 1997 while maximum temperature anomalies are positive from years 2003 to 2018 in all crops growing areas. The anomalies of minimum temperature almost followed the same pattern as that of maximum temperature anomalies in teff and wheat growing areas. The anomaly of minimum temperature in maize growing areas were, however, the reverse of those of maximum temperature anomalies, where anomalies of minimum temperature were consecutively positive from 1981 to 1996 and negative from 2006 to 2018.

The study results in terms of yield anomalies and coefficient of variation (CV) confirmed the presence of crop yield variations over the study period. The yield anomalies for the three crops under study (teff, wheat and maize) showed pronounced yield variability (both negative and positive values) over the study period of 1981 to 2018. The coefficient of variations (CVs) also witnessed crop yield variability among crops studied. The study exhibited high variability in yield of wheat and maize with magnitude of 32% and 31% respectively, which implies instability in yield of the crops. The CV also portrayed that the yield of teff is moderately variable with magnitude of 30%.

Furthermore, the estimates obtained from teff yield regression model revealed that the coefficients of rainfall variables during *crop growing* (F-S) and *long-rainfall* (J-S) seasons were both negative; but only long-rainfall season was significant at 1% significance level. The results indicate that an increase in rainfall during long-rainfall season, the period when crop vegetative and reproductive growth is high (J-S), revealed harmful impact on the yield of teff. This witnesses that excessive rainfall affects the yield of teff crop negatively.

The coefficient of minimum temperature during crop growing period in teff growing areas is negative, but statistically insignificant. On the other hand, the estimated regression coefficient for maximum temperatures during crop growing season (F-S) in teff growing areas is positive and significant at 5% significance level. This indicates that a rise in maximum temperature in teff growing areas would increase the yield of teff per unit area, i.e., would affect teff yield positively. Further, CO_2 showed positive and significant (5% level) impact on teff yield per unit area.

Conversely, the estimated coefficients for land area under teff and irrigated area under teff crop production are positive, but only land area under teff cropping system is found significant at 1% level. The result implies that use of land for teff production has vital role in increasing yield of teff crop. However, use of fertilizer has resulted in negative impact, but non-significant.

The results of wheat yield regression model showed that *short-season rainfall*, *long- season rainfall* (J-S) and maximum temperature variables during crop growing period (F-S) are negatively associated with yield of wheat, but only long-season rainfall and maximum temperature were found significant at 10% level. Indeed, this result implies that rise in maximum temperature during crop growing period and rise in *long- season rainfall* could have adverse impact on the yield of wheat crop. The crop growing period refers to both *short-rainfall* and *long-rainfall* seasons. The short-rainfall season is the period when land preparation tasks are performed and the long-rainfall season is the period when the planting, weeding, and harvesting operations are performed. The long-rainfall season is also the period when crop vegetative and reproductive growth takes place.

In addition, the non-climatic factors included in the current model estimation; that is, quantity of fertilizer and improved wheat seed used, irrigated area under wheat crop all showed positive and significant impact at 1% level, which were as expected. The results imply that use of these inputs, fertilizer, improved seed and irrigation have vital role in increasing yields of wheat crop. This indicates that use of fertilizers, improved wheat seed, and irrigation are among the ways to increase the productivity of wheat in the country. Differently, land area under wheat cropping system has shown negative as well as significant reduction on yield of wheat crop, implying that any increase in land area could result in reduction of wheat crop yield.

In maize yield regression model, all climatic variables included in the model showed negative relationship with maize yield, except minimum temperature and CO_2, which are in line with expected results. The regression coefficients of crop growing season mean rainfall (F-S), *short- season rainfall* (F-M), and mean maximum temperature (F-S) are found significant at 1%, 5% and 10% respectively. This signifies that excess rainfall and temperature reduces yield of crops. Conversely, the coefficient estimates for minimum temperature during crop growing period (F-S) and CO_2 are negative, but only minimum temperature has significant impact (significant at 5% significance level) on maize yield. The result indicates that rise in minimum temperature over crop growing period has significant impact on maize yield. The crop growing period in this study refers to the period from February to September (F-S), when all agricultural operations from land preparation to crop harvesting are performed.

Furthermore, the socio-economic variables included in the maize yield model estimation such as quantity of fertilizer and improved maize seed used portrayed positive and significant impact at 1% and 10%, respectively. This implies that maize yield is highly responsive to use of fertilizer and improved seed inputs. The coefficients of land area under maize and irrigated area under maize cropping system, however, have negative impact on maize yield, but only the coefficient of land area under maize cropping systems is significant at 1% level. This shows that any further rise in land area cultivated under maize production significantly reduces yield of maize crop.

In order to examine the effects of weather variables (precipitation, temperature, $CO_{2,}$ etc.) and socio-economic variables (area under specific crop, fertilizer quantity used, and price of output) on crop output supply, an ARDL model was estimated and fitted for teff, wheat and maize crops time series data sets. The coefficient estimates of *short-season rainfall* with first order difference depicted negative sign, but statistically insignificant. However, coefficients of *short*- season *rainfall* showed positive sign, but have insignificant impact in its first lag and zero and second order differences. On that basis, the findings of the study signify that the volume of rainfall from February to May, a season that comes before the main crop growing season, marked by onset of long-rains in June, does not affect the volume of teff output. This impact of short-season rainfall is explained with a view that the large output of teff is produced during long-rainfall season including land preparation and sowing of seed which normally starts in the middle of the month of June. Contrastingly, the estimated teff output supply response model showed that the coefficient estimate of rainfall during *long-rainfall* season (J-S) in zero order difference and first lag order were negative, although statistically insignificant. This implies that an increase in *long*- season *rainfall* leads to a reduction in teff production. This factual outcome can be attributed to the occurrence of excessive *long-rainfall* season rainfall that eventuates into storm, flooding and crop lodging, and a consequent decrease in teff output in specific teff belt areas. Equivalently, shortage of rainfall during planting and vegetative growth period also decreases wheat outputs.

The coefficient estimates of crop growing period (F-S) mean temperature in its first lag order showed negative sign but statistically insignificant. Conversely, the regression coefficient estimates for the mean temperature over the crop growing period were positive in the first and second lag order differences. The result indicates that an increase in the mean temperature over the crop growing period is positively associated with output.

The regression coefficient of CO_2 emission from agriculture showed positive sign in all first lag order and first and second order differences. The coefficient estimate of CO_2 emission was significant in the first lag order only. Accordingly, the result signifies that an increase in CO_2 in previous year leads to respective increment in teff output.

The regression coefficient estimates of non-climatic variables, i.e., price of teff, land area under teff, and fertilizer quantity used, in their first lag order showed negative sign, but statistically insignificant. The regression coefficient estimates for price of teff in their zero and second lag order differences denoted negative relationship with teff output, but significant in zero order difference only. Consequently, the negative sign in coefficient estimate for producer price of teff indicates that a rise in the price of teff crop leads to a decrease in teff output supply.

Although the coefficient estimate for area under teff crop presented negative sign in first lag order, the coefficient estimates articulated positive sign in zero order, first and second lag order differences, but significant at 5% level in the zero order difference (current year) only. The results in the three cases evidenced that an increase in area put under teff crop production results in an increase in teff output supply. This implies that teff output is responsive to area put under the current production year and non-responsive lagged year area increase in teff production. Furthermore, the coefficient estimates of fertilizer quantity consumed on teff production in all lag and lag differences revealed negative sign, but statistically insignificant.

Considering wheat output supply response to climate variables, the coefficient estimates of mean temperature and *short-season rainfall* with first and second lag order differences showed negative relationship with wheat output. Equally, the coefficient estimates of crop growing period mean temperature in the first and second lag orders displayed negative and significant impact at 5% level. This implies that wheat output is negatively responsive to changes in mean temperature as wheat crop needs cool temperature. On the other hand, coefficient estimates of *short-season rainfall* (F-M) enunciated positive sign in its first lag and second lag orders, but the finding is signification at 1% level in the first lag order only. Consequentially, the result affirmed that an increase in *short-season rainfall* would increase wheat output in the first lag order, meaning, wheat output is highly responsive to lagged year increase in short-rainfall season as land preparation is thoroughly carried out during this season.

However, the coefficient estimates for *long-rainfall* (J-S) in zero and all lag orders showed positive relationship with wheat output. The results for the first and second lag orders were positive and significant at 1% level, indicating that a rise in *long- season rainfall* would lead to a boost in wheat output in first and second lag orders. The result is not unexpected since wheat needs sufficient water during *long-rainfall* season, the period when wheat crop planting, vegetative and flowering processes takes place.

In general, the result indicates that wheat output is positively and highly responsive to lagged year rainfall during both short-rainfall and long-rainfall seasons, signifying that wheat crop needs optimum and sufficient rainfall during land preparation, planting, vegetative and grain filling periods.

The coefficient estimates of CO_2 showed positive relationship with wheat output in all zero, first and second lag orders. The results was, however, significant at 1% level in the zero and first lag orders only, thus implying that wheat output was highly responsive to CO_2 emission from agriculture in first lagged year.

Among the socio-economic variables, the coefficient estimate of producer price of wheat showed positive and significant (at 1% level) impact on the wheat crop output in the first lag order, therefore ascertaining that as price of wheat increases output of wheat also increases. As price increases, farmers are encouraged to increase wheat crop production. However, the coefficient of wheat price in zero and second lag order differences showed negative and significant (at 1% level) impact on wheat output. This implies that wheat output is negatively responsive to changes in price during zero (current year) and second lags order differences.

The coefficient estimates of area under wheat as well as quantity of fertilizer used on wheat crop production showed negative impact and significant at 1% level in their first lag order and second lag difference. The result indicates that wheat output is negatively responsive to changes in quantity of fertilizer used during lagged years.

In this study, the coefficient estimate for crop growing period mean temperature has demonstrated mixed results in maize output supply. The coefficient estimate for mean temperature during crowing period in its zero order difference has exhibited harmful and considerable influence on maize production. Ergo, the result implies that a rise in the temperature variable in current year is depressingly related with output of maize crop. The justification for this result lies in the fact that temperature that exceeds the optimum requirement may affect the development of crops by disturbing the crop growing degree days (GDD). The GDD is a measure of warmth accretion used to forecast crop as well as pace of pest growth such as the date requird for a crop to reach its maturity. On the other hand, the coefficient of mean temperature in first lag order difference has positive impact on maize output, but statistically insignificant. This indicates that maize output is moderately responsive to first lagged year growing season mean temperatures.

The coefficient estimates for *short-season rainfall* in zero and first lag order differences showed negative and significant impact on maize production. Based on that, the result indicates that maize output supply is negatively and highly responsive to a change in *short-season rainfall* in zero and first lag order differences. Since maize is extremely sensitive to any shortage in rainfall during *short-rainfall* season, changes in rainfall during same season will reduce maize output. In Ethiopia, maize is a long period crop in which all land preparation and planting/sowing works are performed during the *short-rainfall* season. Therefore, shortage of rainfall during this season would highly affect maize production which even compelled farmers to replant burnt or wilted young maize plants. The results of *long-rainfall* (main crop season) in zero order difference also showed negative impact on maize output, but found insignificant. This can be justified by the fact that any change in *long-season rainfall* in zero difference (current year), be it shortage or above normal, would affect maize output negatively. On the other hand, coefficient estimates of *long-rainfall* in the first lag order difference showed positive and considerable effect on output of maize crop. This implies that maize output is positively and more responsive to changes in *long-season rainfall* of previous year (first lag *long-season rainfall*) than the zero order difference *long-season rainfall* (current year long-season rainfall).

Additionally, the coefficient estimate for the first lag price (previous year) of maize crop showed negative impact on maize output, but statistically insignificant. Conversely, the coefficient estimate of producer price of maize in zero and first lag order differences showed positive relationship with maize output, but are statistically insignificant, implying that the responsiveness of maize output to price changes both in zero order (current) and first lag order (previous year) is not a significant variable to explain changes in maize output.

Furthermore, the coefficient estimates of area cultivated under maize crop production in zero order difference and first lag order showed positive and significant impact on maize output. As a result, the finding implies that maize output is highly responsive to both first lag (previous year) and zero order difference (current year) of area cultivated under maize crop.

Differently, although the coefficient estimates for quantity of fertilizer used in maize production showed positive relationship in zero order difference (current) and first lag order (previous year) with maize output, but statistically insignificant. The analysis suggests that the output of maize is moderately responsive to lagged quantity of fertilizer (previous year) used on maize production.

Finally, the projected change in crop growing season mean temperature in teff growing belts showed an increasing trend (rise from -4.85^{0}C to 0.195^{0}C) while it has shown a decreasing trend in wheat (drop from -1.3^{0}C to -5.94^{0}C) and maize (-0.172^{o}C to -0.906^{0}C) growing areas. Furthermore, the forecasted change in rainfall (both short- and long-season rainfalls) discovered a declining trend in all crop growing belts over the selected scenarios or period, i.e., from -0.06mm to -1.58mm in teff growing belt, from -0.11mm to -1.3mm in wheat growing belt, and from -0.01mm to -0.17mmin maize growing areas. This will have negative impact on the yield of crops under study.

Although projected future changes in climate variables, particularly crop season rainfall are significant, the projected future changes in yields of wheat,maize and teff are minimal as the future projection showed an increase in yield of all crops over the selected scenarios (periods). By 2080, the forecasted future mean yield of wheat showed significant increase (237%) while that of teff and maize showed an increase of 48% and 10% respectively. In the short-run scenario of 2045, the changes in yield of all three crops compared to the baseline scenario (1981-2018) are minimal. However, the change in yield of maize is marginal showing that maize yield is more vulnerable to changes in climate variables.

