IMPACTS OF CLIMATE CHANGE ON DURUM WHEAT(*Triticum turgidum L var durum*) PRODUCTION: ANALYSIS OF FUTURE ADAPTATION MEASURES IN THE CENTRAL RIFT VALLEY OF ETHIOPIA

M.SC. THESIS

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Impacts of Climate Change on Durum Wheat (*Triticum turgidum L var durum)* Production: Analysis of Future Adaptation Measures in the Central Rift Valley of Ethiopia

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I hereby certify that I have read and evaluated this thesis prepared, under our guidance, by **Olivier Abayisenga,** entitled**: Impact of Climate Change on Durum Wheat** (*Triticum turgidum L var durum)* **Production: Analysis of Future Adaptation Measures in the Central Rift Valley of Ethiopia,** I recommend that it be submitted as fulfilling the Thesis requirement.

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As member of the Board of Examiners of the MSc. Thesis Open Defense Examination, we certify that we have read, evaluated the Thesis prepared by Olivier Abayisenga and examined the candidate. We recommended that the Thesis be accepted as fulfilling the Thesis requirement for the Degree of Master of Science in Agrometeorology and Natural Risk Management.

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Final approval and acceptance of the Thesis is contingent upon the submission of its final copy to the Council of Graduate Study (CGS) through the candidates department or school graduate committee (DGC or SGC).

DEDICATION

I dedicate this thesis manuscript to my father **Gustave Mayimbikiza** and my mother **Suzanne Bakundukomeye.**

STATEMENT OF THE AUTHOR

By my signature below, I declare and affirm that this thesis is my own work. I have followed all ethical and technical principles of scholarship in the preparation, data collection, data analysis and compilation of this thesis. Any scholarly matter that is included in the Thesis has been given recognition through citation.

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BIOGRAPHICAL SKETCH

The author was born in 1983 in Burundi, Rumonge Province, 86 km away from Bujumbura, the capital city, to his mother Suzanne Bakundukomeye and his father Gustave Mayimbikiza. He attended his primary school at Mugara in Rumonge Province and secondary school at Mugara (Lycee of Mugara) and Rumonge Secondary School (Lycee of Rumonge). He joined the University of Burundi in 2005/2006 academic year and graduated with B.Sc. degree in General Agronomy as Engineer Agronomist in February, 2012. Soon after his graduation, he was employed by Non-Government Organization. First, as the project Coordinator of National Association for Environment Assessment. This is involved in regional network which gathers professionals in environmental assessment from all Central African Countries: Secretariat for Environmental Assessment in Central Africa "SEACA. Second, as Assistant Coordinator in ADISCO projects (Empowering Communities) worked directly with farmers through agriculture cooperatives focusing on agriculture production and livestock until October 2013, where he joined the School of Graduate Studies at Haramaya University in 2013/14 academic year to pursue his MSc program in Agrometeorology and Natural Risk Management.

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ABBREVIATIONS AND ACRONOMYS

AMCEN	The African Ministerial Conference on the Environment
AOGCM	Atmosphere-Ocean General Circulation Model
AR4	Fourth Assessment Report
CERES	Crop Environment Resource Synthesis
CLL	Crop Lower Limit
CO_2	Carbon Dioxide
CSA	Central Statistical Agency
CRV	Central Rift Valley
CV	Coefficient of Variation
DSSAT	Decision Support System for Agrotechnology Transfer
DUL	Drained Upper Limit
DZARC	Debre Zeit Agricultural Research Center
EIAR	Ethiopian Institute of Agricultural Research
ETo	Reference Crop Evapotranspiration
FC	Field Capacity
GDD	Growing Degree Days
GCM	Global Circulation Model
GDP	Gross Domestic Product
GHG	Green House Gases
HadCM3	Hadley Centre Coupled Model, version 3
LAI	Leaf Area Index
LGP	Length of Growing Period
MARC	Melkassa Agricultural Research Center
NMA	National Meteorology Agency
PWP	Permanent Wilting Point
SD	Standard Deviation
SRES	Special Report on Emission Scenarios

ABBREVIATIONS AND ACRONOMYS (Continued)

SSA	Sub Sahara Africa
SDSM	Statistical Downscaling Model
WRB	World Reference Base
WRSI	Water Requirement Satisfaction Index

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Impacts of Climate Change on Durum Wheat (*Triticum turgidum L var durum*) Production: Analysis of Future Adaptation Measures in Central Rift Valley of Ethiopia

ABSTRACT

Assessing impact of climate change on durum wheat production and analysis of future adaptation measures bears enormous advantages in general and in Ethiopia in particular, owing to the country's low adaptative capacity.The analysis shows that climate change will reduce durum wheat production in Central Rift Valley through time horizons i.e till the year 2030s, 2050s and 2080s.This study was conducted to characterize climate, assess its impact on durum wheat production and identify management options for the climate future dates in Ada'a district of the Central Rift Valley of Ethiopia. Daily climate data, normalized large scale Hadley Centre coupled Model version 3 model predictors and crop and soil data were analysed. Past and present climate variability characterization was assessed through seasonal rainfall amount, monthly rainfall statistics and dry spell length using R analytical tool and INSTAT climate guide. Temperature variability was examined in terms of pattern and trend. For future projection, Climate change scenarios for rainfall, minimum and maximum temperatures were developed for the period 2001-2099 by using the Hadley Centre coupled Model version 3 under A2a and B2a Special Report on Emission Scenarios using Statistical Downscaling Model version 4.1software. Decision Support System for Agro-technology Transfer, crop model was used to simulate future changes in durum wheat yield (Ude and Yerer cultivars) and to determine best adaptation measures in Ada'a area under modified environment. Seasonal rainfall amount was found to decrease with significance for 42 years period ($P<0.05$) while monthly rainfall statistics showed a high variation(CV of 80.6 to 34.4 % across months). Minimum and maximum temperatures showed an increasing trend at inter annual scale (0.21ºC per decade and 0.14ºC per decade respectively). The future projection analysis showed a decreasing trend of annual rainfall and increasing trend for temperatures during the period from 2001-2099. Accordingly, the average annual minimum temperature was found to rise in 2020, 2050 and 2080s for A2a and to decrease for B2a emission scenarios. While maximum temperature was predicted to increase in 2020, 2050s and 2080s under both emission scenarios. In 2080s, the average annual maximum temperature increment would be high for B2a scenarios. The crop model simulation indicated a positive impact on the cultivars in all time slice except in 2030 with Yerer. Furthermore, for Ude, yield will increase between 11.89 to 49.58 % across climate change scenarios relative to the baseline due to climate change by 2100s while for Yerer wheat yield will increase between 0.21 to 10.75 % across climate change scenarios relative to baseline due to climate change by 2100s. As adaptation options under changed climate conditions, Ude is the best than Yerer. And best agricultural practices have been found to be a combination of late planting date, high plant population and high fertilizer application rate. The cultivar has been found to be more sensitive on high fertilizer application rate. Therefore, growing Ude cultivar under future climate condition with improved management options such as high fertilizer application rate, improved soil water and planting in third dekad of July could ensure high yields during a good rainy season. Likewise, good yield could also be observed during a poor rainy season.

1. INTRODUCTION

Today, climate change has become one of important emerging issues and the biggest concern of mankind as a consequence of scientific evidence about the increasing concentration of greenhouse gases (GHG) in the atmosphere. Globally, temperature is increasing and the amount and distribution of rainfall is being altered differently from one region to another (IPCC, 2014a).

According to the Intergovernmental Panel on Climate Change (IPCC, 2007a, 2007b, 2014a), successive scientific assessment reports proved that global average temperature would rise between 1.4 and 5.8°C by 2100 with the doubling of the CO_2 concentration in the atmosphere, change in rainfall pattern and change in other local climate conditions (Cubash *et al.*, 2001).

The impacts of increased temperature from global warming and changes in rainfall patterns resulting from climate change are expected to reduce agricultural production and put further pressure on marginal land (Attri and Rathore, 2003; Lobell and Field, 2007; Van de Steeg *et al.*, 2009; Philip and Ralph, 2009; Travis and Daniel, 2010; FAO, 2011; Beddington *et al*., 2012; Valizadeh *et al*., 2013).

The IPCC findings from previous reports indicated that developing countries, such as Ethiopia, will be more vulnerable to projected temperature and rainfall trends. The recent fifth IPCC report officially published in 2014a indicates warming in all four seasons over Ethiopia, which may result in more frequent heat waves. In terms of projected rainfall, the climate will be wetter, with more intense wet seasons and less severe droughts in October-November-December and March-April-May.

The essentiality of Ethiopian agriculture related to climate change impacts analysis and adaptation measures is self-evidenced by agriculture's multiple roles in the country. Food security, employment, income and significant portion of GDP are drawn from agriculture. Agriculture accounts about 41 % of the GDP, 90 % of the exports, and serves as the

direct source of employment and livelihood for about 85 % of the population (NMA, 2001; Declan and Lisa, 2010; CSA, 2011).

The increasing frequency and magnitude of extreme weather events coupled with unprecedented changes in the climate is also imposing new and potentially overwhelming pressure on the capacity of existing adaptation strategies (Seleshi and Zanke, 2004; ILRI, 2006; Rosell, 2011; Arndt *et al.*, 2011). Therefore, deliberate and conscious adaptation that can cope with these evolving impacts is an immediate concern in agriculture. Particularly in countries line Ethiopia, where agriculture is highly tied with climate, adaptation is a priority (NMA, 2001; IPCC, 2014a). This lines with World Bank report (2006) that has shown that Ethiopian agriculture and in general the economy, and climate are highly intertwined. The report showed the correlation between rainfall variability and the overall performance of the country´s GDP: years of poor rainfall were associated with low GDP, whereas years with high rainfall were associated with high country‘s total and agricultural GDP.

Around three out of every four Ethiopians are engaged in agriculture, mainly in subsistence and rain-fed farming and livestock production for their livelihood. With little access to irrigation, these predominantly smallholding farmers depend on rainfall to cultivate their crops (http://www.farmafrica.org/ethiopia/ethiopia). Addressing future climate change impacts is therefore, no longer an option but it requires new level of thinking for the society to come to terms with anticipated climate change (EIAR, 2011).

Ethiopia is the largest producer of wheat in sub-Saharan Africa. The National Research Program has developed and released 31 cultivars of durum wheat which is the basic daily consumed food crop in Ethiopia (DZARC, 2014). It is cultivated on 70 % on the total wheat areas and it is one of the officially announced strategic crop for contribution to food security and livelihood improvement of smallholder farmers in Ethiopia (Kassahum *et al.*, 2014; DZARC, 2014). In the Central Rift Valley, many studies have been focused mainly on assessing impacts of climate change on maize and sorghum, very few studies empirically examine the impact of climate change on wheat (Mamo, 2005; Belay, 2014; DZARC, 2014).

On the other hand, wheat research programs have been based on improved wheat crop management practices, breeding improved wheat varieties, crop protection and fertilizer management. However, the productivity did not show significant improvement over the years. Major causes reported are low rainfall and poor distribution, , poor soil and water management (Reynolds *et al.,* 2008). Moreover, late onset of rains, intermittent dry spells and early cessation of rains are common causes of fluctuating annual production with occasional drastic reduction in crop yields (Jeffrey *et al.,* 2001; Nhemachena and Hassan, 2007, Habtamu et *al.,* 2010).

DFID commissioned Cranfield University to undertake a systematic review of the impacts of climate change on 12 agricultural productivity including wheat in Africa and South Asia. Their analysis reinforced the evidence that mean overall reduction in crop yield due to climate change was identified with significant variation for the 2030, 2050 and beyond especially for C_3 crops such as wheat (Knox *et al.,* 2001).

In addition to the clearly observed environmental condition, there is a hypothesis that climate change might reduce durum wheat yield in Central Rift Valley significantly till the year 2030s, 2050s up to 2080s mainly due to increased average temperature out of the cardinal range and reduced yearly average precipitation below the optimum required, that might affect the food security and household income.

Experiments conducted in controlled environments have provided a lot of information about the impacts of rising temperature degree and carbon dioxide concentration on plants' growth and development processes, but these studies are very costly and their implementation depends on availability of measuring instruments. Development of modeling techniques is a suitable and low-cost compared to these types of studies that has already been considered by researchers. The Decision Support System for Agrotechnology Transfer (DSSAT) is one of software most used to facilitate the evaluation and application of the crop models for different purposes (Jones *et al.,* 2003).

General circulation model (GCM) is the right and accurate tool for the projection of future climatic condition and provides necessary data to run impact models of the crops'

growth and development under climate change condition (Koocheki *et al.*, 2001; Valizadeh *et al.*, 2013).

Thus, the need for downscaling global or regional information to localized scales is becoming quite evident in the face of alternate decisions for localized adaptation. This entails the need to downscale outputs of global climate models to a local level, particularly in areas where variability in topography is high like Ethiopia. Climate change impact is global, but adaptation is local. As the signal of climate change strengthens, change in surface temperature and moisture is becoming possible at increasingly smaller scales even at a country level (Schoof *et al.*, 2008; Mengistu and Eyale, 2011; Habtamu *et al.*, 2012).

Therefore, this experiment was conducted at Debre Zeit Research Center, in the Central Rift Valley of Ethiopia. The research questions addressed in this study were (i) What is the temporal change: trend of temperature and rainfall from the year 2001 till 2099 from the base period (1970-2000) level? (ii) What is the impact of this change on the durum wheat production in Central Rift Valley? (iii) What are the possible adaptation measures to live with this change?

Objectives

General objective: To characterize climate, assess its impact on durum wheat production, and identify management options for future adaptation in Ada'a district of the Central Rift Valley of Ethiopia.

Specific objectives:

1. To characterize the climate and identify temporal changes in rainfall and temperature

2. To assess impact of climate change on grain yield of rainfed durum wheat and identify management options for future adaptation.

2. LITERATURE REVIEWS

2.1. Definitions of Climate, Climate Change and Climate Variability

This sub-section briefly explains the difference between climate, climate change and climate variability and shows the influences of weather producing system on long rainy season in Ethiopia.

Climate: This is the long-term average weather conditions (usually taken over a period of more than 30 years as defined by the World Meteorological Organization, (WMO) of a region including typical weather patterns such as the frequency and intensity of storms, cold spells, and heat waves (IPCC, 2007b).

Climate Change: Climate change in IPCC usage refers to a change in the state of the climate that can be identified (e.g. using statistical tests) by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer. It refers to any change in climate over time, whether due to natural variability or as a result of human activity. This usage differs from that in the United Nations Framework Convention on Climate Change (UNFCCC), where climate change refers to a change of climate that is attributed directly or indirectly to human activity that alters the composition of the global atmosphere and that is in addition to natural climate variability observed over comparable time periods (IPCC, 2007b, WMO, 2014).

Climate Variability: Variations in the mean state and other statistics (such as standard deviations, the occurrence of extremes, etc.) of the climate on all temporal and spatial scales beyond that of individual weather events. The term is often used to denote deviations of climatic statistics over a given period of time (e.g. a month, season or year) from the long-term statistics relating to the corresponding calendar period. In this sense, climate variability is measured by those deviations, which are usually termed anomalies. Variability could be due to natural internal processes within the climate system (internal variability), or to variations in natural or anthropogenic external forcing (external variability) (IPCC, 2007b, WMO, 2014).

A key difference between climate variability and change is in persistence of anomalous conditions. For instance, an event or sequence of events occurs that has never been witnessed before (or recorded before), such as flood or drought. If such a season does not recur within the next 30 years, we would call it an exceptional year, but not an indication of change (WMO, 2014).

2.2. Influence of Climate Change on Main Rainy Season in Ethiopia

The climate influences on Ethiopia have been described by different authors where they show that it is affected by global and regional synoptic systems, which prevail in different seasons of the year. Moreover they converge that during the main rainy season which provides enough amount of rain (more than 85 % of annual rainfall) for crop growing. It covers the period from June to September. The major rain producing components during this season are mainly seasonal migration of the Inter-Tropical Convergence Zone (ITCZ) and a complex local topography. It is dictated primarily by El Nino-Southern Oscillation (ENSO), and secondarily reinforced by more local climate indicators near Africa and the Atlantic and Indian Oceans. On the other hand, development and persistence of the Arabian and Sudan thermal lows along 20˚N latitude; development of the deepening and persistence of the Indian subcontinent's depressions and the associated monsoon trough, and development of tropical easterly jet (TEJ) and its persistence are weather producing system that influence the main rainy season (Tesfaye, 1987, NMA, 2001 updated by Diriba, 2007; Boko *et al.*, 2007, Dawit, 2010).

2.3. Effects of Climate Change on Wheat Production

Globally, many researchers have conducted to downscale GCM outputs to location of interest, to study the vulnerability, assess impact on crop production and then identify adaptation options. In agricultural terms, climate change study is to assess the effect of increasing CO_2, minimum and maximum temperature as well as water availability such as rainfall during crop growing season (Broad, 1987; Attri and Rathore, 2003; Ludwig and Asseng, 2005; Alemu, 2005; Matthew, 2010; Mesfin and Tekalign, 2011; Ibrahim *et al.*, 2012; Gerba *et al.*, 2013; Valizadeh *et al.*, 2013; IPCC, 2014b). The WMO

Commission for Climatology has recommended to adopt 30 years baselines to notice a significant change in climatic studies that scientists and meteorological services use to monitor the weather and climate, and make comparisons to past and future conditions (WMO,2014).

However, climate change associated with rising atmospheric CO_2 alters ecosystem carbon balance through rising temperature, increased growing season, and increased atmospheric water content (http://www.serc.si.edu/labs/co2/co2_overview.aspx).

Temperature and CO_2 influence plant growth and development through their effects on stomatal opening and rate of physiological processes. Higher temperatures speed up the biochemical reactions and also increase transpiration losses. Stomatal conductance declines with increasing CO_2 concentration for crop which fix and reduce inorganic CO_2 into organic compounds (C_3 plants). This seems to benefit more in terms of dry matter production from a higher CO_2 level, due to higher leaf expansion, increase in the photosynthetic rate per unit area, increase in water use efficiency and increase in photorespiration rates (Warrick *et al*., 1986). However, temperature effect on yield is less variable and more certain than CO_2 effect. Furthermore, doubling of CO_2 concentration enhance photosynthetic rate of leaves by 25-50 %. This stimulates canopy leaf formation, thereby increasing light interception. This adds up to the increase in photosynthetic yielding an increase in plant productivity up to 30-60 % (Mulholland *et al.,* 1997).

Wheat is classified among C_3 plants with optimum temperature of about 25˚C. Its cardinal temperature varies from one region to another. For instance, in Iran, wheat is grown in the range of 2.30-38˚C with 100.7 mm annual rainfall. In Egypt, mean temperature for the months of June, July and August is about 32˚C with 17 mm rainfall. However in that region, wheat is grown with supplemental irrigation. In Ada'a, the annual mean rainfall is about 851 mm with annual mean temperature of 18˚C. Thus, wheat environmental requirements are shifting due to climate change in different areas of production (Attri and Rathore, 2003; DZARC, 2008; Ibrahim *et al.,* 2012; Valizadeh *et al.,* 2013).

Wheat yield is the net photosynthetic accumulated as a result of the various plant processes occurring during the crop life cycle, and this is influenced by variations in temperature, CO_2 and rainfall. Phenology, evapotranspiration and nitrogen uptake are mostly affected (Broad, 1987; Attri and Rathore, 2003; Harpal and Graeme, 2004; WMO, 2010). For instance, failure of N acquisition to keep pace with growth enhancement can be caused by N becoming an increasingly scarce resource, by effects on the shoot system nitrate assimilation capacity or by the root system nutrient uptake capacity. As a very large fraction of N in other parts of the plant is translocated to the grain of wheat during the maturation period and nitrogen harvest index, the proportion of plant N in the grains at harvest values are typically in the range of 80–90% (Luo *et al.,* 2009; Turner and Rao, 2011).

Wheat is a tetraploid specie and traditionally grown on heavy black clay soils (Vertisol) of the central and northern highlands of Ethiopia between 1800-2800 meters above sea level (MoA, 2010, MoA, 2011). In Ethiopia, durum wheat (*Triticum turgidum L var durum*) is cultivated on 2 million hectares under rainfed agriculture by smallholder farmers. It is economically important industrial crop for the manufacturing of pasta. Some of the food recipes are Ethiopian bread, boiled grain, roasted grain, loosely crashed kernels cooked with milk or water and mixed with spiced butter (Kassahum *et al.,* 2014; DZARC, 2014).

2.4. Effect of Carbon dioxide on Wheat Plant Growth

Carbon dioxide is a key molecule for photosynthesis. In plants, photosynthesis occurs mainly in the leaves. The chemical reaction driven by solar energy involves the reduction of CO_2 through water to create carbohydrates and release oxygen (Equation 1). The resulting carbohydrates are used for plant growth and provide the energy source for living things. Under normal conditions, the atmospheric CO_2 concentration is very low. The photosynthetic reactions under high temperatures and high light intensities are limited by the CO_2 concentration, and the photosynthetic rate does not exceed a certain value. (Masahumi *et al.,* 2011).

$$6CO_2 + 6H_2O \text{ ------> } C_6H_{12}O_6 + 6O_2 \qquad (1)$$

Where: CO_2: carbon dioxide; H_2O : water; $C_6H_{12}O_6$: glucose; O_2 : oxygen

The response of crop growth to enhanced CO_2 in the biosphere is known to depend on climatic condition and it is difficult to quantify due to complexity of the physiological and environmental processes involved. Higher temperature during vegetative phase enhances the effect of elevated CO_2 levels. Total biomass and grain yield increased per 100 ppm of CO_2 enrichment by 7 % of the yields under ambient atmospheric CO_2. The additive effect of elevated CO_2 concentrations and predicted temperature change will result in a 25 to 30 % increase of the current potential yield level (Mulholland *et al.*, 1997).

Therefore, it has been established that rising CO_2 stimulate plant growth. For wheat and other C_3 crops, reduction in evapotranspiration under enhanced CO_2 results in higher water use efficiency and in yields (Attri and Rathore, 2003).

2.5. Effect of Temperature on Wheat Plant Growth

Crop production is affected by global warming due to an increase in atmospheric CO_2 concentration resulting in world-wide food shortages and insecurity. Rise in temperature is already affecting crop growth rate that is accelerated due to increased temperature, which reduces the window of opportunity for photosynthesis since the life cycle is truncated. In other words, the effect of increased temperature depend on the net result of the effect on photosynthetic rates of leaves and of the effect on the rate of crop development and senescence, while both heat and drought stress may also inhibit growth directly at the metabolic level (Matthew, 2010). Furthermore, harvest index may be reduced if reproductive processes are impaired by stress that occurs at critical developmental stages (Gordon, 2009; Matthew, 2010).

For wheat, the rising temperature leads to a rapid accumulation of Growing Degree Days (GDD); hence, growth and development of the crop are faster, resulting in a reduction of phenophase duration (Attri and Rathore, 2003). The number of wheat tillers decreases in response to high temperatures, especially high night-time temperatures. In such conditions, shoot elongation is promoted but there are more immature grains and decreased yields because of dark respiration. Moreover, unusually panicle initiation caused by warm winters can increase the risk of frost damage (WMO, 2010; Masahumi *et al.,* 2011).

Temperature stress intensity is severe under late sowing, causing a reduction in the duration of late growth phases. The rate of photosynthesis and respiration increases with an increase in temperature until a maximum value of photosynthesis is reached. This value is maintained over a broad range of temperatures (Harpal and Graeme, 2004; WMO, 2010; Masahumi *et al.,* 2011).

For instance, Mulholland *et al*. (1997) and WMO (2010) reported that increased temperature affect wheat growth duration and yield at 10 % yield reduction for 1ºC temperature rise. In the same line, the authors noted that increase of 1-2ºC during total growth period and 2-3ºC during reproductive phase were sufficient to negate the grain yield increase due to doubling of ambient atmosphere CO_2.

High temperatures decrease grain setting, increase the grain-filling rate and decrease the duration of grain filling, thus resulting in lower yield. Also, high temperatures during grain filling often have a negative effect on grain quality (Ritchie *et al.,* 1998; WMO, 2010).

2.6. Water and Wheat Crop Production

In general, crops require water in particular quantities for their optimum growth. Excessive or deficit amount of water could retard crop growth and ultimately lower crop yield. For instance, under particular climatic conditions, wheat requires different amounts of water during its stage of growth. Initially during seedling, sprouting and early growth, crop uses water at relatively slow rate. As growth proceeds this rate will increase

reaching a maximum and then declining toward maturity (Jeffrey *et al.,* 2001; Quraishi, 2014).

For wheat production with a doubling of CO_2 level (700 ppm) is projected to increase productivity and yield on average by 35 % under optimum condition, mainly through the simulation of photosynthetic precedes in the plant and improvement in the water use efficient. Water stress during the vegetative and reproductive development reduces tillering. During grain filling water stress affect mainly current assimilation through reduction in both photosynthetic area and activity (Mulholland *et al.,* 1997).

Plants capture water in their biomass and put it back to the atmosphere by means of transpiration a process which positively influences micro-climatic conditions. Changing in rainfall pattern lead to imbalances between crop water needs and rainfall during vegetation and have a strong impact on yields and the quality of agricultural products. The amount of water required for crop production varies depending on soil conditions and crop variety.
(Source: http://copa-cogeca.eu/img/user/file/Climate/5660%20version%20E.pdf).

The ratio between transpiration and assimilation is strongly influenced by stomatal behavior. When stomatal aperture is governed by CO_2 concentration inside the stomatal cavity has been demonstrated for various wheat cultivars. The ratio between assimilation and transpiration is around 100 kg H_2O per kg CH_2O for C_3 species under average conditions of radiation and humidity. In terms of dry matter, this value then ranges between 125 and 150 kg H_2O per kg dry matter (Mulholland *et al.,* 1997).

The influence of rainfall on wheat production can be related to its total seasonal amount or its intra-seasonal distribution. In the extreme case of droughts, with very low total seasonal amounts, wheat production suffers the most. This means that the number of rainy days during the growing period is important, if not more, as that of the total seasonal rainfall. However, the effect of rainfall variability on wheat production varies with types of varieties grown, types and properties of soils and climatic conditions of a given area (Mannava and Raymond, 2007; Woldeamlak, 2009; Badege *et al.,* 2013).

Wheat responds best to inputs at certain stages of plant development. Therefore, it is important to understand wheat development and recognize wheat growth stages for timely applications of water, pesticides, nitrogen, and other inputs in order to offset the intra seasonal stress periods. Wheat plants progress through several growth stages (Figure 1), which are described in terms of developmental events (Chad *et al.*, 1995). Organ differentiation defines the various stages of wheat development. Physiologically, the following stages are usually distinguished: germination, emergence, tillering, floral initiation or double ridge, terminal spikelet, first node or beginning of stem elongation, boot, spike emergence, anthesis and maturity. These stages may be grouped into: germination to emergence (E); growth stage 1 (GS1) from emergence to double ridge; growth stage 2 (GS2) from double ridge to anthesis; and growth stage 3 (GS3), which includes the grain-filling period, from anthesis to maturity (Figure 1). Physiological maturity is usually defined as the time when the flag leaf and spikes turn yellow (Hanft and Wych, 1982).

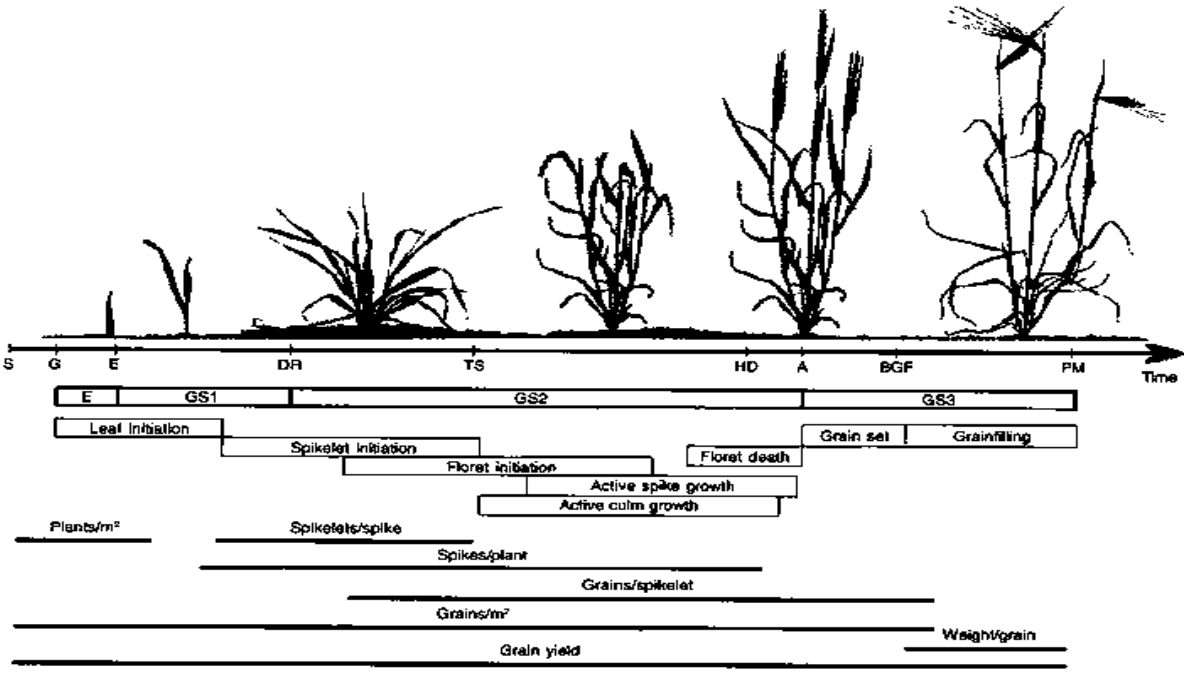

Figure.1. Growth and development of wheat (source: http://www.fao.org/docrep/006/y4011e/y4011e06.htm)

A critical period of undesirable water stress is seed germination and emergence. If soil moisture in the seedbed zone is below optimal, germination and seedling emergence rates will be reduced, leading to slower and delayed emergence, which has many negative ramifications for the remainder of the growing season and final yield. The period from anthesis to maturity (and therefore grain-filling duration) is also critical in wheat yield and quality. Water deficits, particularly if coupled high temperatures, cause significant deterioration in pollen viability and grain set. Water deficits during grain filling not only reduce carbon assimilation rates, but increase canopy temperature via reduced transpiration rates and canopy senescence via accelerated leaf senescence (WMO, 2010). After filling, moisture content provides the best indication of ripening until grains are dry enough to harvest. Decreases in percentage moisture arise first through filling with dry matter and then through water loss. On average grain takes about two weeks for adequately dry and to be readily harvested (Broad, 1987).

Water deficits results in earlier occurrence of later growth stages such as heading, anthesis and physiological maturity, by as much as 16 days. Wheat yield can be affected not only by water deficits, but also high rainfall conditions, especially if accompanied by moderate-to-high temperatures. Therefore, change in temperature and rainfall would change phenological requirements of future crops and would be in fact likely be the first factor to explore in explaining differences in yields (Ludwig and Asseng, 2005; Mannava and Raymond, 2007; WMO, 2010).

2.7. Alternate Decisions under Climate Changed Conditions towards Adaptation Responses

Climate change adaptation practices and options can be divided in two: at macro and micro-levels. At macro-level, adaptation deals with adjustments of agricultural production systems at national and regional levels vis-à-vis domestic institutions, international policies, climatic factors, markets and other strategic issues. Whereas, at micro-level it is concerned with adjustments and decision making at farm level (Nhemachena and Hassan, 2007). On the other hand, adaptation might be proactive or reactive. Proactive adaptation is an adaptation that takes place to anticipatory climate

stimuli; whereas reactive adaptation refers to an adaptation that takes place in response to already observed climate stimuli (IPCC, 2007b). On the other hand, adaptations fall into two broad overlapping categories (Vermeulen *et al.,* 2013): (i) practices evolved over time through farmers‘ long-term experiences in response to perceived impacts and (ii) planned adaptations to on-going and future climate change, for example, integrated packages of improved agricultural technologies such as breeding, agronomic practices and policy options.

For example, farmers grow cereal varieties adapted to shorter and more variable growing seasons, they build bunds to capture rainwater and reduce soil erosion, they use reduced tillage practices, manage crop residues to bridge dry spells when fodder is scarce and adjust planting dates to match shifts in rainfall patterns (Rao, *et al.,* 2011). Conservation agriculture can both improve food production and enable farmers to better manage climate risks (Rao, *et al.,* 2011; IPCC, 2014a). Farmers may change cropping decisions without awareness of changes in environmental risk or as intentional modification of farming practices in response to changing and variable environmental conditions. Climate variability has been shown to significantly impact crop yields. Climate information provides farmers with predictive knowledge about environmental risks that helps them overcome. Information assists researchers and policymakers in deciding which agricultural technologies, research orientation and adaptation mechanisms at all levels may be most useful in responding to climate variability and climate change (Adger, 2003; Gordon, 2009; Agarwal, 2010).

At global scale, the Consultative Group on International Agricultural Research (CGIAR) Research Program on Climate Change, Agriculture and Food Security is working in order to sustainably increase the productivity of wheat systems. For this, it applies the best of biotechnology, breeding and capacity building to create sustainable solutions with lasting impact and a strong focus on climate change, hunger, rural community development, and the environment (http://www.cgiar.org/cgiar-consortium/research-centers/international-maize-and-wheat-improvement-center-immyt).

Locally, a key advancement in wheat breeding has been the introduction of semi-dwarfing genes in durum wheat for instance in Ude and Yerer released in 2002. However, in the realm of climate change and adaptation measures, still much to be done (Awulachew, 2006; ILRI, 2007; Yemenu and Chemeda, 2010).

To adapt, it requires understanding of these issues of climate change. In the process, IPCC (2007a) suggested a protocol for climate change impact assessments. Climate studies use different climate models to project the future climates, but the most acceptable tools, used in IPCC reports, are Global Climate Models (GCMs) and Regional Climate Models (to downscale results of GCMs) (AMCEN, 2011).

2.8. Climate Modeling

Climate models are the primary tools available for investigating the response of the climate system to various forcings, for making climate predictions on seasonal to decadal time scales and for making projections of future climate over the coming century and beyond. Climate models have continued to be developed and improved since the AR4, and many models have been extended into Earth System Models by including the representation of biogeochemical cycles important to climate change. These models allow for policy-relevant calculations such as the carbon dioxide (CO_2) emissions compatible with a specified climate stabilization target. In addition, the range of climate variables and processes that have been evaluated has greatly expanded, and differences between models and observations are increasingly quantified. Model evaluation is to compare model output with observations and analyze the resulting difference. (Flato *et al.*, 2013).

The nucleus of the most complex atmosphere and ocean models, called General Circulation Models, GCMs, (Atmospheric General Circulation Models (AGCMs) and Ocean General Circulation Models (OGCMs) are based upon physical laws describing the dynamics of atmosphere and ocean, expressed by non-linear mathematical equations. The only means available to quantify the non-linear climate response is by using numerical models of the climate system based on well-established physical, chemical and biological principles, possibly combined with empirical and statistical methods. These are

designed mainly for studying climate processes and natural climate variability, and for projecting the response of the climate to human-induced forcing (Badege *et al.,* 2013).

2.8.1. Future climate scenarios

To generate future impact scenarios for agriculture, crop physiology often imbedded in models is linked with climate projections. However, the climate change information required for such impact studies is of a spatial scale much finer than that provided by GCMs with resolutions of hundreds of kilometers. The most straightforward means of obtaining projections of higher spatial resolution is to apply coarse-scale change projections to a high resolution observed baseline the 'change factor method' (Wilby and Dawson, 2004). However, this approach does not consider any potential changes in rainfall distribution and intensity. Fine resolution climate information can also be obtained via more sophisticated statistical downscaling, assuming that the present day climate is valid under the different forcing conditions of possible future climate (Flato *et al.,* 2013).

For the first, second, third, fourth and fifth assessments reports, the IPCC provided the terms of reference, reviewed the scenarios, and ultimately approved them, while modeling teams around the world prepared the scenarios. Previous sets of IPCC scenarios were published in 1990, 1992, 2000, 2007 and the last in 2014 (IPCC, 2007c, IPCC, 2014a).

2.8.2. The SRES Emissions Scenarios

A1. The A1 storyline and scenario family describe a future world of very rapid economic growth, global population that peaks in mid-century and declines thereafter, and the rapid introduction of new and more efficient technologies. Major underlying themes are convergence among regions, capacity building and increased cultural and social interactions, with a substantial reduction in regional differences in per capita income. The A1 scenario family develops into three groups that describe alternative directions of technological change in the energy system. The three A1 groups are distinguished by their technological emphasis:

- Fossil intensive (A1FI)
- Non - fossil energy sources (A1T), or
- Balance across all sources (A1B)

(balanced is defined as not relying too heavily on one particular energy source, on the assumption that similar improvement rates apply to all energy supply and end use technologies).

A2. The A2 storyline and scenario family describe a very heterogeneous world. The underlying theme is self-reliance and preservation of local identities. Fertility patterns across regions converge very slowly, which results in continuously increasing population. Economic development is primarily regionally oriented and per capita economic growth and technological changes are more fragmented and slower than in other storylines.

B1. The B1 storyline and scenario family describe a convergent world with the same global population, that peaks in mid-century and declines thereafter, as in the A1 storyline, but with rapid change in economic structures toward a service and information economy, with reductions in material intensity and the introduction of clean and resource-efficient technologies. The emphasis is on global solutions to economic, social and environmental sustainability, including improved equity, but without additional climate initiatives.

B2. The B2 storyline and scenario family describe a world in which the emphasis is on local solutions to economic, social and environmental sustainability. It is a world with continuously increasing global population at a rate lower than A2, intermediate levels of economic development, and less rapid and more diverse technological change than in the B1 and A1 storylines. While the scenario is also oriented towards environmental protection and social equity, it focuses on local and regional levels (IPCC, 2000).

2.8.3. Downscaling technique

There is a need to downscale GCM outputs before using them for regional and local impact assessments. This is because GCMs typically work at a spatial resolution of 200-300 km, which is useful for projected future climate at a global scale. However, at a regional scale GCMs are less useful because they cannot resolve local scale features (for example, sea-breeze, lake-breeze, or mountain-induced flows) which play an important role in regional climate or local scale (IPCC, 2007b). Therefore, the technique of downscaling is typically used to produce projections at a finer spatial scale. There are two possible approaches for downscaling, namely: statistical and dynamical regional climate models. The statistical model uses statistical/empirical equations to represent the relationship between the large features and local climate variables at stations, while dynamical models use physically based laws (similar to those in GCMs) to represent the relationship. Each method has advantages and disadvantages (Gary *et al.*, 2006; IPCC, 2007b; Julian and Andy, 2010). However, some studies are now combining statistical versus dynamical model (Robert and Christian, 2007).