7.3 Conclusions

It was found from the preceding analysis that *short-season rainfall* (FMAM season) showed a decreasing trend in all crops growing belts (teff, wheat and maize) while *long-season rainfall* (JJAS season) exhibited a rising trend in teff and wheat growing belts, but a declining trend in maize growing areas. It was further explored that the rainfall parameter was significantly variable during *short-season rainfall* and less variable during *long-season rainfall*. Conversely, the trend analysis demonstrated a rising trend in the maximum temperature in all crops growing belts while minimum temperature revealed a decreasing trend in teff and wheat growing areas. The study results confirm occurrence of a coherent warming temperature and significant variability of rainfall, particularly during short-season rainfalls, which adversely affected crop production as well as livelihood of community residing in the areas. From these, the study concludes that there exist high variations in rainfall and temperature parameters in the crop growing belts through the observing period.

Consequently, the study result revealed that teff yield has a log-linear relationship with both *short-* and *long-season rainfall* as well as mean temperature during crop growing period. The results revealed that higher temperatures may be helpful to teff crop up to the level favorable for the growth and development of the crop. The combined impact of higher temperatures and erratic rains affects teff crop during crop vegetative growth and flowering period as well. Furthermore, these noted variations as a matter of course associated with temperature and rainfall could make land presently assigned for teff crops unsuitable for growing (Yumbya*et al.*, 2014). These conditions invariably would lead producer farmers to extreme climate risks as it activates a shift in crop production that eventualy reduce the quantity and quality of teff output. Thus, this study revealed that rainfall variables during crop growing season (F–S) and *long-rainfall* (J-S) seasons have negative impact on teff yield, but only long- season rainfall has significant impact (1% level).

The outcome of Cobb-Douglas Production Functional model indicated that analysis for the yield of wheat discovered a log-linear association between wheat yield and seasonal rainfall. The study revealed that increase in *long-season rainfall* (J-S) and maximum temperature during crop growing period (F-S) have negative and significant effect on wheat yields. The log-linear association shows that, and increase in amount of rainfall during long-rain season had negative and significant impact on the yield of teff, which significantly reduces yield. Therefore, it is a requirement to have timely and quite adequate distribution of rainfall at different stages of crop development to improve the yield of teff crop.

From this study, it has been learnt that water is a necessary condition and input for maize production practices, and not in small quantity, but adequate quantity of rainfall during crop growing period becomes crucial to boost up yield of maize. Thus, low and undependable as well as excessive rainfall during crop growing period hampers fitness of maize crop production. This situation was found as major contributing factor leading to declining yield of maize in the years under study. Rainfall shortage during short-rainfall seasons and excessive rainfall during long-rainfall season are indicators that make it hard for producer farmers to make appropriate and timely decisions against changing rainfall patterns prevailing in the country. The irregular and unpredictable rainfall and its declining trend during short-rainy season are likely to increase climate risk faced by smallholder farmer producers thereby elevating uncertainty to food security of the country.

The study also found that an elevating maximum temperature during the crop growing period had a harmful and considerable effect on the yield of maize crop over the observation period. Thus, it implies that a rise in maximum temperatures beyond its most favorable level even during wet seasons lowers yield of maize. However, minimum temperature is positively and significantly associated with maize yield.

In general, based on the validating proofs of this study, the hypothesis stating there is *''no impact of rainfall and temperature variables on yield of cereal crop''* is rejected, signifying that changes in climate adversely affects yields of teff, wheat and maize crops.

Basically, analysis of supply responses of output provides an insight on how unpredictability climate factors affect crop output. The findings of the current study depicted that teff, wheat and maize outputs were being adversely impacted by changes and variability in climate as well as non-climatic factors. Likewise, the analysis evidenced that increase in rainfall during *long-rainfall* season (J-S) decreases teff output, signifying that a rise in *long-rainfall* season leads to a reduction in teff production. This result is a verified fact as excessive *long-season rainfall* results in storm, flooding and crop lodging which leads to decrease teff output in specific teff belt areas. Shortage of rainfall during planting and vegetative growth period also decreases teff outputs. Furthermore, the coefficient estimates of mean temperature during crop growing period and CO_2 emission from agriculture have positive impact on teff crop output.

The coefficient estimate of temperature in first and second lag order difference showed negative relationship with wheat output. This implies that wheat output is negatively responsive to temperature as temperature is above normal and variable during crop growing period. Conversely, rainfall has an affirmative effect on wheat supply during both *short-rainfall* (short) and *long-rainfall* (main) seasons, both in first and second lag orders (previous years). This indicates that increased rainfall boosts wheat production. This is an estimated calculation since wheat needs sufficient water during both *short-rainfall* and *long-rainfall* season (plowing plots, crop planting, and flowering takes place). Besides, wheat output is positively responsive to CO_2 concentration in zero, first and second lag orders.

Regarding the supply response of maize output to changes and variability in temperature during crop growing period, the study found that mean temperature in its zeroorder difference (current year) has negative and significant impact on maize production. This postulation can be justified since temperature elevated than required may be damaging for development of crops under consideration by affecting the crop growing degree days (GDD). Conversely, maize output supply is positively responsive to increase in temperature in first lag order (previous year), but statistically insignificant. The result indicates that maize output is moderately responsive to first lag order temperature.

The study results also indicate that maize output supply is negatively affected by both short-rainfall and long-rainfall season. Rainfall shortage during *short-rainfall* season would highly affect maize production which even results into a forced replanting of burnt or wilted young maize plants. The negative impact during *long-rainfall* (main crop season) on maize output can be justified by the fact that any change in *long-rainfall* rain in current year, be it shortage or above normal, would affect maize output negatively. On the other hand, the coefficient estimates of long-rainfall season in their first lag order have affirmative and considerable effect on output of maize crop. This implies that maize output is positively and more responsive to changes in *long-rainfall* of previous year (first lag *long-rainfall*) than the zero order difference *long-season rainfall* (current year long-rainfall).

Furthermore, the examination ascertained that from the forecasted future changes in temperature and rainfall that predicted future mean temperature showed increasing trend (rise from -4.85^{0}C to 0.195^{0}C by 2080) in teff growing belt while forecasted future changes in rainfall variables (both short- and long-season rainfall) showed a decreasing trend in teff (from -0.06mm to -1.58mm), wheat (from -0.11mm to -1.3mm), and maize (from -0.01mm to -0.17mm) growing belts over the selected scenarios. These projected future changes in weather (temperature and rainfall) variables have a depressing effect on the yield of crops under study.

Although projected future changes in climate variables (particularly crop season rainfall) are significant, projected future changes in yields of wheat, maize and teff are minimal since projection of future changes in yield of all crops showed an increasing trend over the selected scenarios (periods). By 2080, the forecasted future mean yield of wheat displayed significant increase (237%) while that of teff and maize demonstrated an increase of 48% and 10% respectively. The projection showed that changes in maize yield is marginal implying that maize yield is more susceptible to changes in climate variables. On the other hand, projected changes in yields of wheat and teff are significant as wheat is a cool temperature crop requiring relatively low rainfall.

Fundamentally, the hypothesis stating that there is no response of crops output to the changes in climatic and socio-economic factors is rejected against the alternative hypothesis stating that there is significant effect of climatic and socio-economic factors on the outputs of the selected cereal crops: teff, wheat and maize outputs.

7.4 Policy Implications

This study has examined the impact of climate change on cereal crop production in Ethiopia. The study established the fact that changes in climate factors had adverse impact on cereal crop yield as well as production. The study findings evidenced substantial responsiveness of teff, wheat and maize output to changes in climate would direct to decline in food production in the future.

In view of the fact that changes in climate had negative and adverse impacts on crop yield and output, the study recommends the following actions:-

7.4.1 Design and Implement Ecosystem Management to reduce warming temperature and variability of rainfall parameters;

It was found that *short-season rainfall* (FMAM season) showed a decreasing trend in all three crops growing belts (teff, wheat and maize) while *long- season rainfall* (JJAS season) showed a rising trend in teff and wheat growing belts, but a declining trend in maize areas. It was further found that the rainfall parameter was significantly variable during *short- season rainfall* and less variable during *long- season rainfall*. Conversely, the trend analysis demonstrated a rising trend in maximum temperature in all crops belts while minimum temperature revealed a decreasing trend in teff and wheat growing areas. The results implied occurrence of coherent rising/ warming of temperature and significant variability of rainfall, particularly during short-season rainfalls, which adversely affect crop production as well as livelihood of community residing in the areas. From these, the study concludes that there was a significant variation of rainfall and temperature in the crop growing belts through the observing period.

In view of the adverse impacts of increased warming temperature and highly variable rainfall parameters, it recommended that policy-driven actions to overcome the challenges of climate-changing impact by transforming the climate-sensitive livelihood systems into climate-smart options. Designing and implementing participatory ecosystem management that ensures the long-term sustainability and persistence of an ecosystems function and services while meeting socioeconomic, political, and cultural needs. Community-based participatory integrated watershed management practices should be adopted to strengthen communities' abilities to adapt and cope with the growing threats of climate change and improve their livelihoods. The main ecosystem management activities include: enclosure of degraded areas, reforestation, improved soil and water conservation activities, water harvesting, etc. The outcome of these activities will stabilize climate, create pleasant environment, absorb CO_2 concentration (carbon sequestration) thereby reducing amount of CO_2 concentration released to the environment.

7.4.2 Introduce mitigation and adaptation strategies to reduce adverse impacts of climatic parameters on crop yields;

The study results revealed that *long- season rainfalls* (J-S) had negative and significant impact on yields teff, wheat, and maize while maximum temperature during crop growing period (J-S) had negative and significant impact on wheat and maize yields, which reduced yield of crops significantly. Conversely, the estimates for maximum temperature and CO_2 emission exhibited positive and significant impact on teff yield. Furthermore, minimum temperature is positively and significantly associated with maize yield.

These results implied that increased warming of temperature (maximum) and irregular and highly variable rainfall during both seasons had adversely affected the yields of crops under study. Rainfall shortage during *short-rainfall seasons* and excessive rainfall during *long-rainfall season* are extreme events that were hard for producer farmers to make appropriate and timely decisions against changing rainfall patterns. The study also found that an elevating maximum temperature during crop growing period had a harmful and considerable effect on the yield of studied crops. In general, the declining trend in relative yields from crop modeling showed that climate factors such as erratic rainfall and rising temperatures had negative effects on agricultural productivity.

In context of the above confirmed events, it is recommended to introduce mitigation and adaptation strategies that reduce the adverse impacts of climatic parameters. It becomes necessary to practice climate-proof agricultural crops through adaptation strategies such as developing crop varieties (teff, wheat, and maize) that tolerate water stress and mature early, practice early planting, increase the awareness of climate change and its impacts on agriculture, and develop appropriate mitigation measures. In this regard, it is recommends that national, regional and local policy makers should integrate efficient agricultural water management practices with productivity-enhancing interventions; promote new drought tolerant variety seeds of teff, wheat and maize and distribute to local farmers. Strategies such as fuel wood conservation technologies (such as stove, solar panel and biogas) should be augmented among rural household which save labor and time as well as reduce CO_2 emissions. National, regional and local policy-makers should be integrated in designing adaptation strategies and setting agenda for development policies. Shitting production from one crop variety to another or to different locally adapted annual or perennial species may be alternative option for reducing emissions.

7.4.3 Establish and Strengthen Provision of Timely Climate Information to Relevant Stakeholders

It is evident that farming-households have less awareness about climate change; therefore, raising awareness among farming communities is more necessary on climate change by up-to-date information related to climate change by policymakers and extension workers. The study recommends establishment of information system that provide timely and accurate climate information such as seasonal forecasts, and early warning systems; which requires a holistic understanding of the impact of climate change on smallholder farmers' livelihoods. In this context, the community should be included in the process of climate information exchange. The community members need considerable skills in planning and implementation of appropriate techniques required for adapting climate change.

7.5 Contribution to Knowledge

The contribution of this study is triple. First, this research narrows the knowledge gap prevailing on effects of changes in climate factors; second, it builds on the various methodological and empirical foundations for studying impact of climate variability in an endeavor to raise production of cereal crops; third the study is expected provide research findings that could be used by prospective students, policy makers, and planners. That would help to formulate appropriate policies and mitigation strategies that would abate the negative effects of climate change on crop yield as well as the livelihood of farm households.

Additionally, this study would contribute to existing knowledge and narrow the gaps in this regard as stated earlier. First, the study found that temperature variability has harmful influences on crop yield as well as crop output beyond those of climate means. Second, the study found that excess rainfall and extreme temperature beyond the crop's optimum requirement have harmful effects on crop yield and output. Third, the research found that shortage in early rains in February to May have negative effects on teff and maize yield, which negates the expectation that increase in rainfall, will increase crop yields. These contributions are useful to stakeholders in agricultural sector, involved in designing and implementing appropriate measures for adaptation and mitigation given that climate projections indicate an increase in climate variability in the future. As such, the findings would contribute to existing knowledge on climate variability (rainfall and temperature), particularly researchers conducting research on the effect of changes in climate factors on crop production would be able to use it as reference. Furthermore, the estimates obtained from yield and output analysis in this study would contribute to the existing knowledge as they can be combined with the climate change forecasts to construct predictions on crop production for the future.

The current study would also contribute a lot in conveying the various methodological and empirical approaches employed in characterizing trends and variability of climatic factors and examining/measuring the response of cereal crop yield and output supply to the changes in climatic and socio-economic variables. The methodologies and empirical analytical approaches employed in this study could build on methodological as well as empirical foundations for studying impact of climate variability in an endeavor to raise production of cereal crops.

The study would also provide research results to policy makers in Ethiopia as well as in other developing countries that would help to design policies, adaptation and mitigation strategies that can significantly abate the harmful effects exerted by the changing climate factors on crop yield and the livelihood of farm households. The study findings could also be used as a policy proposition by concerned policymakers and planners to assess the effects that could be exerted by climate change on agriculture and food supply.

7.6 Areas of Further Research

This study was restricted to examination of the supply responses of three major crops in Ethiopia, namely teff, wheat and maize. Further research should be carried out on other important crops like barley, sorghum, vegetables, and root crops that would have food security implication.

In addition, this study focused on the examination of the effects of changes in climate factors on yield of crops and output supply and left adaptation and mitigation component to be studied by other researchers. Therefore, further research should be carried out on the adaptation and mitigation measures towards the observed influences of climate changes. In this regard, studies on how individual farmers can adapt to changes in climate factors as well as assessment of the cost of implementing the adaptation and mitigation interventions would be integral part in finding out economically feasible ways that would minimize the farmers' exposure to climate risks.

REFERENCES

Abera, K., O. Crespo, J. Seid and F. Mequanent, 2018; Simulating the impact of climate change on maize production in Ethiopia, East Africa, *Environmental Systems Research, Vol 7(4):* pp1 - 12.

Abiola, M. O. and C. I. Ada-Okungbowa, 2012; Estimation of farmers' response to price dynamics in partial adjusted autoregressive and distributive lagged models: An application to rubber production in Nigeria, *Nigerian Journal of Agricultural Economics (NJAE)*, Vol. 3(1): pp 1 – 8.

Acquah, H. D. G. and C.K. Kyei, 2012a; The effect of climatic variables and crop area on maize yield and variability in Ghana, *Russian Journal of Agricultural and Socio-Economic Sciences*, Vol. 10(10), pp 10-13.

Acquah, H. D.G. and C.K. Kyei, 2012b; Estimating the effect of climatic variables and crop area on maize yield in Ghana, *Journal of Social and Development Sciences*, Vol. 3(9), pp 328-336.

Adams, A.M., J. Cekan, and R. Sauerborn, 1998; Towards a Conceptual Framework of Household Coping: Reflections from Rural West Africa, *Africa J. Int. African Inst.*, Vol. 68 (1998), pp. 263-283.

Adekoya, A. F. and N. A. Abdul-Razak, 2019; Unemployment and Violence: ARDL Endogeneity Approach. *Ensayos Revista de Economía*, Vol. 37(2), pp 155-176.

Ademe, A. S., 2017; Effects of Climate Variability on Crop Yield, Income and Rural Labor Displacement in Central Ethiopia, Unpublished PhD Dissertation, School of Agricultural Economics and Agribusiness, Haramaya University.

Ademe, A. S., *et al*, 2017; Impact of Climate Variability on Cool Weather Crop Yield in Ethiopia, available at: https://www.researchgate.net/publication/321529951/.

Admasu, H., G. Mezgebu, T. S. Thomas, M. Waithaka and M. Kyotalimye, 2013; ''Ethiopia'', *In* : East African Agriculture and Climate Change: A Comparative Analysis, M. Waithaka, G. C. Nelson, T. S. Thomas and M. Kyotalimye, (eds); 149 – 182, Washington, DC. IFPRI.

Admasu, S. 2004; Rainfall Variation and its Effect on Crop Production in Ethiopia; Unpublished MSc Dissertation, School of Graduate Studies, Addis Ababa University.

Agba, D.Z, *et al,* 2017; Analysis of the Effects of Climate Change on Crop Output in Nigeria; American Journal of Climate Change, 6: pp. 554-571.

Agele, S. and A. Bolarinwa, 2018; Trends of Changes in Weather and Crop Yields in Nigeria between 1960 and 2013: *Implications for Food Security,* Res. Rev. J Ecol. Environ. Sci. Vol. 6 (3).

Ahmed, M., F. Hassan, and F.F.Ogtrop, 2014. Can models help to forecast rainwater dynamics for rainfed ecosystem? *Weather Clim. Extrem*. Vol. 5–6, pp 48–55.

Ajay, K., and S. Pritee, 2013; Impact of climate variation on agricultural productivity and food security in Rural India. Discussion Paper No. 2013-43: available at http://www.economicsejournal.org/economics/discussionpapers/.

Akanni, K.A and Okeowo, T.A. 2011; Analysis of Aggregate output supply Response of selected Food Grains in Nigeria. *Journal of Stored Products and Post Harvest Research*, Vol. 2 (14): pp 266 – 278

Akinsanola, A. A. and K. O. Ogunjobi, 2014; Analysis of Rainfall and Temperature Variability Over Nigeria, *Global Journal of Human-Social Science, Vol. 14 (3).*

Akter, N. and H. Seung-Jee, 2011; Education and Economic Growth in Haryana (India):*Application of Cointegration Analysis and Vector Error Correction Model on Supply Response of Pulses in Bangladesh*; Michigan State University.

Alam, S.A., 2013; Impact of climate change on savannah woodland biomass carbon density and water use: a modelling study of the Sudanese gum, *American Economic Review*, Vol. 84, pp 753–771.

Alemu, M. M. and G. T. Bawoke, 2019; Analysis of spatial variability and temporal trends of rainfall in Amhara region, Ethiopia, *Journal of Water and Climate Change;https://iwaponline.com/jwcc/article-pdf/doi/10.2166/wcc.2019.084/610736/jwc2019084.pdf*

Ali, E., 2018; Impact of Climate Variability on Staple Food Crops Production in Northern Togo, *Journal of Agriculture and Environment for International Development*, Vol. 112 (2): pp 321 – 341.

Ali, S., Liu, Y., Ishaq, M., Shah, T., Abdullah, Ilyas, A. and Din, I.U. 2017; "Climate change and its impact on the yield of major food crops: evidence from Pakistan", *Foods*, Vol. 6 (6), available at: https://doi.org/10.3390/foods6060039

Amin, M. R., J. Zhang and M. Yang, 2015; Effects of Climate Change on the Yield and Cropping Area of Major Food Crops: A Case of Bangladesh, *Sustainability*, Vol. 7; pp 898-915.

Amponsah, L., G. K. Hoggar, S. Y. Asuamah, 2015; Climate change and agriculture: modeling the impact of carbon dioxide emission on cereal yield in Ghana, Munich Personal RePEc Archive; available at: https://mpra.ub.uni-muenchen.de/68051/.

AMS (American Meteorological Society), (.); Earth's Climate as a Dynamic System, available at: http://www.ametsoc.org.

Anderson, B., and Strahler, A. H., 2008; Visualizing weather and climate.Wiley Global Education.

Aninagyei, I. and D.O. Appiah, 2014; Analysis of rainfall and temperature effects on maize and rice production in Akim Achiase, Ghana, J. Biosci. Vol. 2; pp 930–942.

Araya, A. et al, 2015; Assessment of maize growth and yield using crop models under present and future climate in southwestern Ethiopia. *Agricultural and Forest Meteorology*, available at: www.elsevier.com/locate/agrformet.

Arayaa, A., L. Stroosnijderb, G.Girmayc, S.D.Keesstrab, 2010; Crop coefficient, yield response to water stress and water productivity of teff (Eragrostis tef (Zucc.), *AgriculturalWater Management*, doi:10.1016/j.agwat.2010.12.001.

Arragaw, A. and B. Woldeamlak, 2017; Local spatio temporal variability and trends in rainfall and temperature in the central highlands of Ethiopia. *Geogr. Ann. Phys. Geogr*. Available at https://doi.org/10.1080/04353676.2017.1289460.

Asfaw, M. *et al*, 2019; Economic efficiency of smallholder farmers in wheat production: The case of Abuna Gindeberet District, Western Ethiopia; *Review of Agricultural and Applied Economics, Vol. 22 (1): pp 65-75.*

Asfaw, A., *et al*, 2018; Variability and time series trend analysis of rainfall and temperature in northcentral Ethiopia: *A case study in Woleka sub-basin; Weather and Climate Extremes*, Vol. 19: pp 29–41.

Askari, H., and J.T. Cummings. 1977; Estimating Agricultural Supply Response with the Nerlove Model: A Survey. *International Economic Review* Vol.18 (): pp 257–92.

Assefa, A., *et al*. 2008; Stakeholders Perception to Climate Change, Ethiopian Economics Association. *Economic Focus* Vol. 11(1).

Assefa, T. Assefa, H, and Kimani, P.M, 2006; Development of improved haricot bean germplasm for mid- and low-altitude sub-humid ecologies of Ethiopia, *Second national workshop on food and forage legumes*, 22 – 26 Sept. 2003, Addis Ababa.

Ayinde, O. E., M. Muchie and G. B. Olatunji, 2011; Effect of Climate Change on Agricultural Productivity in Nigeria: *A Co-integration Model Approach*, J Hum Ecol, 35(3): pp 189-194.

Bachewe, F., G. Berhane, B. Minten, and A. S. Tafesse, 2015; Agricultural Growth in Ethiopia (2004-2014): Evidence and Drivers; Ethiopia Strategy Support Program working paper 81.

Bayecha, D. K., 2013; Economic impacts of climate change on teff production in Lume and Gimbichu Districts of Central Ethiopia (Masters' thesis). Agricultural and Applied Economics, Sokoine University of Agriculture, Morogoro, Tanzania.

Befekadu, E. *et al*, 2018; Trends in Extreme Climate Events over Three Agroecological Zones of Southern Ethiopia; Hindawi Advances in Meteorology, available at https://doi.org/10.1155/2018/7354157

Benti, F. and M. Abera, 2019; Trend analysis of temperature and rainfall and their response to global CO2 emission in Masha, Southern Ethiopia; *Journal of Sustainable Agriculture*, Vol. 34(1): pp 67 – 75.

Bewket, W., 2009; Rainfall variability and crop production in Ethiopia; Case Study in Amhara Region; *In*: Proceedings of the 16th international conference of Ethiopian Studies; S. Ege,H. Aspen, B. Tefera and S. Bekele (eds), Trondheim.

Bewket, W. 2008; Rainfall variability and agricultural vulnerability in the Amhara region, Ethiopia. *Ethiopian Journal of Development Research* Vol.29, pp 1-34.

Birthal, P. S, *et al*, 2014; Impact of climate change on yields of major good grain crops in India: *Implications of food security*. *Agricultural Economics Research Review*. 27(2): pp 145-155.

Birara, H., R. P Pandey and S. Mishra, 2018; Trend and variability analysis of rainfall and temperature in the Tana basin region, Ethiopia, Journal of Water and Climate change Vol. 9(10): jwc2018080DOI:10.2166/wcc.2018.080.

Bhanumurthy, K. V., 2002: Arguing a case for the Cobb-Douglas production Function, *Review of Commerce Studies,* Delhi, India

Blanc, E., 2011; The impact of climate change on crop production in Sub-Saharan Africa, Unpublished PhD Thesis, University of Otago, Dunedin, New Zealand.

Bocher, T. F., 2016; Modeling Crop Yield and Farmer Adaptation to Rainfall Variability The case of Southern Ethiopia; Faculty of Agricultural Sciences, University of Hohenheim.

Bond, S., A. Leblebicioglu and F. Schiantarelli, 2010; Capital Accumulation and Growth. A New Look at Empirical Evidence. *Journal of Applied Econometrics*, Vol.25: pp 1073-1099. Available at https://doi.org/10.1002/jae.1163.

Bosani, D., 2017; Effect of Climatic and Non-Climatic Factors on Cassava Yields in Togo: Agricultural Policy Implications, *Climate*, Vol. *5(*28), Available at: https://doi.org/10.3390/cli5020028.

Byishimo, P., 2017; Assessment of climate change impact on crop yield and farmers' adaptation measures: a case of Rwanda, *Unpublished MSc Dissertation*, University of Zimbabwe.

Cairns, *et al*., 2013; Adapting maize production to climate change in Sub-Saharan Africa. *Food Security* Vol. 5, pp 345-360.

Camberlin, P and N. Philippon, 2001; The east African March-May rainy season associated atmosphere dynamics and predictability over the 1968-97 period. *Am. Meterol. Soc.* Vol. 15: pp 1002-1019.

CGIAR (Consultative Group for International Agricultural Research), 2018; Climate Resilient Green Economy Strategy, Sector-wise GTP II Implementation Monitoring Checklist, CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS), East Africa. Available at: https://ccafs.cgiar.org/publications/climate-resilient-green-economy-strategy.

Chandio, A. A., Y. Jiang and A. Rehman, 2019; Using the ARDL-ECM approach to investigate the nexus between support price and wheat production: An empirical evidence from Pakistan, *Journal of Asian Business and Economic Studies*, available at https://doi.org/10.1108/JABES-10-2018-0084;

Chandio, A.A., Y. Jiang and H. Magsi, 2018; Climate Change Impact On Rice Production in Pakistan: *An ARDL-Bounds Testing Approach to Cointegration*; *Preprints* (www.preprints.org).

Chao, J.C., Swanson, N.R., 2005; Consistent estimation with a large number of weak instruments, *Econometrica*, Vol. 73, pp 1673-1692.

Chauvin, N. D., F. Mulangu, and G. Porto, 2012; Food production and consumption trends in sub-Saharan Africa*: Prospects for the transformation of the agricultural sector.* Addis Ababa: UNDP WP 2012–11. UNDP, Regional Bureau for Africa.

Chen, C.C., B. A. McCARL and D. E. Schimmelpfennig, 2004; YIELD VARIABILITY AS INFLUENCED BY CLIMATE: A STATISTICAL INVESTIGATION, *Climatic Change* Vol. **66: pp** 239–261.

Chisasa, J., 2014; An Empirical Study of the Impact of Bank Credit on Agricultural Output in South Africa, Unpublished Doctoral Thesis, University of South Africa.