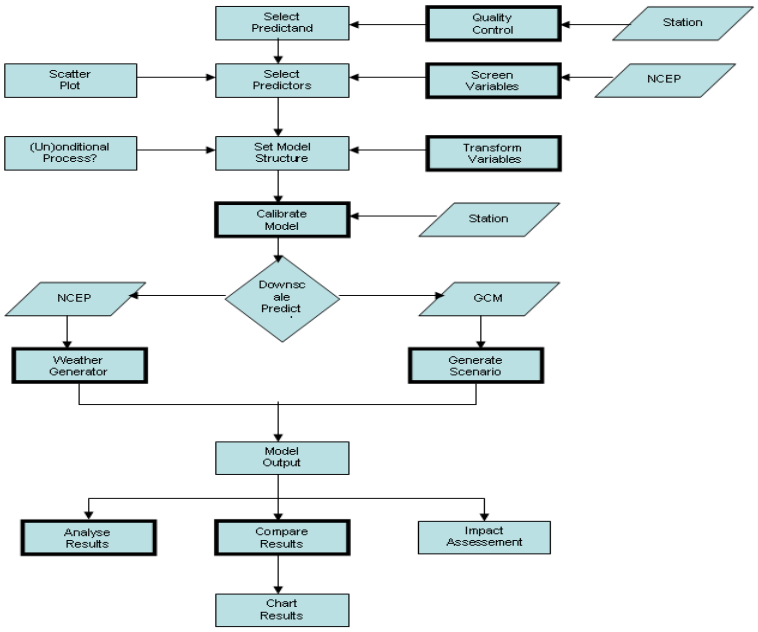

Figure 2. SDSM Version 4.2.9 climate scenario generation (Robert and Christian, 2007)

2.9. Crop Modeling

Modelling approaches and fundamental components of crop models emphases on genetic (G), environmental (E), management (M) and then G×E×M drivers of grain yield. Crop modelling is one of the approaches of combining the complexity of climate change with the complexity of physiological functions and other bio-physical aspects of crop–soil–atmosphere systems. The first crop simulation models were developed in the 1980s and used to simulate wheat growth, using conservative crop physiological functions. These models were ARCWHEAT1, the Dutch models SUCROS and SWHEAT and five crop models from the ARS Wheat Yield Project of which the CERES-Wheat and WINTER WHEAT were the most prominent. Most crop models simulate the dynamics of crop development, growth, water and nitrogen in an atmosphere–crop–soil system, driven by daily weather information from rainfall, maximum and minimum temperatures and solar radiation. Pests, diseases, frost and heat damage, phosphorus nutrition, biological effects of rotations and lodging that may affect crops are usually not considered. These models calculate yield for a specific environment, as the maximum yield reached by a crop in a given environment is limited only by temperature, solar radiation, day-length and include water and nitrogen supply (Flato *et al.*, 2013).

CERES-Wheat is one of the various models embedded in DSSAT. The CERES-Wheat, hereafter referred to as DSSAT, simulates crop development and growth, and the partitioning of assimilates to various plant parts as a function of environmental factors such as soils, weather and crop characteristics. Phenological development and growth of a crop are specified in DSSAT by cultivar-specific genetic coefficients (Ritchie *et al*., 1998; Hoogenboom *et al.*, 2004).

3. MATERIALS AND METHODS

3.1. Description of Study Area

The study was conducted at Ada'a District, which is located in range of 8°25'0" and 9°55'0" North latitude and 38°45'0 and 39°10'0" East longitude in Oromia National Regional State about 47 km southeast of the capital city of Ethiopia, Addis Ababa. The average altitude is about 1950 m above sea level. It is characterized by moist tropical climate and experiences mainly long rainy season extending from June to September with an average annual rainfall of 800 mm of which 85 % is in the long rainy season (June to September). The dry season extends from October to February. The mean annual maximum and minimum temperatures are 25.5 and 10.5^{0}C, respectively (NMA, 2007). Mean annual relative humidity level is 61.3%. Debre Zeit is the center of Ada'a district. The district has a total land area of about 1610.56 km^2 and divided into three agro-ecological zones regarding altitude namely midland (94%), highland (3%) and lowland (3%) (CSA, 2006; NMA, 2011). The study area is located in the midland. The majority of trial fields are heavy soils (Vertisol) with few pockets of light soils (Alfisols/Mollisols) (WRB, 2006). Geologically, these soils are from alkaline basalt and trachyte belonging to the Bishoftu Formation of the Cenozoic volcanic eruptions (Tefera *et al*., 1996).

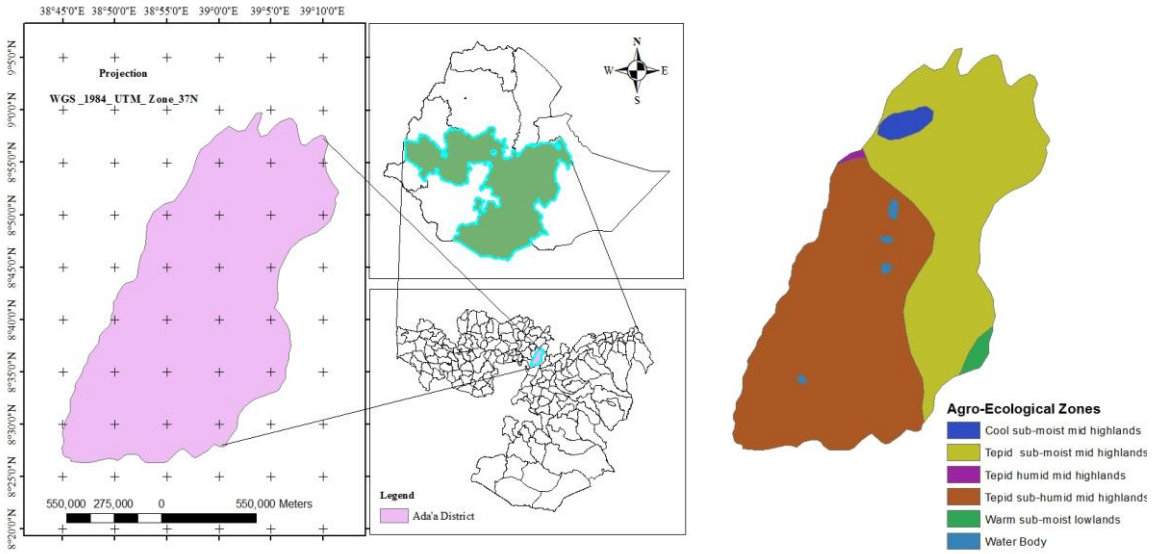

Figure 3. Map for Study Area and Agro-Ecological Zones

3.2. Characterization of Variability and Changes of Climate under Ada'a conditions

3.2.1. Data sources and quality assessment

The daily meteorological data were obtained from Ethiopian Institute of Agricultural Research (EIAR) of Ethiopia for a period of 42 years (1970-2012). These include daily rainfall, minimum and maximum temperatures. Data were captured into Microsoft Excel 2007 spreadsheet following the days of year (DOY) entry format. The standard or meteorological dekades are constructed in such a way that each month of a given year was divided into three dekads (Yemenu and Chemeda, 2010).

The daily time series from the station were plotted to identify obvious outliers, which were excluded from the data series. Outliers were detected using the weatherMan in DSSAT. In fact, WeatherMan is the program for importing, analyzing, and exporting climate data. In addition, the program has a built-in function that can read weather data with different system of measurement (Arnold, 2010).

3.2.2. Quality control and homogeneity test

The data used in this study were carefully analyzed in order to identify missing values and eliminate outlying observations. The homogeneity of the data series of Debre Zeit weather station was checked by using R analytical tool (Xuebin and Feng, 2004). In fact, the lack of homogeneity may be due to records of station moves, changes in instrumentation, problems with instrumentation, sensor calibration and maintenance logs, changes in surrounding environmental characteristics and structures, observing practices, and other similar features (Nathaniel, 1998).

In the process, quality control and homogeneity test were done for both temperature and rainfall from daily record. Quality control was checked with ClimDex which is a Microsoft Excel based program that provides an easy-to-use software package for the calculation of indices of climate extremes for monitoring and detecting climate change. RClimDex (1.0) is designed to provide a user friendly interface to compute indices of climate extremes (Xuebin and Feng, 2004).

Homogeneity test was done. The adjustment values depend on the empirical frequency of the datum to be adjusted. As a result, the shape of the distribution is often adjusted although the tests are meant to detect mean-shifts (Ho Ming and Fadhilah, 2012; Xiaolan and Yang, 2013a; Xiaolan, and Yang, 2013b).

The Figure 4 shows two graphs related to the results of homogeneity test for daily precipitation. The upper panel shows the original daily rainfall pattern series for 1970-2012. The software has detected 4 change points respectively at 04/08/1972, 24/07/1973, 17/07/1998 and 03/11/2011. These changes could have been resulted of any of the cause of inhomogeneity. However, the data series were thus adjusted for homogeneity (lower panel) in order to reflect changes in weather conditions. Therefore, there is no change points detected in lower panel, hence, the data series can be used for further analysis.

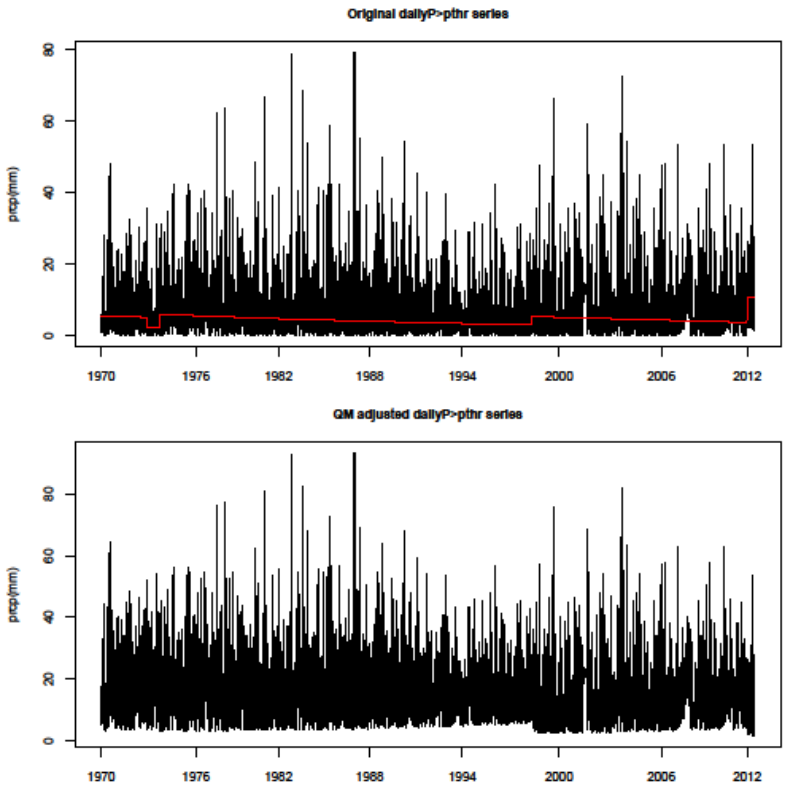

Figure 4. Daily precipitation pattern series for 1970-2012 (above), and Adjusted daily precipitation pattern series for the same period(below)

3.2.3. Analytical methodology

3.2.3.1. Onset, cessation and length of growing season (LGS)

The variability of seasonal rainfall was analysed for its onset, end date, LGS; amount and the number of rainy days. The availability of sufficient water at appropriate times is the most crucial factor determining the type and productivity of crops. It has been observed that water is the most important factor of a crop, which does not just need water to grow, but also requires it as a vehicle in which other nutrients are transported. Knowledge of the amount available and its distribution in relation to other nutrients in the soil is therefore a fundamental importance in the study of crop growth and production (Rita, 2007, Mannava and Raymond, 2007; Woldeamlak, 2009; Badege *et al.*, 2013).

The beginning or the start of the main growing season was identified based on two methods, firstly with INSTAT method and secondly Hargreaves method FAO (1978).

The INSTAT method is based 20 mm of total rainfall received over three consecutive days that were not followed by greater than 10 days of dry spell length within 30 days from planting. On the other hand, the end of the growing season is mainly dictated by the stored soil water and its availability to the crop after the rain stops. In this study, the end of the rainy season was defined when the soil water balance reaches zero (Stern *et. al*, 2006). In determining the end date, a fixed 1.5 mm of evapotranspiration per day and 100 mm/meter of the plant available soil water were considered (Mamo, 2005).

Hargreave method is based on simple soil water balance model which suggested that a growing period starts when a dekadal (ten-days) rainfall amount is equal or greater than half of the reference evapotranspiration (ETo) during the beginning of the rainy season. Accordingly, the end of the rainy seasons was set when the dekadal rainfall amount during the end of season is again less than half of the corresponding reference evapotranspiration (ETo). Finally, the length of the growing period (LGP) was defined by counting the number of days between the start and the end of the growing period. And the ETo is computed with temperature-based method (FAO, 1996; Yemenu and Chemeda, 2010).

As climatic parameters are the only factors affecting ETo, it can be computed from weather data. The FAO Penman-Monteith method is the recommended method for determining ETo. In a situation like the study area where solar radiation, wind speed, relative humidity and other data are completely absent, reference evapotranspiration can also be estimated using the equation (2) (FAO, 1998), in the same line, Shakib (*et al.*, 2010) recommended the use of ETo equation that require fewer variables:

$$ET_0=0.0023 \times (T_{mean}+17.8)(T_{max}-T_{min})^{0.5}\times R_a \qquad (2)$$

where;

ETo is reference evapotranspiration [mmd^{-1}];

$T_{mean} = (T_{max}+T_{min})/2$, average air temperature;

T_{max} and T_{min} are maximum and minimum air temperatures;

R_a is the extraterrestrial radiation [$MJ^{m-2}d^{-1}$].

The extraterrestrial radiation, R_a, for each day of the year and for different latitudes can be estimated from the solar constant, the solar declination and the time of the year by:

$$R_a = \frac{24(60)}{\pi} G_{SC}\, d_r [\omega \,\mathrm{Sin}(\emptyset)\mathrm{Sin}(\delta) + \mathrm{Cos}(\emptyset)\mathrm{Cos}(\delta)\mathrm{Sin}(\omega_s)] \qquad (3)$$

Where:

R_a: extraterrestrial radiation [$MJm^{-2}day^{-1}$]

G_{SC}: solar constant: 0.0820 [$MJm^{-2}min^{-1}$]

d_r: inverse relative distance Earth-Sun

ω_S: sunset hour angle [rad]

$\emptyset$: latitude [rad]

δ: solar declination [rad]

The inverse relative distance Earth-Sun, dr, and the solar declination, d, are calculated using:

$$d_r=1+0.033 \cos(\frac{2\pi J}{365}) \qquad (4)$$

$$\delta=0.409\mathrm{Sin}(\frac{2\pi J}{365}-1.39) \quad (5)$$

Where J is the number of the day in the year between 1 (1 January) and 365 or 366 (31 December). And, the sunset hour angle ω_S is given by:

$$\omega_S=\mathrm{arcos}[\tan(\emptyset)\tan(\delta)] \quad (6)$$

In Equation (3), Ra is expressed in $MJm^{-2}day^{-1}$. The corresponding equivalent evaporation in $mmday^{-1}$ is obtained by multiplying R_a by 0.408.

$$\text{Equivalent Evaporation } [mmday^{-1}] = 0.408\times\text{Radiation}[MJm^{-2}\ day^{-1}] \quad (7)$$

In the Hargreave method, the onset and cessation of growing season were determined from graphical representation of rainfall amount and reference evapotranspiration (ETo) relationship. Mean dekadal rainfall amounts were determined and plotted against their corresponding 0.5 ETo values for the 42 years average. The first point of intersection of the rainfall 0.5 ETo graph indicates the onset date and the second point of intersection gives the cessation date. Time interval within which an onset or cessation date falls is considered as duration of growing season (FAO, 1996). Mawunya (*et al.,* 2011) has also employed the same methodology and achieved meaningful result.

Variability of rainfall was expressed by statistical parameters such as mean, standard deviation, quartiles, maximum, minimum and the coefficient of variation (CV). Coefficient of variation is used to classify the degree of variability of rainfall events as less, moderate and high. When CV < 20% it is less variable data wise, CV from 20% to 30% is moderately variable, and CV > 30% is highly variable. Areas with CV > 30% are said to be vulnerable to drought (Hare, 1983).

Finally, the characteristic rainfalls over Ada'a area have been analyzed using box plots and whisker technique (Mamo, 2005). These are best graphical representation when analysing variability in fact they differentiate box and whiskers plotting, the box represents the middle 50% of the whole dataset, while whiskers represent the magnitude of the spread of the rest of the dataset about the median or mean (Stern *et al.,* 2002 cited

by Mamo, 2005). Statistical packages were determined and interpreted based on box plot graphs. Instat Statistical programme Version 3.36 (Stern *et al*., 2006) was used for analysis using the January to December calendar.

3.2.3.2. Trend Analysis

The analysis of rainfall records for long periods allows the time series analysis that serve for program evaluation, policy analysis and decision making. In the process, it decomposes the series into the trend components that helps to examine whether there is a change in rainfall pattern over time. Time series analyses are used to monitor predict/forecast future values of the series, with the assumption that naturally the past and the future atmospheric phenomena are interrelated stochastically. Accordingly, the future values have a probability distribution which is conditioned by an intimate knowledge of the past rainfall behaviour (Mamo, 2005).

In this case, the annual data series with 42 years long data on record were tested for the existence of significant trend (T-Test) with P-value as well as coefficient of determination (R^2) method being fitted to determine the direction as well as the magnitude of change of linear trend and for testing of slope (Lucio *et al.*, 2011). Similar method was used by Woldeamlak (2009) and Mamo, (2005) for their rainfall analysis.

The trend of a variable was computed using a linear regression model which is given by:

$$Y_i = \beta_0 + \beta_{1xi} + e_i \qquad (8)$$

where Y_i is the ith scalar response, β_0 is the intercept, X_i is the ith vector of input data, β_1 is the scalar coefficient (slope), e_i is the ith scalar noise term which is independent random variable.

The regression coefficients β_0 and β_1 can be estimated as β_0 and β_1 using least squares estimation in which the sum of squared differences between the observed values of the response variable Y_i and the values predicted by the regression equation $Y_i = \beta_0 + \beta_{1xi}$ is minimized, leading to the estimates:

$$\beta_1 = \frac{\sum_{i=1}^{n}\left(Y_i - y\right)(x_i - x)}{\sum i=1^{n}(x_i = x)} \qquad (9)$$

and $$\beta_0 = y = \beta_{1x} \qquad (10)$$

where y and x are mean values (Everitt and Hothor, 2010).

The coefficient of determination (R^2) indicates the variation of the climate variable with time in the linear regression model which is defined as:

$$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} \qquad (11)$$

Where SSE is the sum of squared error, SSR is the sum of squared regression, SST is the sum of squared total. In general, R^2 measures how successful the fit is in explaining the variation of the data. P-value is a statistical measure that helps to determine whether the hypotheses are correct. Usually, if the p-value of the dataset is below the pre-determined amount (say 0.05 which is the 95% confidence interval), the variabilities of the dataset has meaningful effect on the result (Wilks, 2006).

3.2.3.3. Dry spell probability

Decisions in rain-fed agriculture always require detail analysis of the weather component. In the principle of the fact that the past gives a clue to the future, probabilistic analysis of the weather records of the past is an important step towards understanding and developing appropriate technologies that support crop growth under varying rainfall regimes (Yemenu, 2013). The intermittent dry spell becomes critical, particularly for the seedling establishment during the first 30 days or so after planting. In fact, a dry spell of any length could occur at any stage of crop growth, however, it is potentially damaging if it coincides with the most sensitive stages such as flowering and grain filling (Mamo, 2005). Dry spell analysis assists in estimating the probability of intra-seasonal water deficit for which management practices can be adjusted accordingly. A kind of work should not only focus to the semi-arid areas where rainfall is erratic but it is also paramount important in the regions where rainfall seems enough on annual scale like

Ada'a while the temporal distribution through a growing season also requires attention (Kumar and Rao, 2005).

Likewise, at Ada'a, rainfall persists relatively less erratic on annual scale, but what a limiting factor is the unexpected occurrence of the dry spell during some of the most important crop development stages and high intensity of rainfall in the middle of the season. Thus understanding of those events is extremely important for reducing the adverse effects through appropriate planning and management of agricultural practices suitable to a certain pattern and characteristics of rainfall regimes in a growing season (Yemenu, 2013).