Chowdhury, I. U. A. and M. A. E. Khan, 2015; THE IMPACT OF CLIMATE CHANGE ON RICE YIELD IN BANGLADESH: *A TIME SERIES ANALYSIS*, RJOAS, Vol. 4(40): pp 12 – 28.

Cline, W.R., 2007: Global Warming and Agriculture: Impact Estimates by Country. Washington DC: *Center for Global Development*.

Cline, W.R. (1996), "The Impact of Global Warming on Agriculture: Comment" *American Economic Review*, Vol. 86(5): pp 1309-11.

CSA, 2017; Report on Area and Production of Major Crops for Meher Season; *Agricultural Sample Survey*, Various Issues of Statistical Bulletins, Addis Ababa.

CSA, 2018; Report on area and production of major crops; Agricultural Sample Survey 2017/18, Addis Ababa.

CSA, 2020; Report on area and production of major crops; Agricultural Sample Survey 2019/20, Addis Ababa.

Daba, M. 2018; Agro Climatic Characterization in Selected Woredas of Western Oromia, Ethiopia, *Journal of Earth Science & Climatic Change*, Vol. 9 (3): pp 1 – 7.

Dagne, G. B., 2018; Climate Change and Variability: *Smallholder Farmers' Perceptions and Indigenous Adaptation Responses in Sekota Woreda, Amhara Region, North-east Ethiopia*, Unpublished MSc Dissertation, Addis Ababa University.

Dandesa, T., D. Korecha, L. Nigatu and B. R. Cheneka, 2017; Assessment of Climatic Variability and Development of Localized Climate Prediction Method for Live-stock Production in Borana Area, Southern Ethiopia; *Environ Sci Ind J*. Vol.13(3): pp 1 - 30.

Daniel, B., *et al*, 2017; Analysis of rainfall trend and variability for agricultural water management in Awash River Basin, Ethiopia; Journal of Water and Climate Change, Vol. 08(1).

De-Graft, A. H. and K. C. Kweku, 2012; The effects of climatic variables and crop area on maize yield and variability in Ghana. *Russian Journal of Agricultural and So-cio-Economic Sciences*, 10(10), pp 633-635.

Deressa, T. T, 2010; Assessment of the vulnerability of Ethiopian agriculture to climate change and farmers' adaptation strategies, University of Pretoria.

Deressa, T.T. and R. M. Hassan, 2009; Economic Impact of Climate Change on Crop Production in Ethiopia: *Evidence from Cross-section Measures*, *JOURNAL OF AFRICAN ECONOMIES*, Vol. 18 (4), PP 529–554.

Deressa, T., 2007; Measuring the economic impact of climate change on Ethiopian agri-culture: *Ricardian Approach*, World Bank Policy Research Working Paper No. 4342, World Bank, Washington DC.

Dewett, K.K and A. Chand, 1983; Modern Economic Theory. Twentieth Revised Edition. Shyam Lal Charitable Trust. New Delhi.

Dong, X. *et al*, 2018; The Application of Cobb-Douglas Function in Forecasting the Du-ration of Internet Public Opinions Caused by the Failure of Public Policies; *Journal of Systems Engineering Society of China*, Vol.27(5): pp 632 – 655.

Donnelly, A. *et al*, 2004; A review of indicators of climate change for use in Ireland, Int J Biometeorol 49:1–12.

Dumrul, Y. and Z. Kilicarslan, 2017; Economic impacts of climate change on agriculture: *empirical evidence from ARDL approach for Turkey*. Journal of Business, Economics and Finance (JBEF), Vol. 6(4), pp 336-347.

Dushko, J., L. Darko and K. Cane, 2011; Cobb-Douglas production function revisited, VAR and VECM analysis and a note on Fischer/Cobb-Douglass paradox, *Munich Personal RePEc Archive,* available at: https://mpra.ub.uni-muenchen.de/33576/.

Duasa. J. (2010). Determinants of Malaysian trade balance: An ARDL bound testing approach. *J. Econ. Coop.*, Vol. 28(3), pp 21–40.

EEA (European Environment Agency), 1999; Information for improving Europe’s Environment, EEA, Copenhagen.

EEA, 1995; Europe’s Environment: the Dobris Assessment, Copenhagen, European Environmental Agency.8pp.

Endale, K., 2010; Fertilizer Consumption and Agricultural Productivity in Ethiopia, EDRI. Addis Ababa, Ethiopia:

Endalew, B. 2017; Teff production and marketing in Ethiopia; Journal of Radix International Educational and Research Consortium, Vol. 6, Issue 4.

Enders, W. 2010; *Applied Econometric Time Series*; Third Edition, John Wiley & Sons, Inc. Publishing, Hoboken, New Jersey.

Engdawork, T., 2009; Understanding Teff: *A Review of Supply and Marketing Issues*.Ethiopia Commodity Exchange Authority.

Engle, R.F. and Granger, C.W.J. 1987; Cointegration and Error Correction: Representation, Estimation and Testing, *Econometrica*, Vol 55, pp 251-276.

Eregha, P.B., J.S. Babatolu and R.T. Akinnubi, 2014; Climate Change and Crop Production in Nigeria: *An Error Correction Modelling Approach*; *International Journal of Energy Economics and Policy* Vol. 4 (2), pp.297-311.

ESSP (Ethiopian Strategy Support Program), 2016; Rural youth and employment in Ethiopia; ESSP WORKING PAPER 98.

Enfield, D. B. 2001; The Atlantic multidecadal oscillation and its relation to rainfall and river flows in the continental U.S., Geographical Research Letters; VOL. 28 (10), pp 2077-2080.

Ethiopian Academy of Sciences, 2015; *An Assessment of Ethiopia's Policy and Institutional Frameworks for Addressing Climate Change,First Assessment Report*, Ethiopian panel on Climate Change (2015).

Fahimifard, S.M. and M.S. Saboui. 2011; Supply response of cereals in Iran: An autoregressive distributive lag approach. *J. Appl. Sci*. Vol. 11(12): pp 2226-2231.

Farook, A.J. and K.S. Kannan, 2017; Climate change impact on rice yield in India – *Vector Autoregression Approach;Sri Lankan Journal of Applied Statistics*, Vol. 16 (3); pp 161 – 178.

FAO (Food and Agriculture Organization), 2020; Water and soil requirements of crops; available at: www.fao.org.

FAO, 2017; FAOSTAT, FAO, Rome, available at: http://faostat.fao.org.

FAO, 2015; Analysis of price incentives for Teff in Ethiopia, Technical notes series, MAFAP by Assefa B., Demeke M., Lanos B, Rome.

FAOSTAT. 2015; http://Faostat.fao.org

FAO, 2013; Food Security Indicators. *Food and Agriculture Organization of the United Nations*. Rome, Italy

FAO, 2012; Climate Change Adaptation and Mitigation in Agriculture; *Climate Change and Food Security Course Learning Notes;* pp 1 – 21.

Forster, P. *et al*, 2007; Changes in Atmospheric Constituents and in Radiative Forcing. In: *Climate Change 2007*: The Physical Science Basis; Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M.Tignor and H.L. Miller (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Fufa, B., and R.M. Hassan, 2005; Stochastic Technology and Crop Production Risk*:* The Case of Small-Scale Farmers in East Hararghe Zone of Oromia Regional State in Ethiopia, *Strategies and Analysis for Growth and Access.* Ethiopia.

Fufa, B. and R. M. Hassan, 2003; Stochastic maize production technology and production risk analysis in Dadar district, East Ethiopia; *Agrekon, Vol 42 (2):* pp 116 – 128.

Gebreegziabher, Z., J. Stage, A. Mekonnen, and A. Alemu, 2011; Climate Change and the Ethiopian Economy: *A Computable General Equilibrium Analysis*, Environment for Development, Discussion Paper Series, available at: https://www.researchgate.net/publication/254448144.

Gezie, M., 2019; Farmer's response to climate change and variability in Ethiopia: *A review,* Cogent Food and Agriculture, Vol. 5(1): pp 1 – 13.

Gillig, D. and B. A, McCarl, 2002; Introduction to Computable General Equilibrium Models (CGE). Department of Agricultural Economics, Texas A&M University, http://ageco.tamu.edu/.

Granger, C. W. J. and Swanson, N. R.: 1996, Further developments in the study of cointegrated variables, *Oxford Bulletin of Economics and Statistics* Vol. 58, pp 374—386.

Greene, W., 2008; *Econometric Analysis*, New Jersey: Pearson Prentice-Hall.

Gujarati, D. N. and D. C. Porter, 2010; Essentials of Econometrics, Fourth Edition, McGraw-Hill International. Singapore.

Gujarati, D. N, 2004; *Basic econometrics*. McGraw Hill: New York

Gujarati, D. N, 1999; *Essentials of Econometrics*, McGraw Hill: New York

Gupta, S., P. Sen and S. Srinivasan, 2012; Impact of climate change on Indian economy: evidence from food grain yields, *Centre for Development Economics Working Paper,* Vol. 218. Delhi.

Hailu, G,M. 1990: Wheat production and research in Ethiopia, IAR, Addis Ababa.

Hassler, U., Wolters, J., 2006; Autoregressive distributed lag models and cointegration. *Allgem. Stat. Archiv*, Vol. 90(1), pp 59–74.

Hatanaka, M. 1996; Time Series based Econometrics; Unit Roots and Cointegration, Oxford University Press, Oxford.

Hatfield, J. L. and J. H. Prueger, 2015; Temperature extremes: Effect on plant growth and development, *Weather and Climate Extremes,* Vol. 10: pp 4–10.

Hayelom, B. Y, Chen, Z. Marsie and M. Negash, 2017; Temperature and Precipitation Trend Analysis over the Last 30 Years in Southern Tigray Regional State, Ethiopia; available at www.preprints.org.

Heij, C. *et al.*, 2004; *Econometric methods with applications in business and economics*. New York: Oxford University Press.

Hill, R. C.*et al.*, 2012; *Principles of econometrics* (4th ed.). New York: John Wiley & Sons.

Huong, N. V. and J. M. Yorobe, 2016; Maize Supply Response in Vietnam, *Asian Journal of Agriculture and Development,* Vol. 14(1): pp 89 – 105.

Idumah, F. O., C. Mangodo, and UB Ighodaro, 2016; Climate Change and Food Production in Nigeria: Implication for Food Security in Nigeria, *Journal of Agricultural Science;* Vol. 8 (2); pp 74 – 83.

Igwe, K. C., et al., 2013; Investigation of the Direction of Causality and Effect of Climate Change on Food Grain Output in Nigeria (1970-2010), *International Journal of Engineering and Science (IJES)*, Vol. 2(3); pp 49 – 54.

International Federation of Red Cross and Red Crescent Societies, 2016; Ethiopia: *Drought - Emergency Appeal Revision*, www.ifrc.org , Saving Lives, Changing Minds.

IPCC (Intergovernmental Panel on Climate Change), 2014(a): Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on climate Change; *In* R.K. Pachauri and L.A. Meyer (eds.), Geneva, Switzerland.

______.2014(b); Climate Change 2014: Synthesis Report, Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland.

______.2014a; Summary for Policy makers, *In Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the IPCC;* C. B. Field, V. R. Barros, D. J. Dokken, K. J. Mach, M. D. Mastrandrea, T. E. Bilir, M. Chatterjee, K. L. Ebi, Y. O. Estrada, R. C. Genova, B. Girma, E. S. Kissel, A. N. Levy, S. MacCracken, P. R. Mastrandrea, and L. L. White. (editors), Cambridge, U.K., and New York, U.S.A. Cambridge University Press, pp 1–32.

_____.2014b; Summary for Policy makers, *In*: Climate Change 2014: Impacts, Adaptation, and Vulnerability, *Part B: Regional Aspects*, Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge.

______. 2013; *Climate Change 2013*: *The Physical Science Basis*. Contribution of WorkingGroup I to the *Fifth Assessment Report* of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

______. 2007 (a); *Climate Change 2007: The Physical Science Basis;* In: Solomon, S.D., et al., eds.: Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge.

______.2007 (b); *Climate Change 2007: The Physical Science Basis.* Cambridge University Press. http://www.ipcc.ch/

Iqbal, M. Z. 2017; Three essays on agricultural supply analysis. Unpublished PhD Thesis, Iowa State University.

Issahaku, Z. A. 2014; Climate Change, Agricultural Productivity and Poverty in Ghana's Context: Macro-Micro Analysis; Unpublished PhD Dissertation, Hiroshima University.

Janjua, P. Z., G. Samad and N. U. Khan, (2013; Impact of Climate Change on Wheat Production: A Case Study of Pakistan, Pakistan Development Review Vol. 49(4II): pp 799-822.

Joshi,N. P. *et al.*, 2011; Effect of Climate Variables on Yield of Major Food-crops in Nepal: A Time-series Analysis, *Journal of Contemporary India Studies,* Vol.1: pp 19 -26.

Just, R. E. and R. D. Pope, 1978; Stochastic specification of production functions and economic implications, *Journal of Econometrics*, Vol. 7 (1), pp 67-86.

Kapuya, T., 2010; Modelling the Impact of the "Fast-track" Land Reform Policy in Zimbabwe's Maize Sector. Unpublished Msc. Thesis. University of Pretoria, South Africa.

Kariuki, G. M., 2016; Effect of Climate Variability on Output and Yields of selected crops in Kenya, Unpublished PhD Thesis, School of Economics, Kenyatta University.

Kassie, B.T, 2014; Climate variability and change in Ethiopia: Exploring impacts and adaptation options for cereal production; Wageningen University, Wageningen.

Kavinya, P., and M. A. Phiri. 2014; Maize Hectarage Response to Price and Non-price Incentives in Malawi, *Scholarly Journal of Agricultural Science,* Vol. 4 (3): pp 142–151.