In the case of dry spell analysis, daily rainfall was fitted to the simple Markov Chain model to determine the probability of dry spell length exceeding 5, 7, 10 and 15 days within the growing season (June-November) using Instat Statistical software Version 3.36 (Stern *et al*., 2006).

The rainfall occurrence of dependable value at 80% probability level was determined and subsequently a comparison analysis with FAO threshold reference crop evapotranspiration was done. Mamo (2005) and Reddy (1990) have already stated that a 3 mm rainfall depth per day is the minimum threshold value for crops to satisfy their crop water requirement. In this regard, dry spell analysis within growing season more or less satisfies the required supportive information for decision making in rainfall water resource management and planning in agricultural sectors (Mamo, 2005).

On the other hand, rainfall in terms of frequency and intensity in a growing season is crucial for planning and management of agricultural practices. It is one of some importance in adapting farming systems to supplementary water resources to know how amount of rainfall and number of rainy days are expected for each month at critical times during the growing season (Yemenu, 2013, Gebremichael *et al.*, 2014).

3.3. Projection of Future Climate Change: Downscaling Global Circulation Model Outputs

3.3.1. Climate change scenarios

While this research is underway, there was a process in shifting from using Special Report on Emission Scenarios (SRES scenarios) to Representative Concentration Pathway (RCP scenarios) in scientific community. The question is *"Will it be possible to explain the differences between the SRES and RCP based climate scenarios?"*

Bowyer (*et al.*, 2014) has given an answer. *"Not really"*. Because the RCP climate scenarios are being performed with different climate models Coupled Model Intercomparison Project 5 (CMIP5) to the SRES Coupled Model Intercomparison Project 3 (CMIP3) based climate scenarios, so it is not possible to say whether differences in projected changes are due to the use of different models or different emissions scenarios. Nevertheless, there is some recent work which indicates that global mean temperature projections at the end of the twenty-first century, spans a similar range for the SRES/RCP scenarios but with important differences in the rates of warming between the two (Bowyer *et al.*, 2014).

It is obvious that there are improvements of using new scenarios; in fact the chief difference between these two groups of emissions scenarios is their starting point. Whereas the IPCC/SRES started with the socio-economic factors and developed emissions from this which would then lead to some change in the radiative forcing of the Earth's atmosphere. On the other hand IPCC/RCPs start with a given level of radiative forcing, under which a range of different socio-economic conditions could be consistent (Simith *et al.*, 2011; Bowyer *et al.*,2014).

The climate change scenarios produced for this study were based on the outputs of GCM results that are established on the SRES emission scenarios.

As the objective here is to get indicative future climate ensembles, the scenarios developed were only for maximum temperature, minimum temperature and rainfall values. The rest of the climate variables were assumed to be constant. The outputs of

Hadly Center Coupled Model Version 3 (HadCM3) GCM model for the A2 and B2 emission scenarios were used to produce the future scenarios. The A2 (medium high) scenario describes a very heterogeneous world and the B2 (medium low) scenario describes a world in which the emphasis is on local solutions to economic, social and environmental sustainability. The selection of these scenarios has been made in terms of the IPCC's fourth assessment guidelines (see also http://www.ipcc data.org/guidelines/TGICA_guidance_sdciaa_v2_final.pdf). The selected downscaling method requires the use of predictor variables from these scenarios.

The SDSM downscaling model was adopted to downscale the global scale outputs of the HadCM3 model into the local District scale.

Development of projections of climate change involves the development of both climate and socioeconomic scenarios. Scenario is defined as a plausible and often simplified description of how the future may develop based on a coherent and internally consistent set of assumptions about driving forces and key relationships. Scenarios may be derived from projections but are often based on additional information from other sources, sometimes combined with a narrative storyline (IPCC, 2007c).

3.3.2. General circulation model (GCM)

General Circulation Models (GCMs) are mathematical equations to represent the general circulation of the planetary atmosphere or the oceans. GCMs are coupled models that include four principal components: atmosphere, ocean, land surface, and sea ice. The GCMs also make use the future forcing scenarios to produce the ranges of the climate change. These scenarios represent a set of assumptions about population growth, economic and technological development, and socio-political globalization and regionalization. SRES recommends choosing among the following six emission scenarios A1F1, A1T, A1B, A2, B1, and B2. AGCM reproduces, with certain accuracy, mass and energy fluxes and storages that occur within the atmosphere, by using an analysis unit (Julian and Andy, 2010).

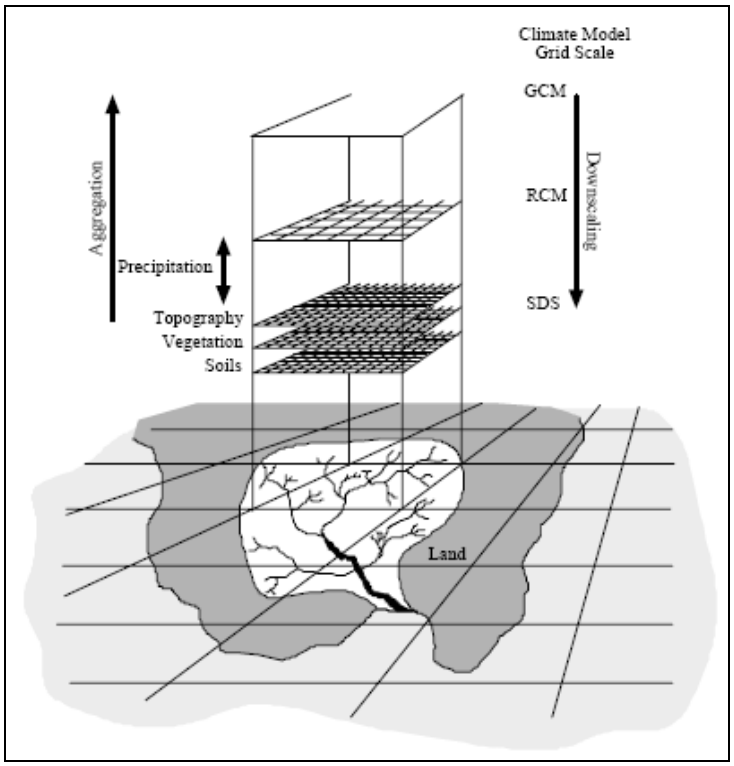

Figure 5. Schematic illustration - general downscaling approach (Robert and Christian, 2007)

3.3.4. HadCM3: Coupled atmosphere-ocean GCM model

The HadCM3 model was selected for this study. Apart from the time shortage to accommodate other models, the HadCM3 was selected due to the availability of a downscaling model called SDSM that is used to downscale the results of HadCM3 and CGCM1 model. This facilitates the rapid development of multiple, low–cost, single–site scenarios of daily surface weather variables under present and future climate forcing. However, the CGCM1/GCM currently does not have predictor files representing the study area window but only the North American Window. Consequently, all the data files used in this study were only for the HadCM3/GCM. For two of these emission scenarios three ensemble members (a, b, and c) are available, where each refer to a different initial point of climate perturbation along the control run (Hanson *et al.*, 2005). During this study data were available only for the “a” ensembles and hence only the A2a and B2a scenarios were considered. HadCM3 is a coupled atmosphere-ocean GCM developed at the Hadley Centre of the United Kingdom’s National Meteorological

Service that studies climate variability and change. It includes a complex model of land surface processes, including 23 land cover classifications; four layers of soil where temperature, freezing, and melting are tracked, and a detailed evapotranspiration function that depends on temperature, vapour pressure, vegetation type, and ambient carbon dioxide concentrations (Palmer *et al.*, 2004, Peter and Thornton, 2012; Flato *et al.*, 2013). The atmospheric component of the model has 19 levels with a horizontal resolution of 2.5° latitude by 3.75° longitude, which produces a global grid of 96 x 73 cells. This is equivalent to a surface resolution of about 417 km x 278 km at the equator, reducing to 295 km x 278 km at 45° latitude. The oceanic component of the model has 20 levels with a horizontal resolution of 1.25° latitude by 1.25° longitude. HadCM3 has been run for over a thousand years, showing little drift in its surface climate. Its predictions for temperature change are average and for precipitation increase are below average (Flato *et al.*, 2013; Peter and Thornton, 2012).

The method was applied over 26 different GCMs from the IPCC Fourth Assessment Report (2007a), directly downloaded from the Earth System Grid (ESG) data portal, for the emission scenarios SRES-A2 (19 GCMs) and for 3 different 30 year running mean periods (i.e. 2020-2049 [2030s], 2040-2069 [2050s], 2070-2099 [2080s]) and their respective changes were determined as deltas (for temperature) and as percentages (for rainfall) from the base period values. Each dataset (SRES scenario – GCM – time slice) comprises 3 variables at a monthly time-step (mean, maximum, minimum temperature, and total rainfall), and at 4 different spatial resolutions (30 arc-seconds, 2.5 arc-minutes, 5 arc-minutes, and 10 arc-minutes). The data are freely available on Canadian Climate Scenarios Network of Environment website: http://www.cics.uvic.ca/scenarios/sdsm/select.cgi

The grid box data downloaded consist of three directories:

- NCEP_1961-2001: This contains 40 years of daily observed predictor data, derived from the NCEP reanalyses, normalised over the complete 1961-1990 period.

- H3A2a_1961-2099: This directory contains 139 years of daily GCM predictor data, derived from the HadCM3 A2(a) experiment, normalized over the 1961-1990 period.

- H3B2a_1961-2099: This directory contains 139 years of daily GCM predictor data, derived from the HadCM3 B2(a) experiment, normalized over the 1961-1990 period.

3.3.5. Selection of downscaling predictor variables

The central concept behind any statistical downscaling method is the recognition of empirical relationships between the gridded predictors and single site predictands. This is the most challenging part of the work due to the temporal and spatial variation of the explanatory power of how predictors can predict temperature and rainfall at different months (Gary *et al.*, 2006; Robert and Christian, 2007, Julian and Andy, 2010). The selection was done at most care as the behaviour of the climate scenario completely depends on the type of the predictors selected. Moreover, the process type that identifies the presence of an intermediate process in the predictor-predictand relationship was defined. For daily temperature, which is not regulated by an intermediate process, the unconditional process is selected. However, for daily precipitation, because of its dependence on other intermediate process like on the occurrences of humidity, cloud cover, and/or wet-days; the conditional process was selected (Robert and Christian, 2007). Several analyses were made by selecting 12 out of 26 predictor variables at a time till best predictor-predictand correlations were found.

Table 1. Selected Generic Predictor Variables for Atlantic Canada Downscaling

Predictors	Descriptions	Predictands		
		Tmax	Tmin	Pcpn
p_u	Zonal velocity component at surface		*	*
p_v	Meridional velocity component at surface	*	*	*
p_z	Vorticity at surface	*	*	*
p_zh	Divergence at surface			*
p5_z	Vorticity at 500hPa			*
p500	500hPa geopotential height	*		
p5zh	Divergence at 500hPa			*
s850	Specific humidity at 850hPa	*	*	*
sphu	Specific humidity at surface	*	*	*
temp	Mean surface temperature	*	*	*

(Source: Gary et al., 2006)

The success of the SDSM based downscaling is dependent on the selection of predictor variables while developing the predictand-predictor relationship. Thus, the first step to calibrate the model starts from the selection of the predictor variables. From the 30 years observed historical datasets of 1961-2001, a baseline of 30 years (1970-2000) was set, then the first 20 years (1970-1990) were used for calibration and the remaining 10 years (1991-2000) were used for validation purposes. Before performing the calibration process, predictor variables from NCEP data were selected through a screening process in SDSM using the values of the explained variances and scatter plots in the predictor predictands relationship.

The adjustment of the variance inflation is performed in order to account for the variance of downscaled daily weather variables by adding or reducing the amount of white noise applied to the regression model. This is also used to enable the SDSM regression model to produce multiple ensembles of downscaled weather variables for the considered area. For rainfall, the selection of predictor variables are performed by transforming to the fourth root without any lag time. However, for the case of maximum and minimum temperatures, normal distribution was considered and hence no transformation function is applied. After routine screening procedures, the predictor variables that provide physically sensible meaning in terms of their correlation value and the magnitude of their probability were selected.

3.3.6. Model calibration

Model calibration is the adjustment of parameters so that simulated values compare fairly well with observed ones (Waha *et al.*, 2013). In order to validate the calibration of downscaled climate data, they were compared with observed climate data from weather station located within Debre Zeit research center. Observed data were taken for the baseline period of 1970-2000 and compared to the downscaling climatic data.

For instance, Tmax and Tmin, the synthesized graphs replicated the actual data using NCEP predictors rather well, inferring that future projections would also be well replicated. In the case of rainfall the annual values were well replicated (Wilby and Dawson, 2004).

For the observed and the NCEP data the year length was set to be the default (366 days), which allows 29 days in February in leap years. However, as HadCM3 have model years that do only consist of 360 days, the default value was changed to 360 days. The base period used for the model was from 1/1/970 to 31/12/2000.

The event threshold value is important to treat trace values during the calibration period. For the parameter temperature, this value was set to be 0 while for daily rainfall calibration purpose this parameter was fixed to be 0.1 mm/day so that trace rain days below this threshold value will be considered as a dry day. Missing data were replaced by -99.

3.3.7. Statistical validation

The parameters established during the calibration process that explains the statistical agreement between observed and simulated data are then used for model validation. The 10 years data (1991-2000) were used to validate the performance of the model.

Monthly rainfall, maximum and minimum temperatures values were generated based on the selected predictor variables of the NCEP data. Twenty ensembles (runs) were generated and the average of these ensembles was taken as a simulated result for each predictand variable.

The SDSM validation is based on the derivation of statistical parameters using the observed historical data. The data on daily precipitation as well as minimum and maximum temperatures for the period of 1970-2000 at Ada'a was used to perform the site analysis. The statistical validation of the result was analysed by using annual mean R squared and standard error of all selected predictor. Figures are produced to show the performance of the model to predict precipitation and temperatures (minimum and maximum temperatures) at local scale as well as for the 12 months at an acceptable critical values of R squared (Fiseha *et al.*, 2012).

Once the downscaling models have been calibrated and validated, the next step is to use the model to downscale the future climate change scenario simulated by GCM. In this

case, this means, the selected large-scale predictor variables to be used as input of the model that is taken from CGCM1 simulation output. This data covers the four distinct periods (baseline, 2030s, 2050s, 2080s) corresponding to the scenarios.

3.3.8. Weather generator and validation

SDSM's weather generator enables to produce synthetic current daily weather data based on inputs of the observed time series data and the *multiple linear regression parameters* produced during the calibration step. Each time-serious-data of the observed climate variable is linked to the regression model weights to generate the synthetic time series data into a series of ensembles (runs). The results among the ensembles differ based on the relative significance of the deterministic and stochastic components of the regression models and mainly due to the stochastic component of the downscaling. As indicated in the SDSM manual, variables like local temperatures are largely determined by regional forcing whereas precipitation series display more "noise" arising from local factors. Hence, larger differences can be observed in precipitation ensemble members than that of temperature.

The result of the weather generator was used to validate the calibrated model using independent observed data not used during the calibration procedure and the synthesized artificial weather time series data representing the present condition. Ten years of simulation from 1990-2000 was selected for the validation.

3.3.9. Scenario generation determination of the impacted climate variables

SDSM has HadCM3 model output with the A2 and B2 SRES emission scenarios with grid boxes containing the study area. Hence for this study, the HadCM3A2a and HadCM3B2a were the two GCM output files used for the scenario generation. The regression weights produced during the calibration process were applied to the time series outputs of the GCM model. This is based on the assumption that the predictor-predictand relationships under the current condition remain valid under future climate conditions too. Twenty ensembles of synthetic daily time series data were produced for each of the two SRES scenarios for a period of 139 years (1961 to 2099). The final product of the

SDSM downscaling method was then found by averaging the twenty independent stochastic GCM ensembles. The target is only to see the general trend of the climate change in the future, it is adequate to consider the average of the ensembles. Using SDSM to downscale the current climate (1961-2001) using CGCM1 driven predictors, and then comparing these outputs to actual values, might have further demonstrated the ability of SDSM to produce accurate projections (Gary *et al.*, 2006).

3.4. Assessing Climate Change Impacts on Wheat Production

The aim of this experiment was to simulate the impact of downscaled climate change projection on the grain yield of two cultivars of durum wheat (Ude and Yerer) under future climate change in Ada'a district, Central Rift Valley of Ethiopia. For this purpose, General Circulation Model, HadCM3 under two scenarios A2a and B2a in three time slice (2030, 2050 and 2080) were used. SDSM model was used for simulating climatic parameters for each period and CERES-Wheat model (Crop Estimation through Resource and Environment Synthesis-Wheat) was used to simulate wheat growth. Calibrated CERES-Wheat model was embedded in the Decision Support System for Agrotechnology Transfer (DSSAT v. 4.5) in order to simulate the yield of durum wheat under future climates scenarios (Jones *et al.*, 2003).

3.4.1. Description of Decision Support for the Agrotechnology Transfer (DSSAT)

Crop simulation model, Decision Support System for Agro-technology Transfer (DSSAT) version 4.5 was used for prediction of wheat yield at different management scenarios in this study. The DSSAT is a good example of a system modelling tool. It has been used for more than 15 years for modelling crop (type and phenotype), soil, weather, and management or husbandry interactions and it has also been employed to assess climate change impacts (WMO, 2010). The DSSAT is a collection of independent programs that operate together, crop simulation models are at its center (Figure 6 below). Databases describe weather, soil, experiment conditions and measurements and genotype information for applying the model to different situations. Software helps users prepare these databases and compare simulated results with observations to give them confidence

in the model or to determine if modifications are needed to improve accuracy (Jones *et al.*, 2003).

As shown in figure 6, each module has six operational steps, (run initialization, season initialization, rate calculations, integration, daily output, and summary output). The main program controls the timing of events: the start and stop of simulation, beginning and end of crop season, as well as daily time loops. This feature, an adaptation of van Kraalingen's (1991, 1995 cited by Jones *et al.*, 2010) work, allows each module to read its own inputs, initialize itself, compute rates, integrate its own state variables and write outputs completely independently from the operation of other modules (Jones *et al.*, 2010).

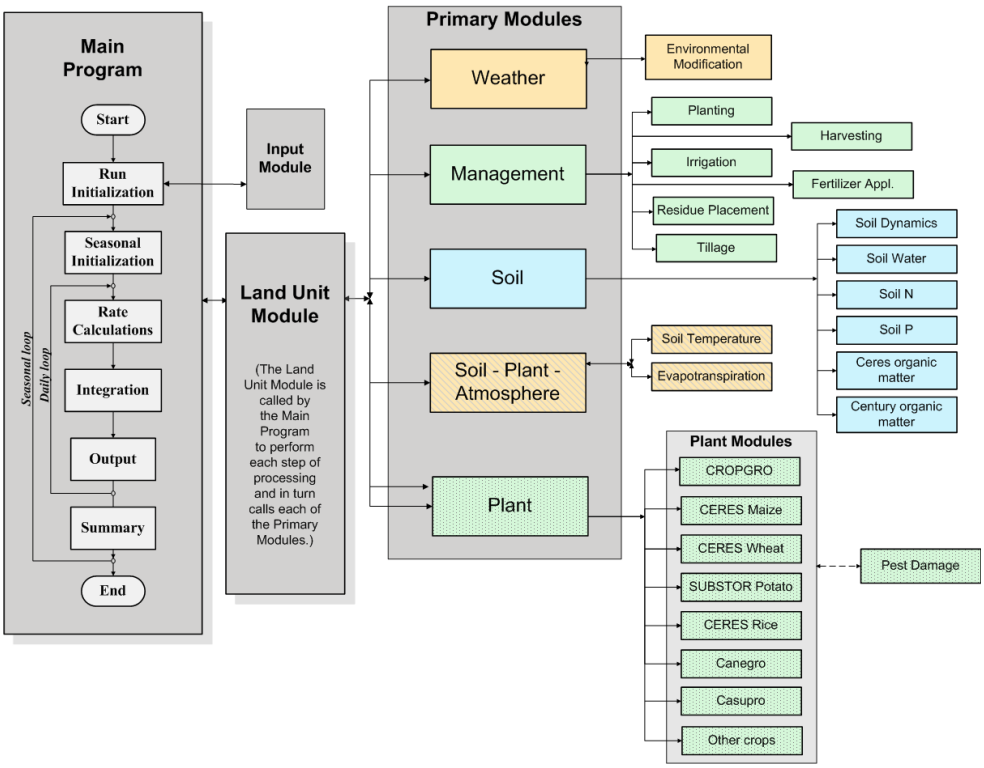

Figure 6. Overview of the components and modular structure of DSSAT-CSM.
Source: Jones *et al.*, 2010

The data set required for DSSAT consists of (i) site weather data describing altitude, latitude and longitude; (ii) climate data describing daily maximum and minimum temperatures, rainfall and solar radiation (stochastic weather generators are provided to create daily data if only monthly mean temperature data are available); (iii) Crop data

describing crop type, variety and phenological observations; (iv) Soil data describing horizonation, texture, soil moisture contents per layer at drained upper limit and lower limit, soil bulk density per layer, organic carbon per layer, NO_3, total soil N of the top layer, pH, aluminum saturation and root distribution (Tables 2; 3 and 4).