Kedir, U. 2017; TheEffect of Climate Change on Yield and Quality of Wheat in Ethiopia: *A Review, Journal of Environment and Earth Science*, Vol. 7 (12): pp 46-52.

Kelbore, Z.G. 2012; Essays on the Ethiopian Agriculture; PhD Dissertation, Graduate School of Social Sciences, University of Trento.

Kenea, Y., G. Ayele and W. Negatu, 2001; Farming Research on Teff: Small Holders Production Practices. *In*: Hailu, T., G. Belay and M. Sorrels (eds.), *Narrowing the Rift: Teff Research and Development,* Ethiopian Agricultural Research Organization, Addis Ababa, Ethiopia, pp 9-23.

Kiiru, M.W., 2007. Determination of the Price Elasticity of Sunflower Supply in Kenya. Unpublished Msc. Thesis, University of Nairobi.

Kiros, G., A. Shetty and L. Nandagirl, 2017; Extreme rainfall signatures under changing climate in semi-arid northern highlands of Ethiopia, Cogent Geoscince, available at: https://doi.org/10.1080/233120411353719

Kollurmath, V. B. *et al.*, 2008; Supply Response of Rice and Maize in Karnataka Pre and Post WTO, *Karnataka J. Agric. Sci.*, Vol. 21(4): pp 535-537.

Korecha, D. and Barnston, A., 2007; Predictability of June–September rainfall in Ethiopia.*American Meteorological Society*, 135, 625–650.

Kumar, V., *et al*, 2018; Greenhouse Gas Emission, Rainfall and Crop Production over North-Western India; *The Open Ecology Journal,* Vol.11; pp 47 –61.

Kumar, A., P. Sharma and S. K. Ambrammal, 2015; Effects of Climatic Factors on Productivity of Cash Crops in India: Evidence from State-wise Panel Data, Global Journal of Research in Social Sciences, Vol. 1 (1), pp 8 – 18.

Kumar, K.S.K. and J. Parikh, 2001; Indian Agriculture and Climate Sensitivity, *Global Environmental Change,* Vol. 11(2): pp 147-154.

Kwiatkowski, D., P. C. Phillips, P. Schmidt & Y. Shin, 1992; Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root. *Journal of Econometrics, 54*(1), pp159-178.

Lee, B. H. *et al*, 2013; Pre-harvest forecasting of county wheat yield and wheat quality using weather information. *Agric. Forest Meteorol*. 168, pp 26–35.

Lemma, Y. Meyene, F and Hundie, B. 2013; Climate Change and Variability: Implications for household food security in agro-pastoral areas of Jigjiga District, Ethiopia, *Ethiopian Journal of Economics*, Vol. 22 (1): pp 71 – 106.

Lia, K-F., B. Tianb, D. E. Waliserb, and Y. L. Yunga, 2010; PNAS

Liu, W.*et al,* 2014; Effect of climatic factors such as temperature, precipitation on maize production in China, Transactions of the Chinese Agricultural Engineering 30(21): pp 138-146. (In Chinese with English Abstract).

Lobell, D. B., W. Schlenker, and J.Costa-Roberts, 2011; Climate Trends and Global Crop Production Since 1980. *Science,* Vol.333: pp 616-620.

Maddison, D., 2006; The perception of and adaptation to climate change in Africa. CEEPA Discussion Paper No. 10. *Centre for Environmental Economics and Policy in Africa,* University of Pretoria, South Africa.

Mahmood, N., B. Ahmad, S. Hassan and K. Bakhsh, 2012; Impact of temperature and precipitation on rice productivity in rice-wheat cropping system of Punjab province, *The Journal of Animal & Plant Sciences*, Vol. 22(4), pp 993-997.

Mahrous, M. S., 2018; Patient safety culture as a quality indicator for a safe health system: Experience from Almadinah Almunawwarah, KSA. *J Taibah Univ Med Sci*, Vol. **13;** pp 377-83.

Mahrous, W., 2018; Dynamic Impacts of Climate Change on Cereal Yield in Egypt: An ARDL Model, *Journal of Economic & Financial Research,* Vol. 5(1): pp 886 – 908.

Mandefro, N. *et al,* 2002; *Enhancing the Contribution of Maize to Food Security in Ethiopia: Proceedings of the Second National Maize Workshop of Ethiopia*, *12-16 No. 2001,* Addis Ababa, Ethiopia.

Mandy, D. M., 2017; Producers, Consumers and Partial Equilibrium; Elsevier Inc. The Academic Press, New York.

Matewos, T., 2019; Climate change-induced impacts on smallholder farmers in selected districts of Sidama, Southern Ethiopia, Climate, 7, 70: pp 1 – 17.

Meals, D. W., J. Spooner, S. A. Dressing, and J. B. Harcum; 2011; Statistical analysis for monotonic trends, Tech Notes 6, Developed for U.S. Environmental Protection Agency by Tetra Tech, Inc., Fairfax, Vol. 23; Available online at: *https://www.epa.gov/polluted-runoff-nonpoint-source-pollution/nonpoint-source-monitoringtechnical-notes*.

Mendelsohn, R. and J. Wang, 2017; The impact of climate on farm inputs in developing countries agriculture, Universidad Nacional Autónoma de México, Centro de Ciencias de la Atmósfera, available at (http://creativecommons.org/licenses/by-nc-nd/4.0/).

Mendelsohn, R., Dinar, A., and Sanghi, A. (2001); The effect of development on the climate sensitivity of agriculture. *Environment and Development economics,* Vol. 6(01), pp 85-101.

Mendelsohn, R. and D. Tiwari, 2000; Two Essays on Climate Change and Agriculture: *A Developing Country Perspective. FAO Economic and Social Development Paper 145*. Rome, Italy.

Mendelsohn, R., Nordhaus, W., and Shaw, D.: 1994. "The Impact of Global Warming on Agriculture: A Ricardian Analysis", *American Economic Review,* Vol. **84**: pp 753-771.

Menya, C. K. 2011; Rainfall Variation due to Climate Change: An Inter-Temporal Investigation into its Impact on Subsistence Crop Revenue; Unpublished Masters Thesis, Norwegian University of Life Sciences.

Miao, R. *et al*, 2015; Responsiveness of Crop Yield and Acreage to Prices and Climate, *Amer. J. Agr. Econ. Vol.* 98(1): pp 191–211.

Michigan Sea Grant, 2011; Climate Variability and Climate Change: What is the difference?, available at: www.miseagrant.umich.edu/climate.

Mideksa, T.K. 2010; Economic and distributional impacts of climate change: The case of Ethiopia. *Global Environmental Change* Vol.20, pp 278-286.

MOA, 2005; *New agro-ecological zones of Ethiopia*. Addis Ababa: Ministry of Agriculture.

MoFA (Ministry of Foreign Affairs), 2018; Climate Change Profile: Ethiopia.

MoFED, 2010a**:** Growth and Transformation Plan (GTP) 2010/11 – 2014/15, Ministry of Finance and Economic Development, Addis Ababa, Ethiopia.

MoFED (Ministry of Finance and Economic Development), 2006: Survey of the Ethiopian economy, Addis Ababa, Ethiopia.

Mose, L.O. 2007; Who Gains, Who loses? The Impacts of Market Liberalization on Rural Households in Northwestern Kenya. Unpublished PhD Thesis, Wageningen University, the Netherlands.

Mosisa, W. *et al.,* 2012; Status and Future Direction of Maize Research andProduction in Ethiopia. Pp 17 -23. *In:* Mosisa, W, Twumasi-Afriyie, S., Wolde, L.,Tadesse, B., Demisie G., Bogale, G., Wegary, D. and Prasanna, B.M. (eds), 2012; Meeting the Challenges of Global Climate Change and Food Security throughInnovative Maize Research. Proceedings of the Third National Maize Workshop ofEthiopia. Addis Ababa, Ethiopia.

Muchapondwa, E., 2009; Supply Response of Zimbabwean Agriculture: 1970–1999. *African Journal of Agricultural and Resource Economics*, Vol. 3(1): pp 28-42.

Mulatu, D. W, *et al*, 2016; The Impact of CO2 Emissions on Agricultural Productivity and Household Welfare in Ethiopia: *A Computable General Equilibrium Analysis;* Environment for Development Centres; Discussion Paper Series.

Mulugeta, D. *et al.,* 2017; Potash fertilization of teff and wheat in the highlands of Ethiopia, Ethiopian Agricultural Transformation Agency (ATA), Addis Ababa, Ethiopia.

Mythili, G., 2008; Acreage and Yield Response for Major Crops in the Pre- and Post-Reform Periods in India: A Dynamic Panel Data Approach. *Indira Gandhi Institute of Development Research,* Mumbai, India.

NASc & Royal Society, 2020; Climate Change: Evidence and Causes; UPDATE 2020, available at: http://www.royalsociety.org/policy/climate-change

National Geographic Society, 2019; Global Warming; Resource Library Encyclopedia, available at: https://www.nationalgeographic.org

National Meteorological Agency (NMA), 2007; Climate Change National Adaptation Program of Action of Ethiopia. Addis Ababa.

National Planning Commission (NPC), 2018; The Second Growth and Transformation Plan (GTP II) Midterm Review Report, June 2018, Addis Ababa.

Naveendrakumar, G., *et al.,* 2018; Five Decadal Trends in Averages and Extremes of Rainfall and Temperature in Sri Lanka, *Advances in Meteorology*, Available at: https://doi.org/10.1155/2018/4217917.

Nastis, S.A., A. Michailidis, and F. Chatzitheodoridis, 2012; Climate change and agricultural productivity, *African Journal of Agricultural Research*, Vol. 7(35), pp 4885-4893.

Niamatullah, M., K.U. Zaman and M.A. Khan, 2010; Impact of Support Price and Fertilizer Offtake on Rice Production and Wheat Acreage in NWFP, Pakistan. The Journal of Animal and Plant Sciences, Vol. 20 (1), PP. 28-33.

Nicholls, N. 1997; Increased Australian wheat yield due to recent climate trends. Nature, Vol. 387: pp 484-485.

Nicholson, 2014; The Predictability of Rainfall over the Greater Horn of Africa. Part I: Prediction of Seasonal Rainfall; *Journal of Hydrometeorology*, Vol. 15(3): pp 1011-1027.

Nicholson, W., Snyder, C., 2008; Microeconomic Theory Basic Principles and Extensions, Eleventh Edition. Thomson Inc., Ohio.

Nkang, N., Ndifoni, H., Edet, E. (2007) Maize supply response to changes in real prices: A vector error correction approach. *Agricultural Journal*, 2(3), 419-425.

NOAA (National Oceanic and Atmospheric Administration), 2021; Temperature Change and Carbon Dioxide Change**,** National Centers for Environmental Information, US Department of Commerce.

Obayelu, A.E., and Salau, S.A., 2010. Agricultural Response to Prices and Exchange Rate in Nigeria: Application of Co-integration and Vector Error Correction Model. *Agri Sci*, Vol. 1(2): pp 73-81.

OECD (Organization for Economic Cooperation and Development); 2003; OECD Environmental Indicators: Development, Measurement and Use; available at: http://www.oecd.org/env/.

OECD, 1993; OECD core set of indicators for environmental performance reviews, Organization for economic cooperation and development**,** Paris, France. Pp 93.

Oloruntuyi, A.O. and A.O. Adigun, 2017; Economic analysis of the effects of the climate change on agricultural productivity in Nigeria; JORIND 15(1), available at www.transcampus.org/journal; www.ajol.info/journals/jorind.

Olwande, J.O., M., Ngigi, and W. Nguyo, 2009; Supply Responsiveness of Maize Farmers in Kenya: A Farm-Level Analysis. Contributed paper presented at the International Association of Agricultural Economists (IAAAE) 2009 Conference, held in Beijing, China.

Olutumise, A. I., E. C. Okogbue and A. G. Omonijo, 2017; Assessing relationship between climate variables, human diseases and crop production using ARDL approach in Nigeria; *Scientific Papers Series Management, Economic Engineering in Agriculture and Rural Development*, Vol. 17 (3): pp 253 – 264.

Omoyo, N. N., J. Wakhungu and S. Oteng, 2015; Effects of climate variability on maize yield in the arid and semi-arid lands of lower eastern Kenya, *Agriculture & Food Security*, Vol. 4(8): pp 1 – 13.

Onono, P. A., 2018; Response of Sorghum Production in Kenya to Prices and Public Investments; *Sustainable Agriculture Research*; Vol. 7 (2); pp 19 – 29.

Onono, P. A., N. W. H. Wawire and C. Ombuki, 2013; The response of maize production in Kenya to economic incentives, *International Journal of Development and Sustainability*, Vol. 2(2); pp 1 – 14.

Onour, I., 2019; Effect of Carbon Dioxide Concentration on Cereal Yield in Sudan, *Management and Economics Research Journal*, Vol. 5 (S3), pp 7.

Oparinde, L. and E. Okogbue, 2018; Analysis of climate-related risk and maize production in southwest, Nigeria. *Environmental Science*, Vol. 18 (1), pp 285-3952.

Otitoju, M. A., 2013; The effects of climate change adaptation strategies on food crop production efficiency in southwestern Nigeria; Unpublished PhD Thesis, University of Nigeria, Nsukka.

Oxera, 2010; How has the preferred econometric model been derived? Econometric approach report, Oxford, UK, available at: www.oxera.com

Oza M. and C. M. Kishtawal, 2014; Trends in Rainfall and Temperature Patterns over North East India; Journal of Earth Science India, Vol. 7 (4), pp. 90 – 105.