Therefore, the models simulate dry matter production as a function of climate conditions, crop characteristics, soil properties and management practices. (Robin and William, 2002; Hoogenboom et *al.*, 2002; Harpal and Graeme, 2004; WMO, 2010). Based on this requirement, the following data were collected and utilized during simulation.

3.4.2. Model input data sets

3.4.2.1. Crop data

Description of wheat varieties

This study was focused particularly on durum wheat (*Triticum turgidum L var durum*) which is the predominant tetraploid wheat species in Ethiopia (DZARC, 2014).

For choosing the varieties, some criteria were set. Those are varieties that are most popular for farmers, high yielders currently, good quality of grain, varieties that are planted every year and have used as baseline for comparison, and varieties that have past all stages of selection and which have historical data for at least 5 years.

Therefore, the selected varieties were Ude (CD95294-2Y) and Yerer (CD94026-4Y) currently registered in National Trial Varieties (NTV) (MoA, 2010/2011).

The crop management data include variety, planting date, planting density and fertilizer (application dates and rates). Crop genetic coefficients included in the model relate to photoperiod sensitivity (thermal time), duration and rate of grain filling, conversion of mass to grain number and vernalization requirements (Ritchie *et al*., 1998).

Crop management data and phenological observations were collected from Debre Zeit Agricultural Research Center. A request letter has been written and submitted to the institution, and then crop date has been given. General cultivar information and experimental

data on phenology and yield components are presented in Tables 2 and 3. The difference between Ude and Yerer is mostly their adaptation conditions where Ude performs well in optimal condition while Yerer in waterlogging conditions (DZARC, 2014). For the model calibration, the treatments with the recommended fertilizer rates, i.e. 60 kg/ha urea and 100 kg/ha Di-ammonium Phosphate, thus 45 kg N/ha and 20 kg P/ha for each variety (MoA, 2010/11).

Table 2. General information of cultivars (DZARC, 2014)

Agronomic Information	Ude	Yerer
Altitude (a.s.l.)	1800-2400	1800-2400
Rainfall requirement (mm)	800-1200	800-1200
Days from Planting to Anthesis	58-67	63-74
Days from Planting to Maturity	93-106	100-110
Plant height (cm)	80	84
Seed rate (kg/ha)	150	150
1000 seed weight (g)	44	44
Seed color	Amber	Amber
Leaf arrangement	Semi erect	Semi erect
Experimental yield (t/ha)	3-5	3-5
Farmers/actual yield (t/ha)	2.5-4	2-3.6
Origin	CIMMYT	CIMMYT
Year of release	2002	2002

Table 3. Management options used for simulation of durum wheat at Ada'a

Planting Date	Emergence date	Planting	Planting distribution	Plant population at Seeding (plants/m^2)	Row Spacing (cm)	Planting depth (cm)	First fertilizer	Second fertilizer
Observed:07-21/July	Automatic	Dry Seed	Row	165	17	4	At planting N=15 kg/ha and P= 20kg/ha	After 21 days, N=30 kg/ha

Rainfed experiments were conducted by DZARC during different years since 2003 in growing season (July to November). The two cultivars of durum wheat (Ude and Yerer) were grown as a check in order to improve other durum wheat varieties currently under production. They were grown since the year of release, however 8 years data for Ude and 9 years data for Yerer were available.

3.4.2.2. Soil data

Soils of the DAZRC were surveyed by fixed-grid technique at 50 by 50 m intensity (1:5.000). The total area of the experimental field of the main research farm was about 234.32 ha. The data were collected from the report and published source (DZARC, 2008).

The dominant soil of the study area is Eutric Vertisols. The major soil data include soil type, slope and drainage characteristics, and chemical-physical parameters for each soil layer, such as saturated soil water content, lower limit (LL), drained upper limit (DUL), initial soil water content, relative root distribution, soil pH, bulk density and soil organic matter (Table 4). (Ritchie *et al*., 1998).

Table 4. Physical and chemical soil properties of the experimental site

Parameters	Soil depth (cm)			
	0-40	40-102	102-126	126-195
Texture	CL	CL	CL	CL/L
Sand	8	12	12	36
Silt	34	38	30	32
clay	58	50	58	32
Bulk density (g/cm^3)	1.48	1.50	-	-
Organic carbon (%)	0.91	0.50	0.45	1.24
pH	7.1	7.3	7.20	7.30
CEC (meq/100g soil)	47.00	42.40	43.2	38.7
DUL	0.41	0.39	-	-
LL	0.28	0.26	-	0.31
T.N. (%)	0.10	0.06	0.06	0.06

DUL: Drained Upper Limit; LL: lower Limit; CL: clay; CL/L: Clay Loam

3.4.2.3. Weather data

The observational weather data (rainfall and minimum and maximum temperatures) had been quality checked. Because of absence of enough solar radiation data, this was estimated using WeatherMan other weather variables such as rainfall, maximum temperature and minimum temperature (Arnold, 2010).

Therefore, DSSAT uses common modules for soil dynamics and soil–plant–atmosphere interactions regardless of the plant growth module selected. The DSSAT suite of crop models includes the CERES modules which simulate for wheat as well as for others. The model computes the daily changes in soil water content by soil layer due to infiltration of rainfall, vertical drainage, unsaturated flow, soil evaporation, and root water uptake processes. The soil has parameters that describe its surface conditions and layer-by-layer soil water holding and conductivity characteristics (Hoogenboom *et al.*, 1991; Hoogenboom *et al.,* 2002).

3.4.3. Crop model calibration

Model calibration is the adjustment of parameters so that simulated values compare well with observed data. The so-called genetic coefficients that influence the occurrence of developmental stages in the DSSAT can be derived iteratively by manipulating the relevant coefficients to achieve the exact match between the simulated and observed number of days to phenological events (Rezzoug *et al.,* 2008; Valizadeh *et al.,* 2013). Model evaluation and testing evaluation involves comparison of model outputs with real data and a determination of suitability for an intended purpose. It is useful to think of model evaluation and validation as a documentation of its accuracy for specific predictions in specified environments, with appropriate consideration given to possible errors in input variables or evaluation data (Jones *et al.,* 2003). Generally, the criterion is to minimize the error between observed and simulated variables (Hoogenboom *et al.,* 2002; Madsen *et al.,* 2002; WMO, 2010).

The most common approach is trial and error. However this technique has been criticized because it is unreliable and difficult to replicate (Lyneis and Pugh, 1996). Moreover it may also be very tedious and time consuming, depending on the number of model parameters and the degree of parameter interaction. Thus, a great deal of research has been directed to development of more effective and efficient automatic calibration procedures. Among the most recent approach of genetic coefficient calibration in crop simulation modelling was GLUE (Generalized Likelihood Uncertainty Estimation).The GLUE program is used to estimate genotype-specific coefficients for the DSSAT crop models (James *et al.,* 2011).

Genetic coefficient determination using Generalized Likelihood Uncertainty Estimation (GLUE)

The main principle of this method is to discretize the parameter space by generating a large number of parameter values from the prior distribution. Likelihood values are then calculated for each parameter set using field observations. Probabilities for empirical posterior distribution of the parameters are calculated using Bayes' equation. The GLUE estimation method is integrated into DSSAT using the R language (R Development Core Team, 2009; http://www.R-project.org), a free software environment for statistical computing and graphics. The GLUE program allows users to select a crop, then a cultivar to be estimated. The program identified all experiments and treatments in the DSSAT data files for the crop that have measurements for that cultivar.

The user then can select one or more experiments and treatments that will actually be used in the coefficient estimation process. Generally, the user would want to estimate all parameters. What happens then is that the GLUE program will make 3,000 simulation runs for phenology coefficients and another 3,000 runs for growth coefficients. The program randomly generates parameters that are being estimated (either phenology or growth) from the prior distribution of parameter values and runs the model for each. The model outputs are used to select the parameter set with the maximum likelihood value based on comparison of simulated vs. observed variables, first for phenology parameters, then for growth parameters. The program also computes the uncertainties of the estimates (variances) for each parameter (Jones *et al.*, 2003).

Table 5. Cultivar-specific parameters in the DSSAT CERES-Wheat model (Jones *et al.*, 2003) that are estimated in the DSSAT GLUE procedure

Coefficient	Minimum	Maximum	GLUE Flag[1]	Definition
P1V	0	60	1	Days, optimum vernalizing temperature, required for vernalization
P1D	0	200	1	Photoperiod response (% reduction in rate/10 h drop in pp)
P5	3	100	1	Grain filling (excluding lag) phase duration (oC.d)
G1	10	50	2	Kernel number per unit canopy weight at anthesis (#/g)
G2	10	80	2	Standard kernel size under optimum conditions (mg)
G3	0.5	8.0	2	Standard, non-stressed mature tiller wt (incl grain) (g dwt)
PHINT	30	150	2	Interval between successive leaf tip appearances (oC.d)

CERES-Wheat determines the yield using six genetic coefficients that differ by variety. Accurate simulation of yield requires the correct genetic coefficients. For the development coefficients, measurements of first flower, physiological maturity, and first reproductive organ appearance dates are all used. For growth coefficients, final grain yield, ground biomass, maximum leaf area during the season, final pod weight, final main stem leaf number, and unit grain weight are used. However in this study only planting date, days to anthesis, days to maturity and grain yield was found from Debre Zeit Agricultural Research Center (DZARC).

[1] GLUE flag is an indicator to show in which round of the procedure the parameter will be estimated.

Table 6. Phenological and yield data of wheat (Ude) from DZARC

Years	Planting date	Days to heading	Days to Maturity	Grain Yield (Kg/ha)
2004	13/07	60	103	2562
2005	13/07	64	100	6482
2006	07/07	67	96	1857
2009	21/07	58	97	902
2010	15/07	63	95	4053
2011	18/07	62	95	2060
2012	19/07	62	93	2977
2013	13/07	62	106	1690

Table 7. Phenological and yield data of wheat (Yerer) from DZARC

Years	Planting date	Days to heading	Days to Maturity	Grain Yield (Kg/ha)
2003	13/07	69	110	1917
2004	13/07	67	110	2300
2005	13/07	63	100	5289
2006	07/07	67	106	1873
2009	21/07	70	110	1654
2010	15/07	73	108	3372
2011	18/07	74	109	2016
2012	19/07	70	104	2289
2013	13/07	65	107	1557

3.4.4. Crop Model evaluation and validation

The performance of the model was validated using an independent crop data from years that were not used for model calibration. For the variety Ude, calibration was done using five years and validation using three years, while for the variety Yerer, calibration has been done using six years and validation with three years. Model performance was assessed through root mean square error (RMSE) and index of agreement or d-statistic. The Root Mean Square Error (RMSE) and normalized Root Mean Square Error (RMSEn) (Equations (12) and (13)) were computed to measure the coincidence between measured and simulated values. The comparison has been done with simulated mean values of days to heading, days to maturity and grain yield (kg/ ha) with measured ones. The value of

RMSE approaching to zero indicates the goodness of fit between the simulated and observed values. The RMSE was computed using the following equation:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \quad (12)$$

where n= number of observations, P_i= predicted value for the ith measurement and O_i= observed value for the ith measurement.

The RMSEn was also computed as follows:

$$RMSEn = \frac{RMSE \times 100}{\overline{O}} \quad (13)$$

where RMSE= root mean square error and $\overline{O}$ = the overall mean of observed values.

RMSEn (%) gives a measure of the relative difference of simulated versus observed data. The simulation is considered excellent if the RMSEn is less than 10%, good if it is greater than 10% and less than 20%, fair if RMSEn is greater than 20% and less than 30%, and poor if the RMSEn is greater than 30% (Valizadeh et al., 2013).

On the other hand, d-statistic provides a single index of model performance that encompasses bias and variability and is a better indicator of 1:1 prediction than R^2. The closer the index value is to unity, the better the agreement between the two variables that are being compared and vice versa (Willmott *et al.*, 1985 cited by Musongaleli *et al.*, 2014). The d-statistic was computed as:

$$d = 1 - \left[\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}\left(|P'_i| + |O'_i|\right)^2} \right], 0<d<1 \quad (14)$$

where n: number of observations, $P_{i=}$ predicted value for the ith measurement, O_i= observed value for the ith measurement, $\overline{O}$ = the overall mean of observed values, $P'_i = P_i - \overline{O}$; $O'_i = O_i - \overline{O}$.

Moreover, linear regression was applied between simulations and observations to evaluate model performance and correlation coefficient (R^2) for each simulation (Loague and Green,1991).

3.4.5. Impact assessment methodology

A simple delta method was used to create climate change scenarios at different time slice (2030s, 2050s, 2080s) for one AOGCM (Coupled atmosphere-ocean general circulation models) HadCM3 from Coupled Model Intercomparison Project phase 3 (CMIP3) and Special Report on Emission Scenarios (SRES). The methodology used in this study considered different time slice with different scenarios as treatment in DSSAT (see Table 8). The simulations were embedded in seasonal setup of DSSAT and were made using a fixed atmospheric concentration of CO_2 at different time slice. The values reported in 2007 for fourth assessment report of IPCC were used (see the table below). CO_2 baseline was set up at 380 ppm (default value in the model). On the other hand, delta rainfall and delta temperature values are output from downscaling part of this research (SDSM results) that have been embedded in environmental modification of DSSAT in order to assess climate change impact of wheat. The observed daily climatic data was embedded in DSSAT as well for calibration. The crop management practices were included in seasonal DSSAT set up. These are planting date, planting density (165 plants per square meter) with rows spacing of 17 cm. Dosage of nitrogen and phosphorus, set at 45 kg N ha^{-1} in two application (first at planting date and second at telliring stage) and 20 kg P ha^{-1} in one application at planting date. Soil conditions were included in seasonal set up as well.

Table 8. Different treatment for DSSAT

Treatment	Time-Slice	Delta-Rainfall (%)	Delta-Tmax (˚C)	Delta-Tmin (˚C)	CO2[2] emission (ppm)
Baseline					380[*]
CC/A2a	2030	-9.88	0.0786	0.345	590
CC/B2a		-12.76	0.301	-1.640	535
CC/A2a	2050	-17.67	0.163	1.597	710
CC/B2a		-14.81	0.935	-2.190	590
CC/A2a	2080	-19.76	0.243	2.442	855
CC/B2a		-18.90	2.638	-2.445	710

[2] IPCC, 2007. Synthesis Report, pp 65-66.
[*]By Default in DSSAT model

To express the impacts on yield, the simulation results on grain yield were compared first from relative yield deviations from baseline yields and on station yield (t/ha) (see table 2 above).

DSSAT predicts wheat yield expectancies under limited environmental resources and various management scenarios (Rezzoug *et al.,* 2008). For a crop model to be useful as a climate change impact assessment tool, it has to reliably predict yield as a function of weather variables and exhibit a relatively limited number of essential variables and parameters. The impact assessment focuses mainly on the effect of elevated CO_2, temperature, rainfall and radiation on yield (WMO, 2010). The model helps to simulate the yield of wheat under soil condition and for specific crop management. This was to investigate responses of wheat mainly yield under future climatic conditions.

The mean simulated grain yield for the site was comparable as well to the national variety trial grain yield of durum wheat. The integration of different treatment by DSSAT model offers options that enable efficient analysis of selected cultivars under different future scenarios and time slice (2030s, 2050s, 2080s).The variability at different time slice and treatment of simulated yields were analysed using box plot and whiskers and evaluated with the coefficient of variation (CV). Yield gap analysis involves quantifying the differences between simulated potential yield and baseline levels and identifying those factors responsible for the yield differences (Lobell *et al.,* 2009; Liang *et al.,* 2011; Belay, 2014). The references for calculating yield gaps are baseline yields.

Crop simulation modeling is the only way through which the impacts of a variety of potential scenarios can be explored. Model-based climate change impact assessment methods are generally categorized into biophysical-based simulations and semi-empirical methods that build on the statistical relationships between crop yield, management and phenological or environmental variables (Robin and William, 2002; Phool, 2008).

Risk analysis using probability of non exceedence

Risk analysis determines a correct and a possible range of target output values that are more correct than the worst, expected and best- case range (Hardaker *et al.*, 1998). It also shows the likelihood of occurrence of achieving specific values, which is very useful for the targeted yield analyses, helping to determine the types and levels of inputs employed to achieve a given target yield. A cumulative density function (CDF) is likely to be the first and most understandable graph of the distribution, in which it is possible to compare the dynamic values of random variables. The stochastic dominance (SD) technique that encompasses first degree stochastic dominance (FSD), second degree stochastic dominance (SSD) and third degree or higher order stochastic dominance is also a method used to analyze CDFs. FSD means the cumulative density function (CDF) of the best alternative must always lie below and to the right of the CDFs of the other distribution curves (Mamo, 2005). The graphs were plotted in Excel Spreadsheet.

3.4.6. Adaptation measures under climate changed future dates

Sensitivity analysis is a prerequisite of making discussion of future adaptation measures related to climate change. For this effect, sensitivity analysis was carried out to assess how the model simulate the response of durum wheat to different management practices that include changes choice of cultivar, planting dates, planting density and fertilizer application rate and changes in climatic conditions especially rainfall and temperature as well as CO_2.

3.4.6.1. Planting date

Adjustment of planting dates is more resilient to variability of climate and improvement in agronomic practices (Attri and Rathore, 2003). Based on climatic data used for crop model calibration that are already imbedded in DSSAT, onset and cessation of the growing season were determined from graphical representations of rainfall amount and reference evapotranspiration (ETo) relationship (Figure 7). The first point of intersection of the rainfall-0.5 ETo graphs indicates the onset date assumed to be potential planting date and the second point of intersection gives the cessation date (Mawunya *et al.*, 2011).

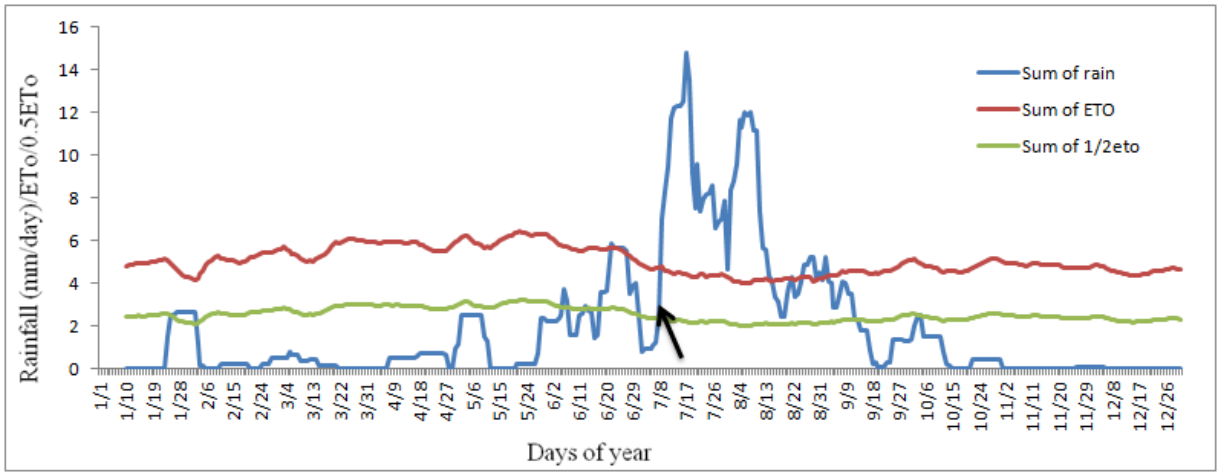

Figure 7. Determination of potential planting date

This figure shows that July 7 is potential date of planting where it coincides with the point 0.5 ETo is less than the rainfall. From this date, the assumptions of very early, early, normal and late were made with interval of 14 days.

3.4.6.2. Planting density

As Chad (*et al.*, 1995) noted, wheat yield potential is based on planting density. Usually, planting density was set at 160-200 plants per square meter in optimum condition of production. And then to achieve a potential yield (75-100%) of wheat, 120, 200 and 350 plants population per square meter have been used for this study. Low, medium and high planting density is to give option of maximizing yield in case of early or late planting date (Roger *et al.*, 2008).

3.4.6.3. Nitrogen fertilizer application rate

In Ada'a, durum wheat is largely grow on central highland vertisols with soil pH ranging between 7.1-7.3 in the soil profile (DZARC, 2008). This pH content of the vertisols favors gaseous loss of ammonia when urea or ammonium fertilizers are applied to the surface (Gerba *et al.*, 2013). Nitrogen is the nutrient requiring the most management. Proper N rate and timing are important for high tiller numbers and yield (Chad *et al.*, 1995). Nitrogen fertilization of durum wheat in Vertisols is therefore important to improve the grain yield.

For this study, different rates of N included in optimum application rate of Nitrogen have been used to check which is recommended under climate changed future dates. Thus, 60, 120 and 180 kg per ha of N have been used.

3.4.6.4. Future changes in climate conditions

Future adaptation measures have been analysed for short term period (2030s), medium (2050s) and for long term period (2080s). The 36 treatments (See in appendix Table) were carried out were for worse situation for each time slice. Table 9 shows worse situation for each time slice and then the adaptation measures have been carried out accordingly.

Table 9. Future climatic conditions

Time slice	Rainfall (%)	Tmax (°C)	Tmin (°C)	CO_2 (ppm)
2030s	-12.77	+0.30	-1.64	590
2050s	-17.68	+0.94	-2.19	710
2080s	-19.76	+2.64	-2.45	855

Therefore, model sensitivity was carried out to various crop management option and environmental parameters by conducting different treatment of simulations designed to understand the best agricultural practices adaptation. Treatments consisted of different possible combination of crop management options under changed climate are presented in appendix table which shows different treatments used to simulate best agricultural management options under changed climatic conditions.

4. RESULTS AND DISCUSSION

4.1. Characterization of Variability and Change of Climate under Ada'a District Conditions

4.1.2. Onset, end, duration and seasonal rainfall amount

Figure 8 indicates mean monthly total rainfall variability; the amount of rainfall during the short rainy season which varies from February to May is less than 60 mm for each month which is less than the threshold of 3 mm/day as explained by Mamo (2005). From the figure, a continuity of rainfall between short and long rainy season is noticeable. In practice, it means that planting at the onset of short-season, rains would expose the maturing wheat crop to high rainfall during the succeeding long season and that is the major reason why the Ada'a farmers do not grow wheat during short rains. The Figure 8 shows also absence of true bimodal nature of the rainfall pattern in production terms which confirms what Gissila (2001) noted as cited by Mamo (2005) that the seasonal rainfall pattern in the Central Rift Valley does not have distinct bimodality and it could be concluded that there is an overlap between the two seasons. There is break period between the two rainy seasons which is brief over the central parts of Ethiopia (Mamo, 2005).

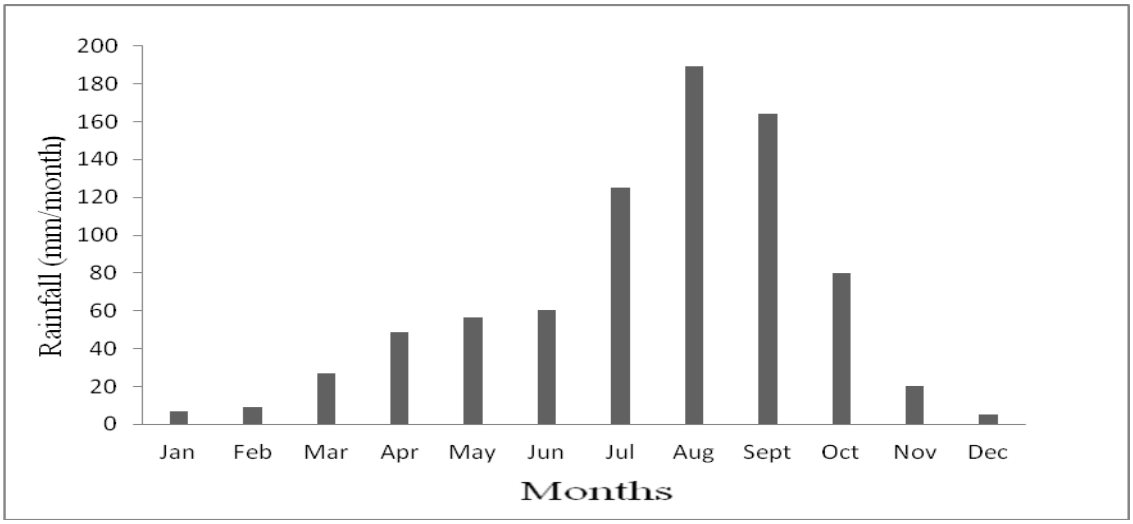

Figure 8. Mean monthly total rainfall variability

Furthermore, Figure 9 indicates that in the short season, rain is low, but evapotranspiration is high. The relationship between potential evapotranspiration (ETo) and dekadal rainfall amount is shown in Figure 9, half of ETo is less than the dekadal rainfall amount only from 21 March up to 20 May (2 months). Therefore, in practice, the results imply that the soil moisture of the growing season in the shorter rainy season is uncertain and subsequently planning of agricultural practices related to crop management is difficult. In addition, the rainfall depth is observed to be much lower than the threshold of the crop water requirements (0.5 ETo). Hence, a substantial amount of rainfall deficit is experienced during this particular season (Figures 9). The result substantiates that rainwater is critically a limiting factor and one can draw a conclusion that the season needs to be out of the major activities of durum wheat production, Evidently, Ada'a farmers are reasonable for planning what production during the long rainy season, when the crop water requirement is dependably met.

However, the moisture during short season could be used to facilitate land preparation activities for early planting in the main rainy season. Consequently, planting could be carried out earlier during the start of the season and the probable loss of moisture for the land preparation activity during main rainy season could be minimized.

The rainfall features only for long season such as onset, cessation date and duration of growing season in Ada'a have been examined using two methods: INSTAT method and Hargreaves's method from graphical representations that use the dekadal rainfall amount and reference evapotranspiration (ETo) relationship (Figure 9).

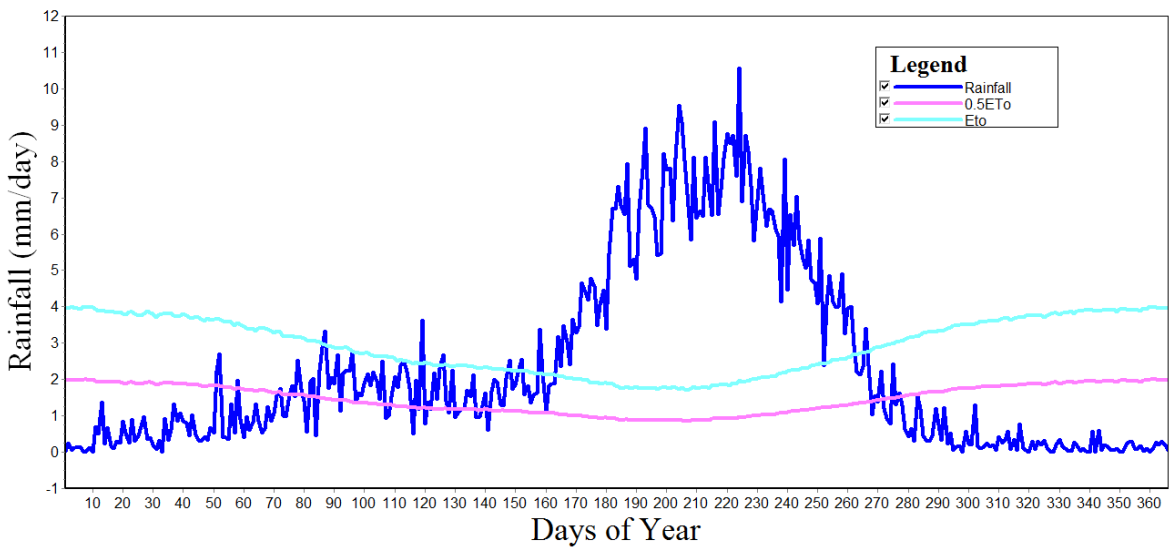

Figure 9. Relationship between Rainfall-Evapotranspiration on dekadal basis

Furthermore, the distribution of the operationally useful rainfall features listed above has formed a good starting point for examination of the series for two methods. The lower (25 percentile), median (50 percentile) and upper quartile (75 percentile) caps of the whiskers in Figure 10 and Table 10 provide a complete and useful explanation of the existing variability in the rainfall features. The amount of water available to plants strongly depends on the rainy season's onset, length, temporal distribution and cessation and can indirectly indicate the climatic suitability of the crop and its success or failure in a season (Ngetich *et al.*, 2008).

The variability in end date for Debre Zeit weather station is low, compared to the one for length of growing period and the onset with Hargreaves's method (Figure 10a) while the variability in onset date is less as compared to the length of growing period and end date with INSTAT method (Figure 10b). The much smaller box for the rainfall cessation date indicates that the end dates vary over a short time span at Ada'a.

Therefore, with Hargreaves's method, as less variability implies that patterns could be more understood, decisions pertaining to harvest could be made more easily than the planting date, while with INSTAT method; a less variability implies that patterns could be more understood, decision pertaining to planting could be made more easily.

For instance, with Hargreaves's method (Figure 10a and Table 10) and for the onset date, the respective lower and upper quartiles fall between 159 (June, 9) and 183 (July, 2) DOY (more than 3 weeks) with 7.8% coefficient of variation (CV).

Therefore, at Ada'a planting earlier than 09 June (159 DOY) is possible only once in every four years time. Further, the upper quartile (75 percentile) statistic extends up to the 183 DOY (in first dekad of July), while for the end date, the respective lower and upper quartiles fall between 283 (Oct, 9) and 293 (Oct, 20) DOY (only 10 days) with 3 % coefficient of variation (CV). In other words, end of growing period earlier than 9 October (283 DOY) is possible only once in every four years time and it ends earlier than 20 October (293 DOY) only three time out of every four years, extends up to third dekad of October with a CV of 3 %.

In the case of duration of growing period expressed in terms of number of days, the respective lower and upper quartiles fall between 103 and 131 days (roughly one month) with 14.7 % coefficient of variation (CV). In other words once in four years time, it is possible to get a LGP of 103 while, three out four years time, there is chance of getting LGP of 131 days with 14.7% CV.

On the other hand, with INSTAT method, for the onset date, the respective lower and upper quartiles fall between 172 (June, 21) and 186 (July, 5) DOY (roughly 2 weeks) with 4.8 % coefficient of variation (CV).

In the study area , planting earlier than 21 June (172 DOY) is therefore, possible only once in every four years time, while it is possible earlier than 5 July (186 DOY) in three out of four years time. For the end date, the respective lower and upper quartiles fall between 269 (Sept, 26) and 303 DOY (Oct, 30) (34 days) with 8.6 % coefficient of variation (CV). In other words, end of growing period earlier than 26 September (269 DOY) is possible only once in every four years time and it ends earlier than 30 October (303 DOY) only three time out of every four years, extends up to the end of October.

Regarding the duration of growing period expressed in terms of number of days, the respective lower and upper quartiles fall between 155 and 183 days (roughly one month)

with 10.7 % coefficient of variation (CV). In other words once in four years time, it is possible to get a LGP of 155 while, three out four years time, there is chance of getting LGP of 183 days.

The seasonal rainfall analysis indicated that the mean seasonal rainfall at Ada'a is 539.21 mm. The respective lower and upper quartiles fall between 457.4 and 638.9 mm, with coefficient of variation of 24.9 %. This shows how high is the interseasonal rainfall variability (CV<30%).

The difference between these two methods is based on definition of onset and end date. Hargreaves's method based on simple soil water balance that suggest that the length of growing season starts when dekadal rainfall amount is equal or greater than the half of reference evapotranspiration while the INSTAT method is based on 20 mm of total rainfall received over three consecutive days that were not followed by greater than 10 days of dry spell length within 30 days from planting was adopted.

In this case more attention is needed for planning of agricultural water for crop production. The introduction of different agronomic practices that prolongs soil moisture holding capacity and reduce evaporation loss could be used as management options in order to offset different magnitude of dry spell.

Similar results were reported by Yemenu and Chemeda (2010) where the mean starting dekade of the main growing season, had low standard deviation amounting to 6 days and hence the onset date of the season was promisingly stable.

Table 10. Descriptive statistics of important rainfall features for Debre Zeit weather station

	Hargreaves's Method			INSTAT method			
Statistical Parameters	Onset date (DOY)	End date (DOY)	Duration (no of Days)	Onset date (DOY)	End date (DOY)	Duration (no of Days)	JJASO (mm)
Minimum	153	275	83	169	259	129	215.9
Quartile 1 (25%ile)	159	282	103	172	269	155	457.4
Quartile 2 (Median)	172	287	117	177	282	173	523.2
Quartile 3 (75 %ile)	183	293	131	186	303	183	638.9
Maximum	200	308	147	200	360	206	881
Average	171.47	287.84	116.37	179.37	288.12	169.26	539.21
SD	13.36	8.6	17.11	8.63	24.68	18.14	134.37
CV (%)	7.8	3	14.7	4.8	8.6	10.7	24.9

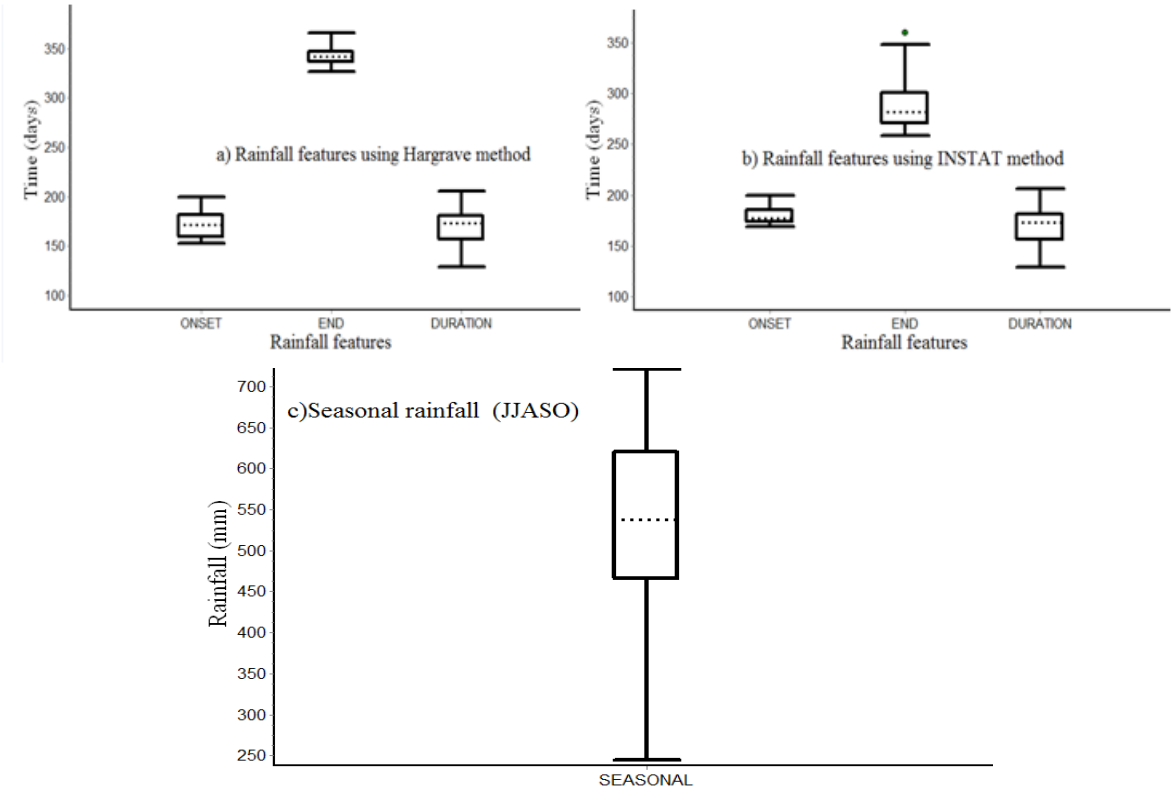

Figure 10. Agriculturally important seasonal rainfall features at Ada'a (1970 - 2012), rainfall onset date, end date and duration

On the other hand, the magnitude of the LGP obtained in the study could not be regarded as high (CV of 14.7 and 10.7 % for both methods) because the length of growing period length (116 and 169 days) is fairly enough to support both durum wheat cultivars which are commonly grown in the areas of the district that require not more 110 days of growing period to their maturity.

In the other words, the rainfall amount at the study area remained adequate (5399.21 mm in average) for crop germination, establishment, and full development until the third dekad of October. The reliable growing season starts respectively from the second dekad of June to the first dekad of July across methods.

Therefore, there is generally enough seasonal total rainfall (Maximum rainfall 881mm, Table 10), the challenge is its poor distribution over time and across the season. In the process, next paragraphs indicate analysis of dry spell and seasonal occurrence of rainfall (number of rainy days) as well seasonal totals can provide deep insight into translation of the rainfall variability into the field level management options through proactive responses.

4.1.3. Probability of dry spell length

The probability of dry spells longer than 5, 7, 10 and 15 days were analysed (Figure 11). This sheds insight into the risks related to a range of dry spell lengths during the entire rainy season. Also, the reason behind including the dry spell length conditions into the later months of the growing season is to provide a complete picture of how the dry spell length of various magnitudes are distributed during the entire growing season and to examine the associated risk at the study area. In fact, as stated in literature review, in Ada'a, wheat is sown in June or July and harvested in October or November.

The parabolic-type curves in Figure 11 explain, for instance, the probability of dry spells longer than 15 days within the 30 days after planting. At Debre Zeit, , the probability of dry spells longer than 15 days at the beginning of June is less than 10%, whereas it shows a certain degree of downward slope at the end of the same month. Thereafter, the probability is 0 till third dekad of August. However, there is less probability (less than 10

%) of dry spell longer than 5 days even at the middle of rainy season (between 29 June to 08 August). The same Figure also demonstrates how the probability of 7 and 10 days of dry spell curves stays at the value of respectively less than 10 and less than 20 % at the onset window (from first up to third dekad of June). The dry spell length probability of greater than 7 and 10 days curves converge to their minimum only during the peak rain period (June and August or DOY 180-222) and turn upward again around September (240-280 DOY), signaling the end of the growing season. Information on the probability of such a range of dry spell lengths is useful for different groups of farmers who work under different capability or resource endowments. For instance, farmer 'A' (a risk taker) who may have access to irrigation water could decide to plant during the earliest /risky months of the growing season. In this way, one can maximize outputs by taking risks associated with such a long dry spell. On the other hand, a resource poor farmer 'B' (a risk averse) lacking water resources or other soil water management techniques or decision tools to manage any risk of dry spell longer than 5 or 7 days has to wait until the sufficient soil water accumulates.