Ozkan, B. , R. F. Ceylan, and H. Kizilay, 2011; Supply Response for Wheat in Turkey: A Vector Error Correction Approach. Faculty of Agriculture, Department of Agricultural Economics, Akdeniz University, Antalya Turkey.

Padhiary, J., D.M. DAS, K.C. PATRA and B.C. SAHOO, 2018; Trend Analysis of Rainfall and Temperature Using the Mann Kendall Test in Jaraikela Catchment of Brahmani River Basin; *International Journal of Agriculture Sciences*; Vol. 10 (19); pp. 7309 – 7313.

Panda, A., & Sahu, N. (2019). Trend Analysis of Seasonal Rainfall and Temperature Pattern in Kalahandi, Bolangir and Koraput Districts of Odisha, India. *Atmospheric Science Letters*, 20, e932, available at: https://doi.org/10.1002/asl.932.

Pesaran, M. H., 1997; An Autoregressive Distributed Lag Modelling Approach to Cointegration Analysis; Norwegian Academy of Science and Letters, Oslo.

Pielke, R., 2009; Climate Change: *The need to consider human forcings besides greenhouse gases, Eos* **90**.

PDC, 2018; Ethiopia Registers a 7.7% Gross Domestic Product Growth, available at: https://www.2merkato.com>alerts.

Poudel, M.P., S. E. Chen, and W. C. Huang, 2014; Climate influence on rice, maize and wheat and yield variability in Nepal, *Journal of Agricultural Science and Technology*, Vol. 4, pp 38-48.

Ramsey, J. B., 1969; Tests for specification errors in classical least-squares regression analysis, *Journal of the Royal Statistical Society*, Series B 31, pp 350-71.

Rao, J. M., 1989; Agricultural Supply Response: A Survey, *Agricultural Economics*, Vol. 3; pp 1-22.

Raza, A. and M. P. Ahmad, 2015; Analysing the Impact of Climate Change on Cotton Productivity in Punjab and Sindh, Pakistan, *MPRA Paper No. 72867*, available at: https://mpra.ub.uni-muenchen.de/72867/

Reda, A. T. 2015; SMHI-RCA Model Captures the Spatial and Temporal Variability in Precipitation Anomalies over East Africa. Journal of Climatology and Weather Forecasting, Vol. 3(3): pp 1 – 8, doi:10.4172/2332-2594.1000138.

RESCAP, UNDP, and RIMES, 2016; Assessment of El Niño-Associated Risks: *The Step-Wise Process*,

Reynès, F. 2011; The cobb-douglas function as an approximation of other functions, Pre-print, *The HAL Archive*, available at: https://hal-sciencespo.archives-ouvertes.fr/hal-01069515

Riaz, B., S. Ali, and D. Jan, 2014; Acreage Response Analysis of Maize Growers in Khyber Pakhtunkhwa, Pakistan; International Journal of Food and Agricultural Economics, Vol. 2 (3); pp 33 – 44.

Richards, M., E. L. Wollenberg, and S. B. Gluck, 2015; Agriculture's contribution to national emissions; *Analysis of national reports to the UN Framework Convention on Climate Change*, CCAFS.

Rosell, S. and B. Holmer, 2007; Rainfall change and its implications for Belg harvest in South Wollo, Ethiopia, *Geogr. Ann.Series,* Vol.89 (4): pp 287–299.

Roy, T. D. and K. K. Das, 2013; Temperature Trends at Four Stations of Assam during the period 1981-2010, *International Journal of Scientific and Research Publications*, Vol. 3(6), pp 1 – 3.

Sadoulet, E., and A. de Janvry. 2003. Quantitative development policy analysis. Baltimore: Johns Hopkins University Press.

Saha, A., C. Shumway, and A. Havenner, 1997; The economics and econometrics of damage control, *American Journal of Agricultural Economics*, Vol. **79**, pp 773-785.

Saros, D. E., 2022; Theories of Utility Maximization, LibreTexts, available at: https://socialsci.libretexts.org/@go/page/46254.

Samuel, G. and Sharp, K. 2007; Commercialization of Smallholder Agriculture in Selected Tef-Growing Areas of Ethiopia, *Ethiopian Journal of Economics*, Vol. XV, No 1: pp 55 – 86.

Sandhu, A.N, and A. Singh, 1983; *Fundamentals of Agricultural Economics*. Himalaya Publishing House. Bombay.

Schimmelpfennig**,** D., J. Lewandrowski, J.Reilly, M. Stigas, and I. Parry, 1996: Agricultural Adaptation to Climate Change: Issues of Long Run Sustainability.

Agricultural Economic Report No. 740, U.S., Department of Agriculture, Washington, DC, USA, pp 53.

Seleshi, Y. and U. Zanke, 2004; Recent changes in rainfall and rainy days in Ethiopia, *Int. J. Climatol.* Vol24: pp 973–983.

Saei, M., H. Mohammadi, S. Ziaee, and S. B. Dourbash, **2019**; The impact of climate change on grain yield and yield variability in iran, *Iranian Economic Review*, Vol. 23 (2), pp. 509-531

Seo, N. S., R. Mendelsohn, and M. Munasinghe, 2006, “Climate Change and Agriculture in Sri Lanka: A Ricardian Valuation”, *Environment and Development Economics* Vol.10: pp 581-596.

Shah, M.M., G. Fischer, and H. van Velthuizen, 2008; Food security and sustainable agriculture: *The challenges of climate change in Sub-Saharan Africa*. International Institute for Applied Systems Analysis, Laxenburg. Austria.

Shamsher, S. A. 2017; What model suits best the mix of I(1) and I(0) variables?. *Retrieved from*: *https://www.researchgate.net/post/What_model_suits_best_the_mix_of_I(1) &_I(0)_variables/*.

Sharma, S. and S. Singh, 2019; The Validity of Wagner’s Law in India: A Post-liberalisation Analysis, M.J.P. Rohilkhand University, Uttar Pradesh, India.

Shakoor, U., et al, 2017; Maize production response to climate change in Pakistan: A time series assessment. *Sarhad Journal of Agriculture*, 33(2): pp 320-330.

Shumetie, A. *et al*, 2017; Impact of Climate Variability on Cool Weather Crop Yield in Ethiopia, *International Journal of Agricultural Management and Development (IJAMAD), Available online on: www.ijamad.iaurasht.ac.ir*.

Siahi, W. V. *et al*, 2018; Effect of Climate Change on Maize Productivity in Kenya: A Vector Error Correction Model, *IOSR Journal of Economics and Finance (IOSR-JEF)*, Vol. 9(2), PP 28-33.

Sibiko, K.W., Mwangi, J.K., Gido, E.O., Ingasia, O.A. and Mutai, B.K. 2013; Allocative efficiency of smallholder common bean producers in Uganda: A stochastic frontier and Tobit model approach. *International Journal of Development and Sustainability*, Vol. 2 (2): pp 640-652. Available at http://www.isdsnet.com/ijds.

Singh, R. *et al*, 2017; Impact of Rainfall and Temperature on the Yield of Major Crops in Gujarat State of India: A Panel Data Analysis (1980-2011), *Journal of Applied Science and Technology*, Vol. 24(5): pp 1-9.

Singh, R. P., Hans P. Binswanger and N. S. Jodha, 1985; Manual of Instructions for Economic Investigators in ICRISAT's Village-Level Studies, International Crop Research Institute for the Semi-Arid Tropics, Hyderabad, India.

Skambraks, A., 2014; Smallholder farmers' adaptation to climate change in Zenzelima, Ethiopia: A case study; Unpublished Masters Dissertation, University of Natural Resources and Life Sciences, Vienna.

Smith, P., D. Martino, Z. Cai, D. Gwary, H. Janzen, P. Kumar, B. McCarl, S. Ogle, F. O'Mara, and C. Rice, **2007;** Policy and technological constraints to implementation of greenhouse gas mitigation options in agriculture. *Agric. Ecosyst. Environ*., Vol. 118, pp 6–28.

Solomon, B. W., 2017: LONG RUN DETERMINANTS OF CEREAL PRODUCTION IN ETHIOPIA: DOES CO2 EMISSION MATTER? *International Journal of Food and Agricultural Economics*, Vol. 5 (2), pp. 109-119.

Solomon, R, B. Simane, and B. F. Zaitchik, 2021; The Impact of Climate Change on Agriculture Production in Ethiopia: Application of a Dynamic Computable General Equilibrium Model, *American Journal of Climate Change*, Vol. 10, pp 32-50.

Ssekuma, R., 2011; A study of cointegration models with applications; Unpublished Master of Commerce Dissertation, University of South Africa.

Stern, N. 2007; The Economics of Climate Change: The Stern Review, p. 3, Cambridge University Press: Cambridge.

Subash N, and H.S.R. Mohan, 2011; Trend detection in rainfall and evaluation of standardized precipitation index as a drought assessment index for rice wheat productivity over IGR in India. *Int J Climatol*; 31: pp 1694–709.

Taffesse, A, S. 1998; An Economic Model of the Ethiopian Household; Working Paper Series, Department of Economics, Addis Ababa University.

Tafoughalti, K., E. M. El Faleh, Y. Moujahid and F. Ouargaga, 2018; Climate Change Impact on Rainfall: How will Threaten Wheat Yield?, E3S Web of Conferences **37**, 03001, available at https://doi.org/10.1051/e3sconf/20183703001.

Tamiru, S., K. Tesfaye and G. Mamo, 2015; Analysis of rainfall and temperature to guide sorghum (*Sorghum Bicolar*) production in Miesso areas, eastern Ethiopia, *International Journal of Sustainable Agricultural Research,* Vol. 2 (1), pp.1-11.

Taye, M.T. and P. Willems, 2012; Temporal variability of hydroclimatic extremes in the Blue Nile basin.*Water Resources Research*, 48, W03513, doi:10.1029/2011, WR011466.

Tchereni, B. H. and T. H. Tchereni, 2013; Supply Response of Maize to Price and Non-Price Incentives in Malawi, *Journal of Economics and Sustainable Development,* Vol. 4(5), pp 141 – 153.

Tembo, F. M, 2018; The Impact of Climate Change on Teff Production in Southeast Tigray, Ethiopia, Journal of Agricultural Economics and Rural Development Vol. 4(1), pp. 389-396.

Tesso, G. Emana, B. and Ketema, M. 2012; A time series analysis of Climate variability and its impacts on food production in North Shea Zone in Ethiopia, *African Crop Science Journal*, Vol. 20, pp. 261 – 274.

Thomas,T., P. Dorosh and R. Robertson, 2019; Climate change impacts on crop yield in Ethiopia; ESSP Working Paper 130, IFPRI.

Tripathi, A., 2019; Profit Maximization Theory and Value Maximization Theory; *International Journal of Scientific Development and Research,* Vol. 4 (6): pp 284 – 289.

Von Braun. J. 1991; A Policy Agenda for Famine Prevention in Africa, *International Food Policy Research Institute* (IFPRI) - Food Policy Statement #13.

Vikas, V. M. and S. K. Goyal, 2018; Estimation of Acreage Response of Major Crops in Haryana using Co-integration Approach. *Int.J.Curr.Microbiol.App.Sci.* 7(03): pp 2890-2903.

Wagesho, N., 2016; Analysis of rainfall variability and farmers' perception towards it in agrarian community of Southern Ethiopia, Journal of Environmental and Earth Science, Vol. 6(4): pp 99 – 107.

Wagesho, N., N.K. Goel, and M.K. Jain, 2013; Temporal and spatial variability of annual and seasonal rainfall over Ethiopia, *Hydrological Sciences Journal*, Vol. 58 (2), pp 354–373.

Waqas, M., S. Ali, S.A. Shah and G. Ali, 2019; Supply response of unirrigated wheat in Khyber Pakhtunkhwa, Pakistan: ARDL approach. *Sarhad Journal of Agriculture*, Vol. 35(3): pp 902-912.

Wang, T., *et al*, 2011; Production potential and yield gaps of summer maize in the BeijingTianjin-Hebei Region. *Journal of Geographical Sciences* Vol. 21, pp 677-688.

Warwade, P., N. Sharma, B. Ahrens and A. Pandey, 2015; Characterization and analysis of the trend of climate variable (temperatures) for the North Eastern Region of India, *International Journal of Recent Scientific Research,* Vol. 6(4): pp.3618-3624.

Wei, T. *et al*. 2014; Climate change impacts on crop yield: *Evidence from China*; *Center for International Climate and Environmental Research*, Oslo, Norway.

Weldegerima, T. M. *et al*, 2018; Analysis of rainfall trends and its relationship with SST signals in Lake Tana Basin, Ethiopia; Advances in Meteorology, available at: https://doi.org/10.1155/2018/5869010.

White, J.W., D.G. Tanner, and J.D. Corbett. 2001; *An Agro-Climatological Characterization of Bread Wheat Production Areas in Ethiopia. NRG-GIS Series* 01-01. Mexico, D.F.: CIMMYT.

Winch, T., 2006; *Growing Food,* Dordrecht: Springer.

Wooldridge, J. M., 2013; *Introductory Econometrics*. *A Modern Approach,* South Western Cengage Learning, pp. 868.

World Bank Group, 2020; Ethiopia: Climate Risk Profile, Washington, DC, www.worldbank.org

WMO (World Meteorology Organization), 2020; 2010-2019 confirmed as warmest decade in history, available at: https://unric.org/en/2010-2019-confirmed-as-warmest-decade-in-history/.

Wust, R. 2008; Review of Climate Change*: A Multidisciplinary Approach (Second Edition)*, by W. J. Burroughs, *Oceanography,* Vol. 21(4): pp 208–209, http://dx.doi.org/10.5670/oceanog.2008.28.

United Nations, 2022; What is Climate Change? Climate Action, available at: https://www.un.org.