Since the two farmer groups do not utilize resources at the same level (time of planting, timeliness of operation, and choice of cultivar) the expected yield level would not be similar for the two farmer categories. In any case, late onset is the least preferred situation, obviously because it shortens the available length of the crop growing period and the potential to satisfy the crop water requirement.

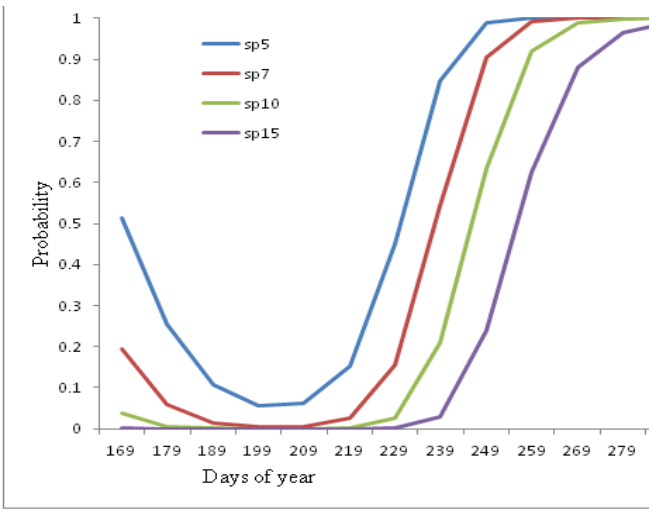

Figure 11. Probability of dry spell longer than 5, 7, 10 and 15 days

Information on the length of dry spells could be used as a guide for planning supplementary irrigation because high water-demand periods can be predicted. Choice of planting date and cultivar selection can be made based on the length of dry spells. For example the probability of dry spells lasting longer than 15 days is very low during the rainy season at this site. However, decisions can be better made if the probability of dry spells is computed after effective (successful) planting dates.

4.1.4. Time series analysis

Graphical visualization of seasonal rainfall data for the period 1970 to 2012 in Ada'a is presented in Figure 12. There is an observed decreasing trend of total seasonal rainfall. Seasonal rainfall totals were regressed against time scale and regression equation is shown on the Figure. The results show statistically significant decreasing trends, P-value=0.013 ($P < 0.05$). In other words, seasonal rainfall amount in the study area is decreasing at a rate of 10.99 mm per decade.

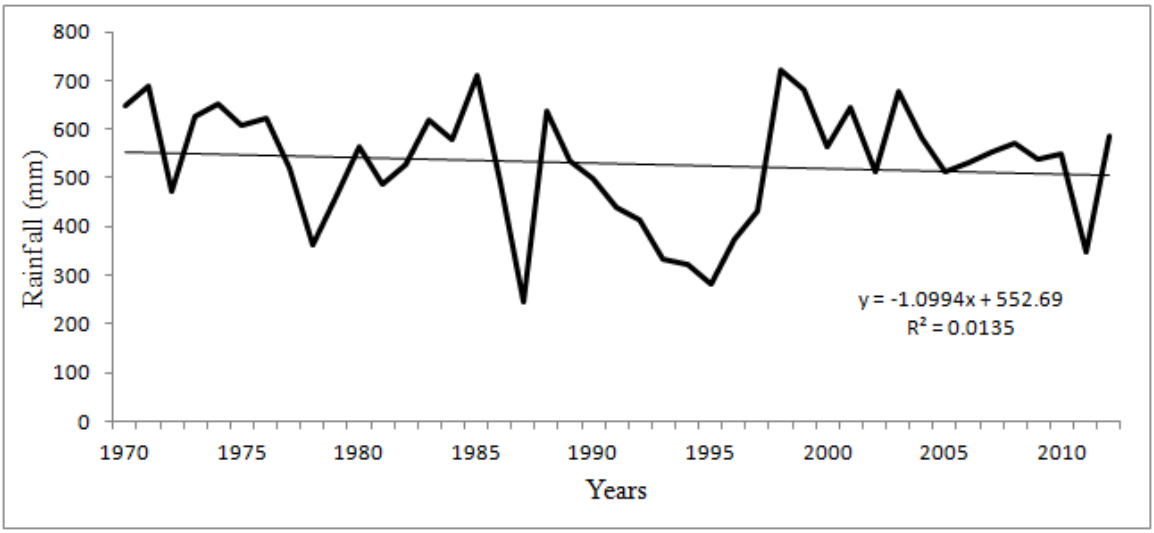

Figure 12. JJASO seasonal rainfall trend for Debre Zeit weather station

The year-to-year variation of seasonal rainfall over Ada'a was expressed in terms of normalized rainfall anomaly (Figures 13). This analysis of rainfall variability shows remarkable anomalies in seasonal rainfall below normal for years of 1976, 1987 and 1995 and the study area receives above average rainfall for 1989, 1997 and 2001.The years with rainfall below normal are related to the years of drought while the years with rainfall above normal are related to the years of floods. This result confirms partially earlier

studies done by Kidane (2010) who have mentioned the years related to floods (1988, 1993, 1994, 1995, 1996 and 2006) and to drought (1984/1985, 1994/1995 and 2000/2001 at national level in Ethiopia.

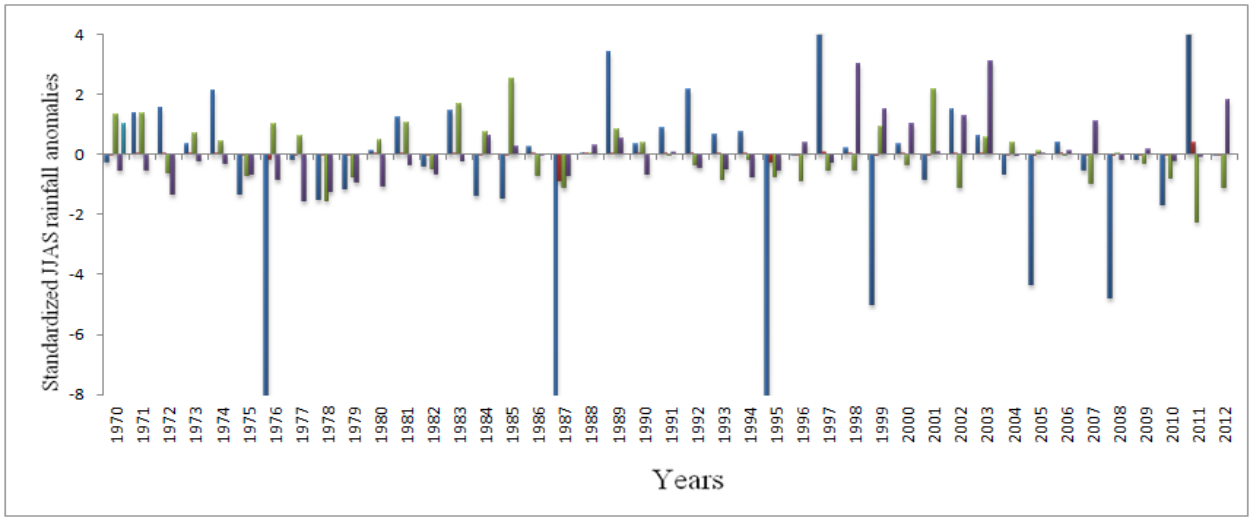

Figure13. JJAS rainfall trend and standardized anomaly for Ada'a weather station

As can be noted in Figure 13, positive anomalies have occurred especially for July and August which are the peak months of the rain season. During JJAS, the main sources of moisture are Mascarene and St Helena high pressure systems from the Indian and Atlantic Oceans, respectively. The intensity and position of these pressure systems as well as the intensity of the East African Low Level Jet (EALLJ) have a controlling effect on the moisture laden wind entering the northeastern Africa region (Gebru, 2007).

Other studies in Ethiopia and government papers also confirm these results indicating decreasing trends in inter-annual and seasonal rainfall (NAPA, 2007; Kidane, 2010; Funk and Rowland, 2011; Gebremichael *et al.*, 2014).

Maximum and Minimum Temperatures

The temperatures in the study area follow a clearly increasing, observed trend during the period of 1970-2012 (Figures 14 and 15). The temporal variabilities of average maximum and minimum temperatures has been examined at inter annual time scale for the period mentioned. The result shows an increasing trend of both maximum and minimum temperature with significant trend at $P<0.05$. In other words, maximum temperature is

increasing at a rate of 0.14ºC per decade while minimum temperature is increasing at a rate of 0.21ºC per decade (P-value: 0.032 and 0.018 respectively).

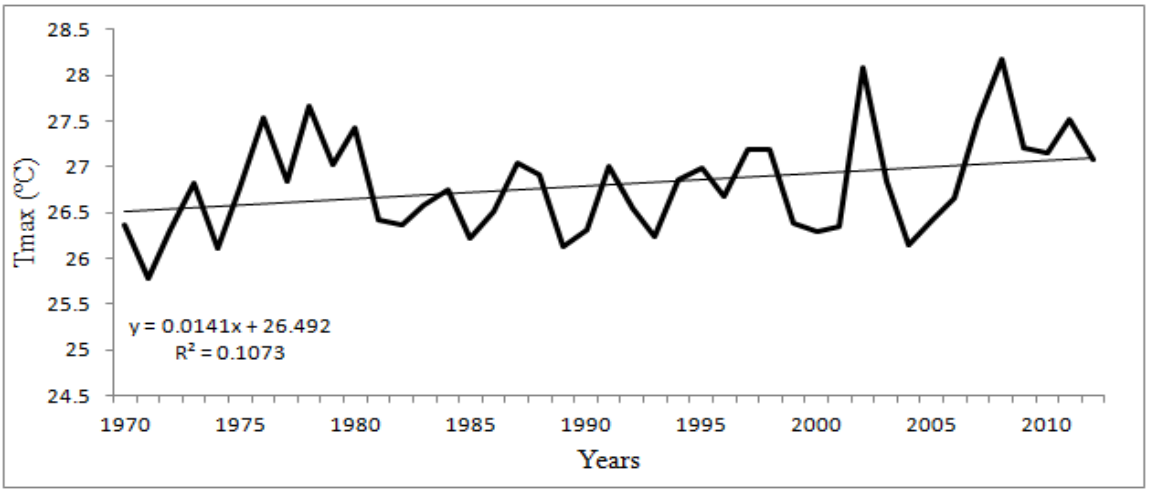

Figure 14. Maximum temperatures trend for 1970-2012

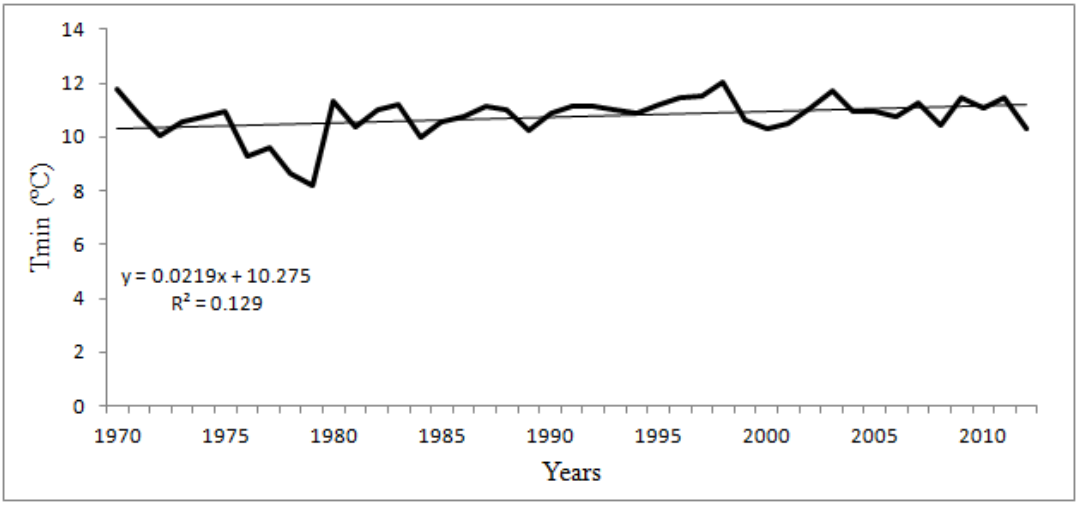

Figure 15. Minimum temperatures trend for 1970-2012

Currently, durum wheat in the study area is grown in condition where annual minimum and maximum temperatures are respectively 10.5 and 25.5ºC (NMA, 2007). Therefore, with this increasing rate of temperature and by assuming that carbon dioxide concentration in the atmosphere will doubt, environmental requirement for durum wheat growing may be out of cardinal range in the future.

In fact, increasing temperature in the study area would increase the rate of evapotranspiration. This in turn would create consistent stress and increase the probability of drought occurrence in the region. High temperature might also shorten the

growth stage of crops that reduces the yield due to low assimilation of photosynthetic products. Moreover, increase in temperature can also affect the irrigation water requirement and decrease yield either due to moisture stress and/or limit the area to be irrigated.

4.1.5.Monthly and length of growing period rainfall statistics

The statistical parameters and variation for both monthly and wheat growing period rainfall data are summarized in Tables 11 and 12 where the mean, standard deviation, coefficient of variation, quartiles, minimum and maximum are provided. Knowledge of monthly distribution of rainfall is important because it tells how much water is available for each month during growing period in rain-fed areas.

As stated so far, wheat is grown during June, July, August, September and October (JJASO) which can be considered as wheat growing period. Rainfall analysis indicated that the mean wheat growing period rainfall at Ada'a is about 539.21 mm. The coefficient of variation during this period is 24.9%. This shows how intraseasonal rainfall is moderate variable even though the associated risk (CV between 20 and 30%).

Monthly rainfall analysis indicated that the Ada'a area receives high amount of rain in August (mean: 189.4 mm) with CV of 34.4 % followed by months of September and July (164.3 and 125.1 mm) with a CV of 39.8 and 62.9 % respectively. The rainfall pattern in Ada'a is general unimodal with August and September contributing up to 35.13 % and 30.47 % respectively of wheat growing period rainfall amount.

Table 11. Descriptive statistics of months of June, July, August. September and October total rainfall (mm)

Months	Minimum	Quartile 1 (25%ile)	Quartile 2 (Median)	Quartile 3 (75 %ile)	Maximum	Average	SD	CV (%)
June (mm)	1.1	20.6	49.9	93.7	201.1	60.4	48.7	80.6
July (mm)	0	65.3	116.2	182	307.4	125.1	78.7	62.9
August (mm)	40.4	140.6	185.2	235.1	353.8	189.4	65.1	34.4
September (mm)	60.9	121.1	150.3	184.2	367.2	164.3	65.4	39.8
October (mm)	0	24.9	66.3	133.6	181.9	79.9	60.4	75.5

On the other hand, Table 12 indicates number of rainy days throughout of JJASO, the mean number of rainy days in wheat growing period increases from June to August and then start decreasing from September. The minimum of 2 rainy days occur in October and maximum of 19 days in July. The months of June and September show high variability (CV>30) of number of rainy days with CV of 37% and 30.2 % respectively. The fact that it drastically decreases in September signifies end of the season.

Ada'a area is almost dry for the month of October. By comparison the amount of rainfall and number of rainy days, the intensity of rainfall is high during July to September so that, runoff and soil erosion would be likely high which need different soil -water management, including cut off drain in order to ensure safe disposal of excess water from wheat field.

Table 12. Descriptive statistics of rainy days for June, July, August. September and October

Months	Minimum	Quartile 1 (25%ile)	Quartile 2 (Median)	Quartile 3 (75 %ile)	Maximum	Average	SD	CV (%)
June (days)	3	10	11	15	30	12.5	4.6	37
July (days)	10	17	20	22	25	19.3	3.6	18.4
August (days)	0	16	19	21	26	18.5	4.3	23.4
September (days)	4	10	12	14	20	11.9	3.6	30.2
October (days)	0	0	1	3	8	2	2.1	107.1

4.1.7. Seasonal and monthly rainfall variability: implications for wheat crop production

The results indicated a decreasing of seasonal rainfall amount, a high rainfall amount and intensity variability throughout of wheat growing period, hence it might affect durum wheat production. Despite, the onset, end date and duration of growing period of the main rainy season have a less variability (CV<20%) (Hare, 1983). However, this does not mean that planning of agricultural activities is fairly simple and involves less risk. In the study area, agricultural operations such as planting time should be adjusted in accordance to the changes. Likewise, as the rainfall tends to concentrate only on two months for instance August and September and high variability across months (Table 11 and 12). In practice, this means that, the option of having waterlogging condition is not excluded

which could affect mostly the variety Ude, because of poor aeration and there might be damages in the downstream areas due to flooding mostly likely in August and September that experience after wet conditions unless there have been strong soil and water management options in wheat field. Terminal drought occurrence is highly foreseeable. In this regard, focusing on agronomic practices such as using early maturing cultivars, in situ moisture conservation practices, etc might help to offset the impact resulted due to terminal drought and prolong the growing period during the main season.

On the other hand, the benefits should be derived from the less moisture month during harvesting period. Hence, durum wheat production during this particular period needs a due attention and monitoring of planted crops. Therefore a considerable attention of maximizing durum wheat harvest during the main rainy season is practically important. In fact, as stated so far, the attention should be made to the management of length of growing season and dry spell probability as long as one out of four years, LGP may be far less (83 days) than number of days to maturity for the two cultivars (< 110).

4.2. Climate Change Projection

Downscaled SDSM results for maximum temperature, minimum temperature and precipitation at Ada'a, Central Rift Valley of Ethiopia for the three time slices centered on the 2030’s, 2050’s, and the 2080’s, are shown by Figures 16 to 21. Figures 16, 17, and 18 give the results of the validation procedure; Figure 19 shows the downscaled results for precipitation, while Figures 20 and 21 show the downscaled results for Tmin and Tmax respectively.

4.2.1. Calibration and Validation of SDSM

4.2.1.1. Selection of Predictor Variables

Table 13 shows the identified predictor variables for the Debre Zeit weather station and predictands (rainfall and temperatures). From the selected predictors, it is observed that one predictor can control two or three local variables. For instance, 500hPa geopotential heights control rainfall, minimum and maximum temperature while 850haPa

geopotential, surface specific humidity and surface zonal velocity are common for minimum and maximum temperatures.

The type and explanations of the predictors, which showed better correlation with the daily rainfall, daily maximum temperature and daily minimum temperature, predictands at $p<0.05$ significance level are shown in Table 13. Partial correlations indicate that rainfall is mostly controlled by predictors localized at 500hPa zone such as 500 hPa geopotential height, 500 hPa meridional velocity, 500 hPa wind direction, 500 hPa vorticity, relative humidity at 500 hPa, while minimum and maximum temperature are controlled mostly by predictors related to the body surface area such as surface airflow strength, surface divergence, surface meridional velocity, surface specific humidity, surface zonal velocity surface wind direction and surface vorticity. Finally, the selected predictor variables were used to derive parameter files that can be used for downscaling after validation with the independent dataset.