USAID, 2016; Ethiopia: Climate Change Risk Profile, Fact Sheet. Available at: https://www.climatelinks.org/sites/default/files/asset/.

Yadav, S., A.K. Sachan and D. Basu, 2019; Decadal trend analysis of rainfall over Uttar Pradesh (India), *Disaster Advances,* Vol. 12 (2): pp 1- 7.

Yalew, A. W, 2018; Climate Change, Agriculture, and Economic Development in Ethiopia, *Sustainability*, Vol. 10: pp 1 – 23.

Yalew, A. W., 2016; Economy-wide Effects of Climate Change in Ethiopia, Paper presented at International Conference on Economic Modeling (EcoMod2016), Lisbon, Portugal.

Yibrah, M., D. Korecha and T. Dandesa, 2018; Characterization of Rainfall and Temperature Variability to Guide Wheat (*Triticum Aestivum*) and Barley (*Horduem Vulgare*) Production in Enderta*District*, Southeastern Tigray, Ethiopia, *International Journal of Research in Environmental Science,* Vol. 4 (2), PP 35-41.

Yihenew, Z., Amdissa, T. and Kassahun, B.; 2013; Drivers' of success for CAADP implementation Ethiopia, *A case study*.

You, L. *et al*, 2009; Impact of growing season temperature on wheat productivity in China. *Agric. Forest Meteorol.* Vol. 149 (6–7), pp 1009–1014.

Yu, B., T. Zhu, C. Breisingeret, and N. M. Hai, 2010; Impacts of Climate Change on Agriculture and Policy Options for Adaptation: *The Case of Vietnam*; IFPRI Discussion Paper 01015, IFPRI.

Yuan. C., S. Liu, and J. Wu, 2009; Research on energy-saving effect of technological progress based on Cobb–Douglas production function, *Energy Policy*, Vol. 37(8): pp 2842-2846.

Yumbya, J. *et al*, 2014; Assessing the effects of climate change on teff in Ethiopia: *implications for food security*, *Technical Report*, African Biodiversity Conservation and Innovations Centre (ABCIC), pp 1 – 39.

Yumbya, J., Kiambi, D., Kebebew, F. and Rao, K. P. C., 2011; Climate Change Effects on Teff Geographic Ranges and Its Impacts on Yield. *Poster, African Biodiversity Conservation and Innovations Centre* (ABCIC), Kenya.

Zelenáková, M.,*et al*, 2018; Trends in Precipitation and Temperatures in Eastern Slovakia (1962–2014), Water, 10, 727; doi:10.3390/w10060727;

Zaied, Y. B. and O. Zouabi, 2015; Climate change impacts on agriculture: A panel cointegration approach and application to Tunisia, University of South Toulon.

Zhai, S., Song, G., Qin, Y., Ye, X. and Lee, J. 2017; "Modeling the impacts of climate change and technical progress on the wheat yield in inland China: an autoregressive distributed lag approach", *PloS One*, Vol. 12 (9), pp eo184474.

Zhang, T. *et al*., 2013; Climatic and technological ceilings for Chinese rice stagnation based on yield gaps and yield trend pattern analysis, Global Change Biology.

Zhang, T. *et al*., 2008: Correlation changes between rice yields in North and Northwest China and ENSO from 1960 to 2004, *Agricultural and Forest Meteorology*; Vol. 148: pp 1021-1033.

APPENDICES

Appendix 2.1: List of weather stations selected for this study

Stations Selected		Zone	Region
1	Gondar	North Gondar	Amhara
2	Woreta	South Gondar	,,
3	Bahir Dar	West Gojam	,,
4	Dangila	Awi	,,
5	Motta	East Gojam	,,
6	Debre Berihan	North Shewa – A	,,
7	Kombolcha	South Wollo	,,
8	Fiche	North Shewa – O	Oromia
9	Chefedonsa	East Shewa	,,
10	Debrezeit	,, ,,	,,
11	Arsi Negele	West Arsi	,,
12	Sinana	Bale	,,
13	Kulumsa	Arsi	,,
14	Arsi Robe	,,	,,
15	Woliso	S/West Shewa	,,
16	Bako	West Shewa	,,
17	Shambu	Horogudru	,,
18	Jimma	Jimma	,,
19	Bedele	Ilubabor	,,
20	Nekemte	East Ellega	,,

Appendix 6.1: Unit Root Test Results

Variables	Type of Test	Form of Test	P-Value	Conclusion
Teff Output Data Series				
LNTEFO	ADF	Intercept	0.9794	Non-stationary
		Trend & intercept	0.0658	Non-stationary
		First difference	0.0000	Stationary (I(1))
	PP	Intercept	0.0833	Non-stationary
LNART	ADF	Intercept	0.8421	Non-stationary
		Trend & intercept	0.0836	Non-stationary
		First difference	0.0000	Stationary (I(1))
	PP	Intercept	0.0846	Non-stationary
LNFERT	ADF	Intercept	0.8719	Non-stationary
		Trend & intercept	0.0444	Non-stationary
		First difference	0.0002	Stationary (I(1))
	PP	Intercept	0.9824	Non-stationary
LNPRIT	ADF	Intercept	0.8524	Non-stationary
		Trend & intercept	0.7290	Non-stationary
		First difference	0.0006	Stationary (I(1))
	PP	Intercept	0.8511	Non-stationary
LNTEMP	ADF	Intercept	0.0126	Stationary (I(0))

Variables	Type of Test	Form of Test	P-Value	Conclusion
		Trend & intercept	0.0446	
	PP	Intercept	0.0350	
LNRAINBEL	ADF	Intercept	0.0000	
		Trend & intercept	0.0003	Stationary (I(0))
	PP	Intercept	0.0003	
LNRAINMEH	ADF	Intercept	0.1217	
		Trend & intercept	0.0003	Stationary (I(0))
	PP	Intercept	0.0002	
LNCO2	ADF	Intercept	0.0447	
		Trend & intercept	0.0022	Stationary (I(0))
	PP	Intercept	0.0015	
Wheat Output Data Series				
LNWHO	ADF	Intercept	0.9964	Non-stationary
		Trend & intercept	0.1814	Non-stationary
		First difference	0.0000	Stationary (I(1))
	PP	Intercept	0.9990	Non-stationary
LNPRIWH	ADF	Intercept	0.8433	Non-stationary
		Trend & intercept	0.6849	Non-stationary
		First difference	0.0001	Stationary (I(1))

Variables	Type of Test	Form of Test	P-Value	Conclusion
	PP	Intercept	0.8540	Non-stationary
LNARWH	ADF	Intercept	0.8794	Non-stationary
		Trend & intercept	0.3331	Non-stationary
		First difference	0.0000	Stationary (I(1))
	PP	Intercept	0.9048	Non-Stationary
LNFERTWH	ADF	Intercept	0.8468	Non-stationary
		Trend & intercept	0.0229	Stationary (I(0))
		First difference	0.0000	Stationary (I(1))
	PP	Intercept	0.9539	Non-stationary
LNTEMP	ADF	Intercept	0.0126	
		Trend & intercept	0.0446	Stationary (I(0))
	PP	Intercept	0.0102	
LNRAINBEL	ADF	Intercept	0.0000	
		Trend & intercept	0.0003	Stationary (I(0))
	PP	Intercept	0.0000	
LNRAINMEH	ADF	Intercept	0.1217	Non-stationary
		Trend & intercept	0.0003	Stationary (I(0))
	PP	Intercept	0.0001	
LNCO2	ADF	Intercept	0.0447	Stationary (I(0))

Variables	Type of Test	Form of Test	P-Value	Conclusion
		Trend & intercept	0.0022	
	PP	Intercept	0.0553	
Maize Output Data Series				
LNMZO	ADF	Intercept	0.8542	Non-stationary
		Trend & intercept	0.0152	
		First difference	0.0000	Stationary (I(1))
	PP	Intercept	0.0168	
LNPRIMZ	ADF	Intercept	0.6681	Non-stationary
		Trend & intercept	0.1665	Non-stationary
		First difference	0.0000	Stationary (I(1))
	PP	Intercept	0.1779	Non stationary
LNARMZ	ADF	Intercept	0.7695	Non-stationary
		Trend & intercept	0.0901	Stationary (I(1))
		First difference	0.0001	
	PP	Intercept	0.1544	Non-stationary
LNFERTMZ	ADF	Intercept	0.9438	Non -stationary
		Trend & intercept	0.1503	Non-stationary
		First difference	0.0000	Stationary (I(1))
	PP	Intercept	0.1642	Non-stationary

Variables	Type of Test	Form of Test	P-Value	Conclusion
LNTEMP	ADF	Intercept	0.0126	
		Trend & intercept	0.0446	Stationary (I(0))
	PP	Intercept	0.0102	
LNRAINBEL	ADF	Intercept	0.0000	
		Trend & intercept	0.0003	Stationary (I(0))
	PP	Intercept	0.0000	
LNRAINMEH	ADF	Intercept	0.1217	
		Trend & intercept	0.0003	Stationary (I(0))
	PP	Intercept	0.0001	
Teff Yield Data Series				
LNTY	ADF	Intercept	0.9198	Non-stationary
		Trend & intercept	0.1801	Stationary (I(1))
		First difference	0.0000	
	PP	Intercept	0.8448	Non-stationary
LNART	ADF	Intercept	0.8421	Non-stationary
		Trend & intercept	0.0836	Non-stationary
		First difference	0.0000	Stationary (I(1))
	PP	Intercept	0.9337	Non-stationary
LNIMS	ADF	Intercept	0.8032	Non-stationary

Variables	Type of Test	Form of Test	P-Value	Conclusion
		Trend & intercept	0.4574	Stationary (I(0))
		First difference	0.0000	Stationary (I(1))
	PP	Intercept	0.3592	Stationary (I(0))
LNFERT	ADF	Intercept	0.8719	Non-stationary
		Trend & intercept	0.0444	Stationary (I(0))
		First difference	0.0002	Stationary (I(1))
	PP	Intercept	0.9824	Non-stationary
LNIRRGAT	ADF	Intercept	0.6267	Non-stationary
		Trend & intercept	0.0014	Stationary (I(0))
		First difference	0.0001	Stationary (I(1))
	PP	Intercept	0.3372	Stationary (I(0))
MEANRAIN	ADF	Intercept	0.0000	
		Trend & intercept	0.0000	Stationary (I(0))
	PP	Intercept	0.0000	
MINTEMP	ADF	Intercept	0.0847	Non-stationary
		Trend & intercept	0.0040	Stationary (I(0))
		First difference	0.0000	Stationary (I(1))
	PP	Intercept	0.0847	Non-stationary
MAXTEMP	ADF	Intercept	0.6878	Non-stationary

Variables	Type of Test	Form of Test	P-Value	Conclusion
		Trend & intercept	0.0358	Stationary (I(0))
		First difference	0.0000	Stationary (I(1))
	PP	Intercept	0.0840	Non-stationary
Wheat Yield Data Series				
LNWY	ADF	Intercept	0.9922	Non-stationary
		Trend & intercept	0.4064	Stationary (I(0))
		First difference	0.0000	Stationary (I(1))
	PP	Intercept	0.8896	Non-stationary
LNARW	ADF	Intercept	0.8421	Non-stationary
		Trend & intercept	0.0836	Non-stationary
		First difference	0.0000	Stationary (I(1))
	PP	Intercept	0.9337	Non-stationary
LNIMS	ADF	Intercept	0.9829	Non-stationary
		Trend & intercept	0.0005	Stationary (I(0))
		First difference	0.0002	Stationary (I(1))
	PP	Intercept	0.3142	Stationary (I(0))
LNFERTW	ADF	Intercept	0.8719	Non-stationary
		Trend & intercept	0.0444	Stationary (I(0))
		First difference	0.0002	Stationary (I(1))

Variables	Type of Test	Form of Test	P-Value	Conclusion
	PP	Intercept	0.9824	Non-stationary
LNIRRGAW	ADF	Intercept	0.6757	Non-stationary
		Trend & intercept	0.1225	Non-stationary
		First difference	0.0000	Stationary (I(1))
	PP	Intercept	0.3013	Non-stationary
MEANRAIN	ADF	Intercept	0.0000	
		Trend & intercept	0.0000	Stationary (I(0))
	PP	Intercept	0.0000	
MINTEMP	ADF	Intercept	0.0847	Non-stationary
		Trend & intercept	0.0040	Stationary (I(0))
		First difference	0.0000	Stationary (I(1))
	PP	Intercept	0.0847	Non-stationary
MAXTEMP	ADF	Intercept	0.6878	Non-stationary
		Trend & intercept	0.0358	Stationary (I(0))
		First difference	0.0000	Stationary (I(1))
	PP	Intercept	0.0840	Non-stationary
Maize Yield Data Series				
LNMZY	ADF	Intercept	0.7798	Non-stationary
		Trend & intercept	0.6891	Non-stationary

Variables	Type of Test	Form of Test	P-Value	Conclusion
		First difference	0.0001	Stationary (I(1))
	PP	Intercept	0.5408	Non-stationary
LNARMZ	ADF	Intercept	0.7695	Non-stationary
		Trend & intercept	0.0901	Non-stationary
		First difference	0.0001	Stationary (I(1))
	PP	Intercept	0.6588	Non-stationary
LNIMS	ADF	Intercept	0.9110	Non-stationary
		Trend & intercept	0.6941	Non-stationary
		First difference	0.0000	Stationary (I(1))
	PP	Intercept	0.9627	Non-stationary
LNFERTMZ	ADF	Intercept	0.8719	Non-stationary
		Trend & intercept	0.0444	Stationary (I(0))
		First difference	0.0002	Stationary (I(1))
	PP	Intercept	0.9824	Non-stationary
LNIRRGARMZ	ADF	Intercept	0.4940	Non-stationary
		Trend & intercept	0.4383	Non-stationary
		First difference	0.0001	Stationary (I(1))
	PP	Intercept	0.5359	Non-stationary
MEANRAIN	ADF	Intercept	0.0000	Stationary (I(0))

Variables	Type of Test	Form of Test	P-Value	Conclusion
		Trend & intercept	0.0000	
	PP	Intercept	0.0000	
MINTEMP	ADF	Intercept	0.0847	Non-stationary
		Trend & intercept	0.0040	Stationary (I(0))
		First difference	0.0000	Stationary (I(1))
	PP	Intercept	0.0847	Non-stationary
MAXTEMP	ADF	Intercept	0.6878	Non-stationary
		Trend & intercept	0.0358	Stationary (I(0))
		First difference	0.0000	Stationary (I(1))
	PP	Intercept	0.0840	Non-stationary

Critical val. at 5% sig level

Source: Authors' Computation

Appendix 6.2: Diagnostic Tests Results for Crop Output Response Equations

Appendix 6.2.1: Residual Properties of Teff Output Response Equation

Type of test	Test statistic	Test statistic value	Probability
Normality test-histogram	Jarque Berra	46.59	0.000
Breusch-Godfrey Serial Correlation LM Test	Obs*R-squared	4.4867	0.106
Heteroskedasticity Test: ARCH	Obs*R-squared	0.01746	0.895

Appendix 6.2.2: Residual Properties of Wheat Output Response Equation

Type of test	Test statistic	Test statistic value	Probability
Normality test-histogram	Jarque Berra	0.2365	0.8885
Breusch-Godfrey Serial Correlation LM Test	Obs*R-squared	0.556336	0.7572
Heteroskedasticity Test: ARCH	Obs*R-squared	2.626617	0.1051

Appendix 6.2.3: Residual Properties of Maize Output Response Equation

Type of test	Test statistic	Test statistic value	Probability
Normality test-histogram	Jarque Berra	0.6419	0.7254
Breusch-Godfrey Serial Correlation LM Test	Obs*R-squared	2.18476	0.3354
Heteroskedasticity Test: ARCH	Obs*R-squared	3.72449	0.0536

Appendix 6.3: Ramsey Reset Tests Results

Dependent variable	F statistic	Probability	conclusion
Log of teff output	2.83957	0.1035	No indication of misspecification error
Log of wheat output	0.425344	0.6582	No indication of misspecification error
Log of maize output	3.34726	0.0780	No indication of misspecification error

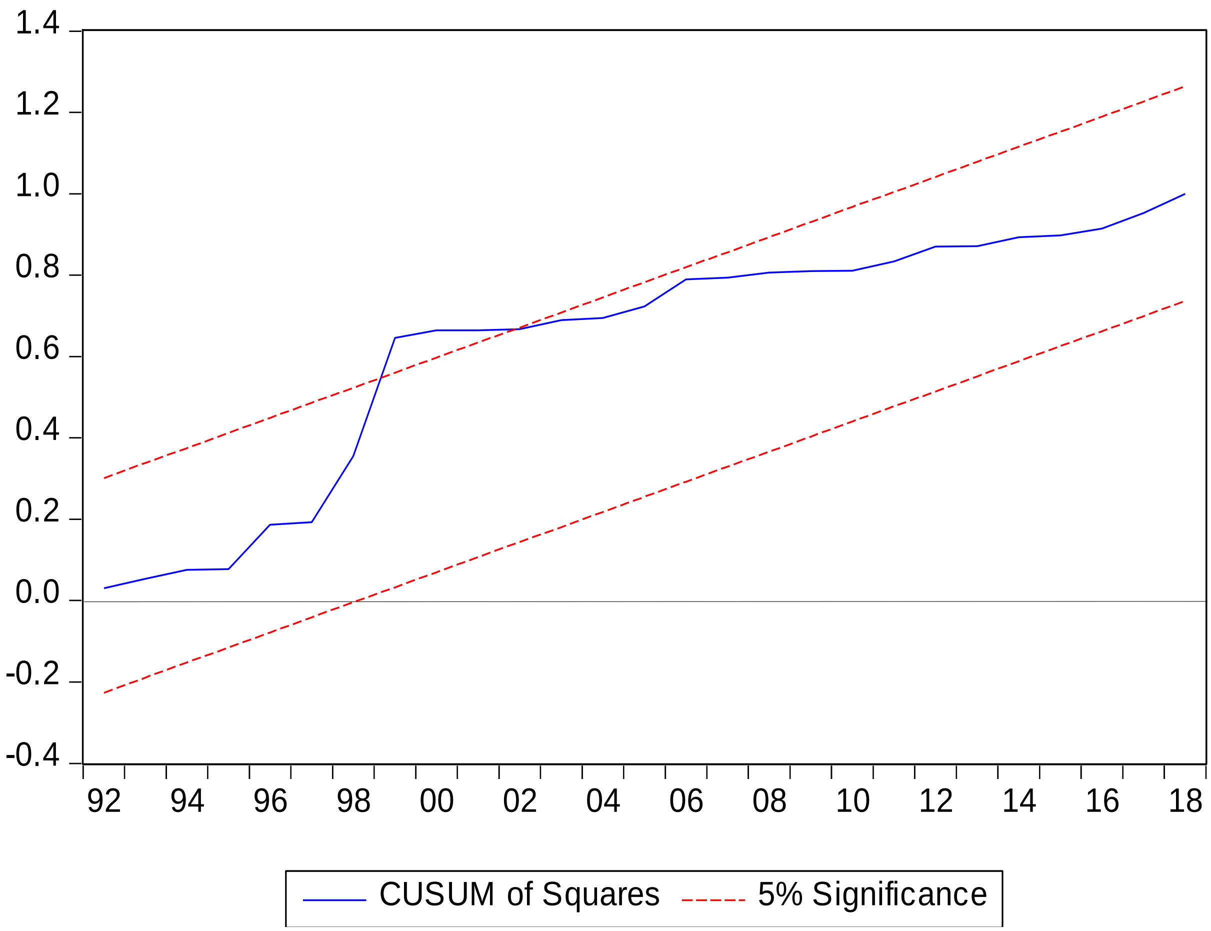


Figure 6.1: Recursive Residuals from the Teff Output Response Equation

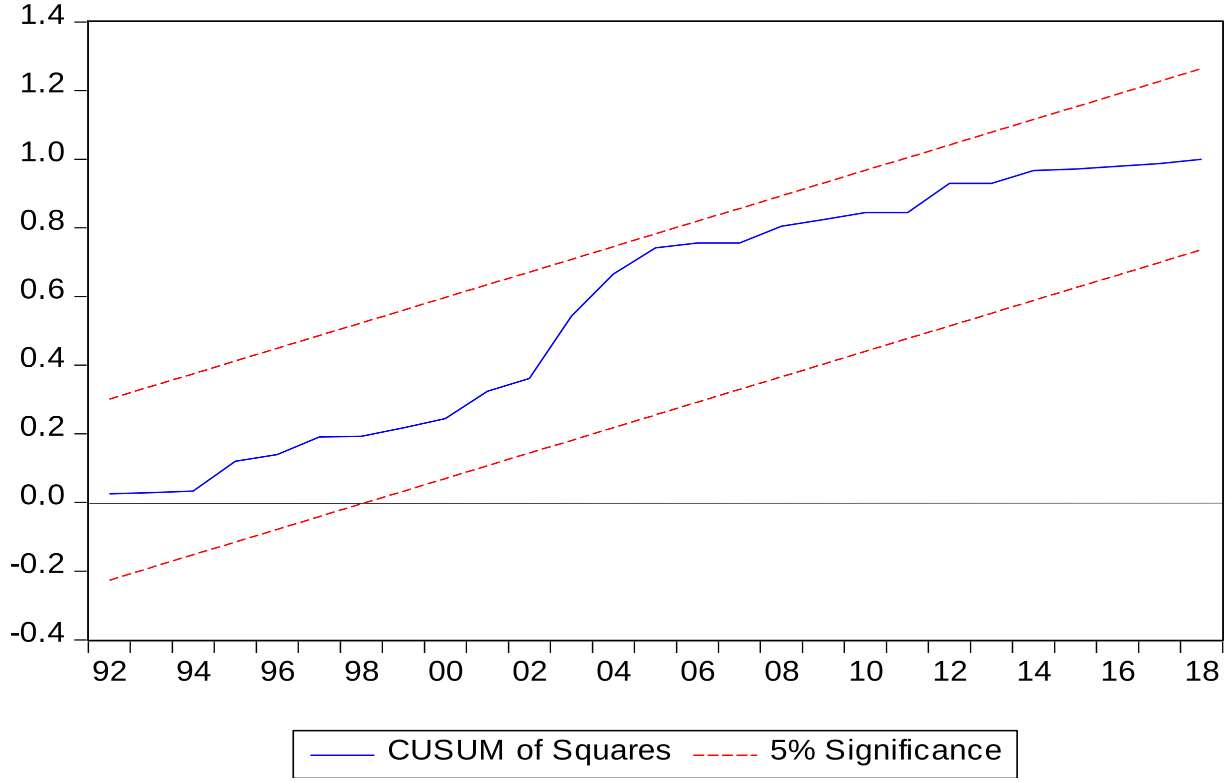


Figure 6.2: Recursive Residuals from the Wheat Output Response Equation

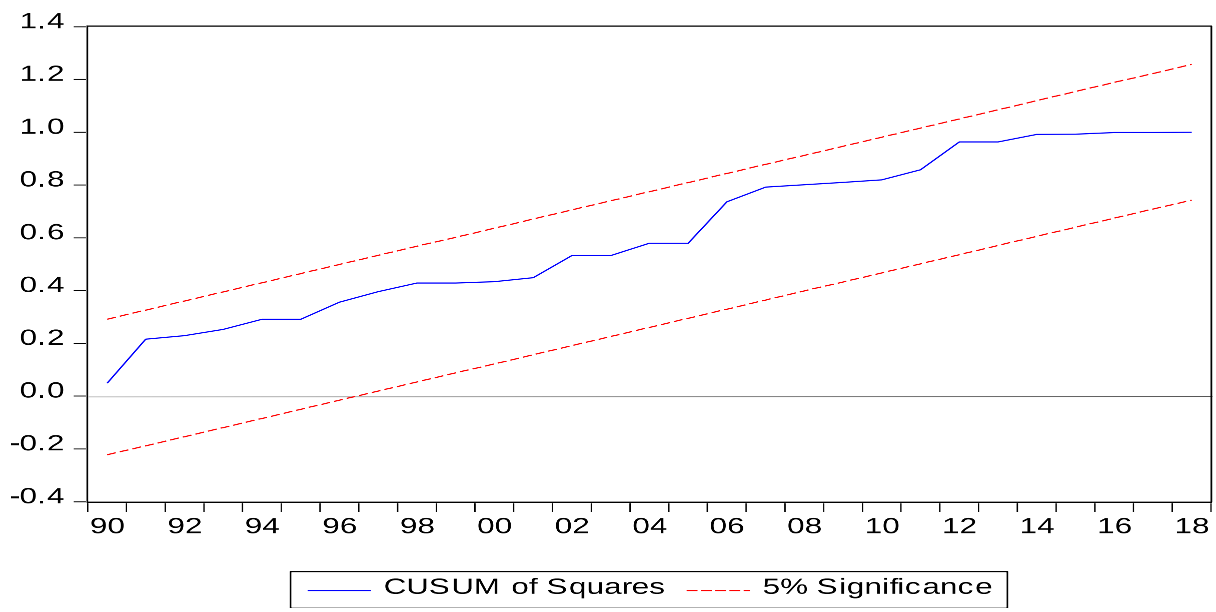


Figure 6.3: Recursive Residuals from the Maize Output Response Equation

Appendix 6.4: Lag Order Selection Criteria for teff, wheat and Maize Output Supply

Appendix 6.4.1: Teff Output Supply

Endogenous variables: log teff output, log price teff, log area, log fertilizer quantity, log temperature (F-S), log rain short-rainfall (F-M), log rain long-rainfall (J-S), log CO2.

Exogenous variables: C; Sample: 1981 - 2018; included observations: 38

Lag	LogL	LR	AIC	SC	HQ
0	11.41753	51.81631	-1.489795	-0.390129	-1.105982
1	36.76531	0.678786*	-0.709184	-0.346495	-0.340723
2	63.61453	2.026397	-1.72548*	-0.347885*	-1.380226*

Appendix 6.4.2: Wheat Output Supply

Endogenous variables: log wheat output, log price heat, log area under wheat, log fertilizer quantity used, log temperature (F-S), log rain short-rainfall (F-M), log rain long-rainfall (J-S), and log CO2.

Exogenous variables: C; Sample: 1981 - 2018; included observations: 38

Lag	LogL	LR	AIC	SC	HQ
0	35.56612	0.6137	-1.381952	-0.946569	-1.228460
1	52.66855	0.6137	-1.449423	-0.752810	-1.224237
2	53.67498	0.3758*	-1.534974*	-1.099591*	-1.381481*

Appendix 6.4.3: Maize Output Supply

Endogenous variables: log maize output, log price of maize, log area under maize, log fertilizer q. used, log temperature (F-S), log rain short-rainfall (F-M), and log rain long-rainfall (J-S).

Exogenous variables: C ; Sample: 1981 - 2018; Included observations: 38

Lag	LogL	LR	AIC	SC	HQ
0	44.84488	0.0445	-1.102493	-0.002827	-0.718680*

1	42.70264	0.0445	-1.039036	0.016644	-0.670575
2	77.03026	0.0001*	-1.151125*	-2.082272*	2.126944

* indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5%level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

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