Table 13. List of predictor variables that gave better correlation results at $p<0.05$

Predictand	Predictorors	Notation	Partial r
Rainfall	Surface divergence	ncepp_zhaf.dat	0.036
	500 hpa meridional velocity	ncepp5_vaf.dat	-0.014
	500 hpa vorticity	ncepp5_zaf.dat	-0.035
	500 hpa geopotential height	ncepp500af.dat	-0.079
	500 hpa wind direction	ncepp5thaf.dat	-0.022
	500 hpa divergence	ncepp5zhaf.dat	-0.014
	850 hpa zonal velocity	ncepp8_uaf.dat	0.036
	850 hpa wind direction	ncepp8thaf.dat	0.011
	Relative humidity at 500 hPa	ncepr500af.dat	-0.02
	Relative humidity at 850 hPa	ncepr850af.dat	0.062
Maximum Tempereture	Mean sea level pressure	ncepmslpaf.dat	-0.005
	Surface air flow strength	ncepp__faf.dat	-0.059
	Surface zonal velocity	ncepp__uaf.dat	0.013
	Surface meridional velocity	ncepp__vaf.dat	0.001
	Surface divergence	ncepp_zhaf.dat	-0.012
	500 hpa geopotential height	ncepp500af.dat	-0.1

The partial correlation coefficient (r) shows the explanatory power that is specific to each predictor. All are significant at $p = 0.05$.hpa – is a unit of pressure, 1 hPa = 1 mbar = 100 Pa = 0.1 kPa

	850 hpa meridional velocity	ncepp8_vaf.dat	-0.002
	850 hpa geopotential height	ncepp850af.dat	0.024
	850 hpa vorticity	ncepp8zhaf.dat	0.021
	Relative humidity at 850 hPa	ncepr850af.dat	-0.003
	Surface specific humidity	ncepshumaf.dat	0.002
Minimum Temperature	Mean sea level pressure	ncepmslpaf.dat	-0.076
	Surface zonal velocity	ncepp__uaf.dat	0.006
	Surface vorticity	ncepp__zaf.dat	0.0014
	Surface wind direction	ncepp_thaf.dat	-0.007
	500 hpa geopotential height	ncepp500af.dat	-0.123
	850 hpa geopotential height	ncepp850af.dat	0.082
	Relative humidity at 850 hPa	ncepr850af.dat	-0.027
	Near surface relative humidity	nceprhumaf.dat	0.06
	Surface specific humidity	ncepshumaf.dat	-0.039
	Mean temperature at 2m	nceptempaf.dat	-0.051

4.2.1.2. Statistical validation

The calibration and statistics validation for the three predictand variables are summarised in Table 14 below, whereas the statistics parameters for each month are given in Tables 15; 16 and 17. The model shows satisfactory agreement based on coefficient of determination (R^2) and standard error between the simulated and observed values. Figures 16, 17 and 18 show also agreement between the downscaled and observed precipitation and temperature (minimum and maximum temperature) during validation.

Table 14. Validation statistics of monthly precipitation, maximum temperature and minimum temperatures

	R^2		Standard Error	
Predictand	Unconditional	Conditional	Unconditional	Conditional
Rainfall	0.018	0.186	0.365	0.8335
Maximum Temperature	0.541		2.922	
Minimum Temperature	0.570		2.024	

These results show that the simulated maximum and minimum temperatures have better agreement with the observed results than the rainfall variable. The simulation of rainfall though showed a relatively lesser agreement (R^2= 0.186) as compared to the maximum temperature (R^2=0.541) and minimum temperature (R^2=0.570). The results are above the

critical values of R^2 (Fiseha *et al.*, 2012). The low R^2 value for the rainfall might due to the fact that rainfall is a conditional process. Conditional processes like rainfall are dependent on other intermediate processes like the occurrence of humidity, cloud cover, and/or wet-days. Hence, larger differences can be observed in rainfall ensemble members than that of temperature (Wilby and Dawson 2004).

Table 15. Statistical validation of rainfall

	Conditional		Unconditional	
Months	**R-Squared**	**SE**	**R-Squared**	**SE**
January	0.377	3.838	0.017	0.161
February	0.208	10.293	0.012	0.261
March	0.063	12.016	0.013	0.34
April	0.034	10.449	0.011	0.433
May	0.035	9.885	0.038	0.414
June	0.095	8.624	0.023	0.429
July	0.026	10.35	0.023	0.529
August	0.034	10.909	0.012	0.497
September	0.014	9.653	0.01	0.513
October	0.038	8.47	0.04	0.0492
November	0.321	5.021	0.007	0.197
December	0.989	0.509	0.009	0.116
Mean	0.1861667	8.33475	0.01791667	0.328267

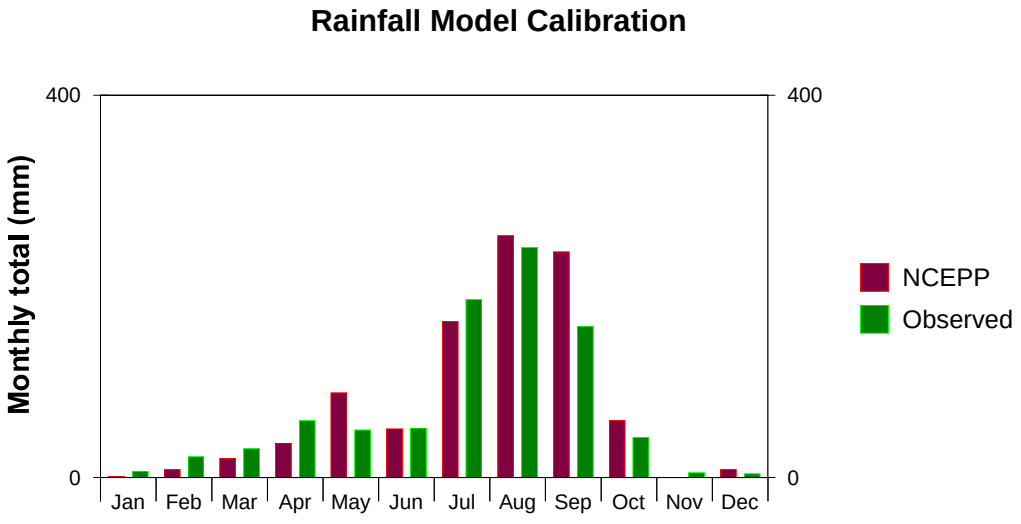

Figure 16.Validation results of SDSM based downscaling for precipitation

As showing in the Table 15 and Figure 16 on monthly scale the simulation of rainfall showed a relatively good agreement is observed for the months of January, February, November and December and a lesser agreement is for the months of September and July. However, the simulated values were overestimated except in the month of July. The fact that the model shows a lesser agreement for rainfall has been observed in many research papers (Gary *et al.,* 2006; Tamiru *et al*. 2011; Fiseha *et al.,* 2012). In fact, this is one of the drawbacks of the model in simulating rainfall. As compared to some other similar downscaling results, this explanation should be considered as appropriate (Fiseha *et al.,* 2012).

For temperatures (Tmax and Tmin), the results (Tables 16 and 17; Figures 17 and 18) indicate a reasonable agreement between the simulated and observed values on monthly timescale at Debre Zeit weather station.

Table 16. Statistical validation of minimum temperature

	Unconditional	
Months	**R-Squared**	**SE**
January	0.546	2.5324
February	0.589	1.5324
March	0.675	2.3324
April	0.487	0.3554
May	0.701	3.0624
June	0.408	1.5066
July	0.581	2.4514
August	0.67	3.8924
September	0.688	1.4354
October	0.589	2.0294
November	0.499	1.1194
December	0.412	2.0384
Mean	0.5704167	2.024

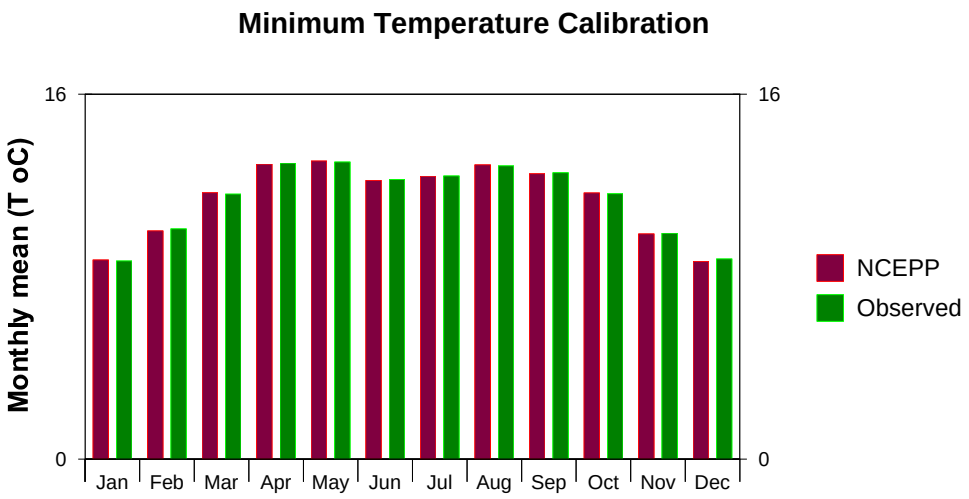

Figure 17. Validation results SDSM based downscaling for minimum temperature

Table 17. Statistical validation of maximum temperature

	Unconditional	
Months	**R-Squared**	**SE**
January	0.66	1.61
February	0.589	2.61
March	0.69	3.41
April	0.499	1.433
May	0.489	4.14
June	0.558	2.429
July	0.408	3.529
August	0.588	4.97
September	0.446	2.513
October	0.688	3.107
November	0.401	2.197
December	0.487	3.116
Mean	0.5419167	2.922

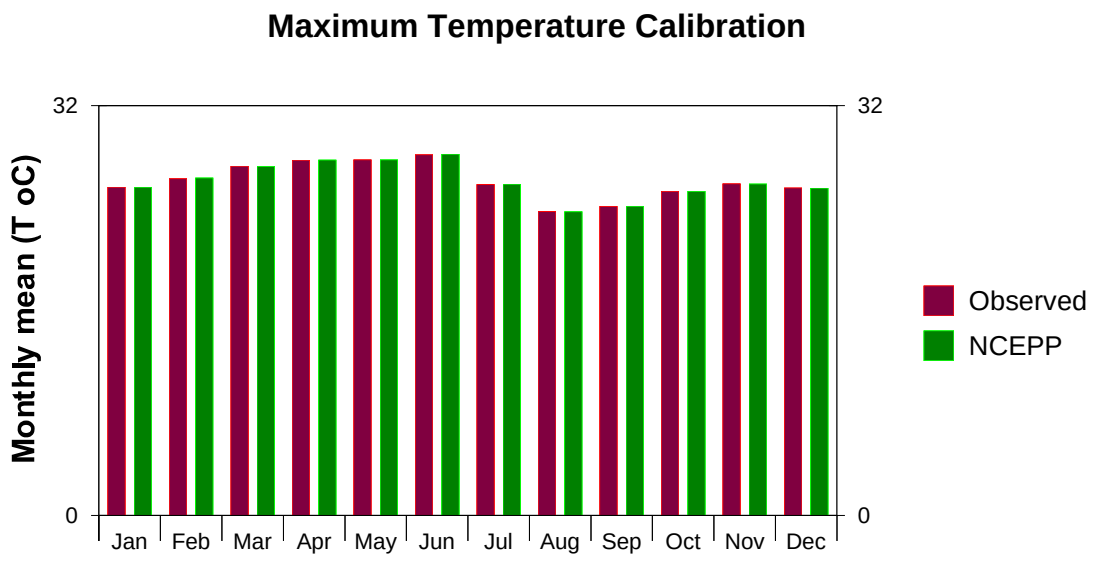

Figure 18.Validation results SDSM based downscaling for maximum temperature

The results show that the simulated minimum and maximum temperatures have better agreement with the observed results for all months of years. This confirms a good performance of the model to project future variation of temperatures. The reason could be due to the fact that temperature is unconditional processes which are not regulated by other intermediate processes. In addition, as indicated in the SDSM manual (Wilby and Dawson, 2004), local temperatures are largely determined by regional forcing whereas rainfall series displays more “noise” arising from local factors.

4.2.2. Downscaling GCM output corresponding to a climate change scenario

Table 18 summarizes the downscaling results of the SDSM model by representing the average changes (positive or negative) between baseline period (1970-2000) and each time slice. The changes for each of these climate variables are discussed below

Table 18. Change in annual values of rainfall and temperature by 2030, 2050 and 2080 from baseline period (1970-2000) at Debre Zeit

	Average Increase/Decrease					
	Rainfall (%)		Minimum Temperature (°C)		Maximum Temperature (°C)	
	A2	B2	A2	B2	A2	B2
2030	-9.89	-12.77	0.35	-1.64	0.08	0.30
2050	-17.68	-14.82	1.60	-2.19	0.16	0.94
2080	-19.76	-18.91	2.44	-2.45	0.24	2.64

These results show a declining trend for rainfall with all scenarios, whereas an increasing trend is observed for temperatures except minimum temperature with B2 scenario.

a. Rainfall

On annual time scale, A2a and B2a scenarios generated a decrease of 19.76 % and 18.9 % of rainfall by 2080s, a decrease of 17.6 and 14.8 % by 2050s and a decrease of 9.8 and 12.7 % by 2030s (Table 18). This is in agreement with what the IPCC reported for Africa in general and over Easter Africa in particular. The fifth report of IPCC (2014a) shows a very likely decrease in annual average rainfall in the mid-21st century. In contrast, across different months, the same report indicated that over Ethiopia a more intense wet season may be observed in April and May (IPCC, 2014a).

Furthermore as shown in Figure 19, the average monthly rainfall shows remarkable peak point for short rains (March to May) and for long rains (June to October) by 2080. In the same line for both scenarios, the average monthly rainfall in June, August and October decrease from the base period level. The decrease in rainfall in August coincides with crucial period of wheat growth and development. On the other hand, for both scenarios, the peak occurrence of rainfall in the month of May might be unusual occurrence of rainfall.

Therefore, there is a decreasing trend of rainfall in the study area in the future, which might have a negative impact on meeting water requirements of durum wheat crop, as well as through increased temperature and enhanced evapotranspiration loss. Traditionally farmers in the study area are used to prepare their land in the months of

May and June (at the end of short rainy season and starting of rainy season). Thus, the declining trend of rainfall in this area of the region will have a significant impact on the farming community. It will affect not only yield but also limits crop choice of the farmers, which in turn may result in shifting of crop type and loss of biodiversity.

By the same token, this confirms IPCC's projection of more intense wet months and less severe droughts in October-November-December and March-April-May (IPCC, 2014a). On the other hand, Zeray (2006) and Tamiru *et al.* (2011) reported increasing trend of annual rainfall at Ziway and Miesso areas of Oromia regional State of Ethiopia. This difference might be evolved due to generate future rainfall. In fact, as Flato *et al.* (2013) noted, future climate projection are quite uncertain and the output depends on the number and type of GCMs used. According to Funk and Rowland (2011) the basic reason for the spatial, inter annual variability of Africa climate is warming and increased convection of the southern Indian Ocean and would also remain as major climate variability drivers in the region.

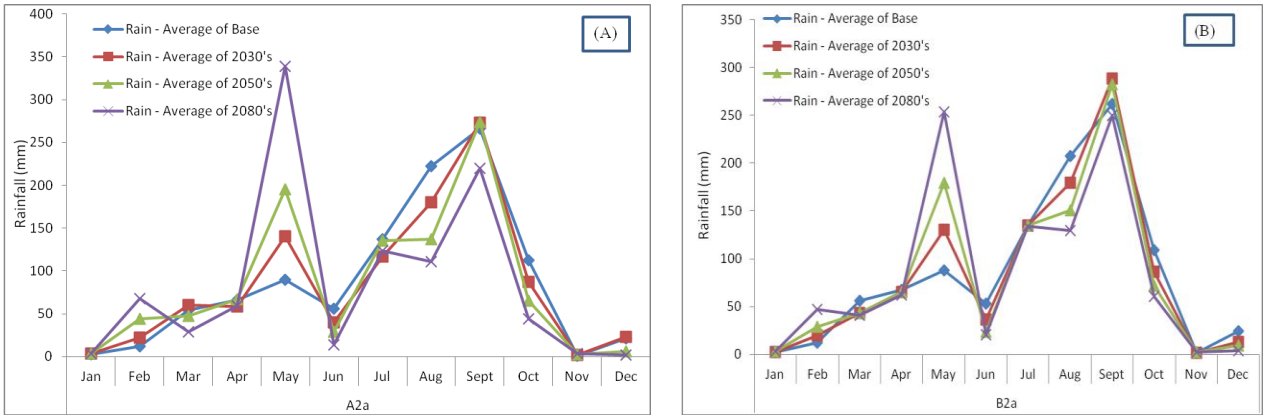

Figure 19. General trends in rainfall at Debre Zeit corresponding to a climate change with A2 (A) and B2 (B) scenarios

b. Minimum Temperature

On annual scale, the average minimum temperature might increase by 0.341°C for 2030s, by 1.59°C for 2050s and by 2.44°C for 2080s under A2a scenario, while it might decrease by 1.6°C in for 2030s, by 2.1°C for 2050s and by 2.4°C for 2080s under B2a (Table 18).

The average minimum temperature exhibit an increasing trend under A2a and decreasing under B2a scenarios. However, the results show a decreasing of minimum temperature in the months of June, July and August under A2a scenario. Figure 20 shows an increasing temperature in the months from January to May and then remarkable extreme decline between June and July under A2a. Under B2a May and July show an increment from baseline.

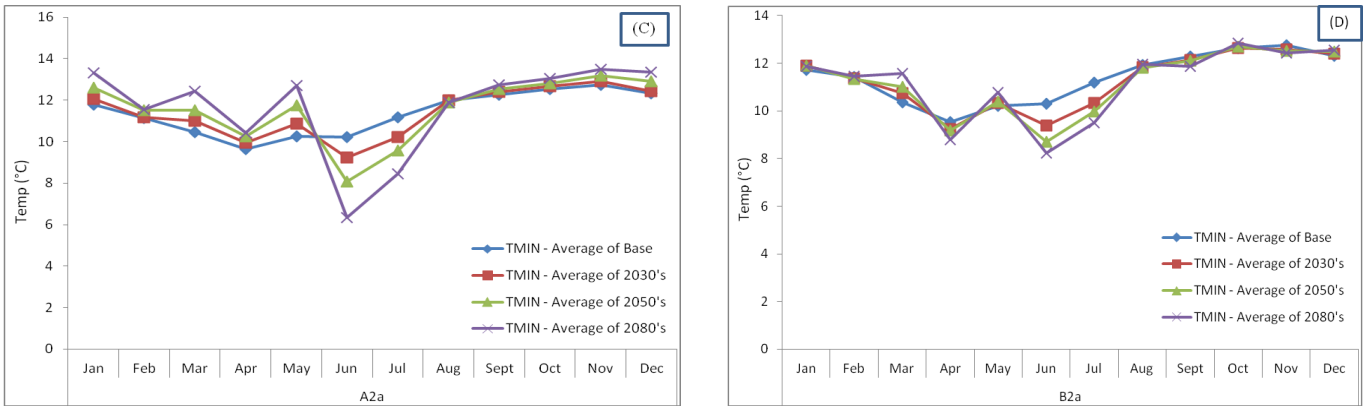

Figure 20. General trend for minimum temperature at Debre Zeit corresponding to a climate change with A2 (C) and B (D) scenarios

c. Maximum Temperature

With regard to maximum temperature, the B2 scenario will be warmer than the A2 scenario. The warming is highest during the October to December months and lowest in August under both scenarios (Figures 21). The overall result shows that the change in average maximum temperature might range between +0.07°C and +0.24°C for the A2a scenario; and between 03°C to +2.63°C for the B2a scenario (Table 18).

On annual scale, there might be a general incremental change under both scenarios and for all time slices from the base period. Under both scenarios, an average increment across the months from January until May and then decreasing from June to September and finally another increment from October and December. The figure shows positive peak in May/June, while a negative peak is observed in August by 2080s. Moreover, the most remarkable increase of maximum temperature might be observed in November which means that is dry season.

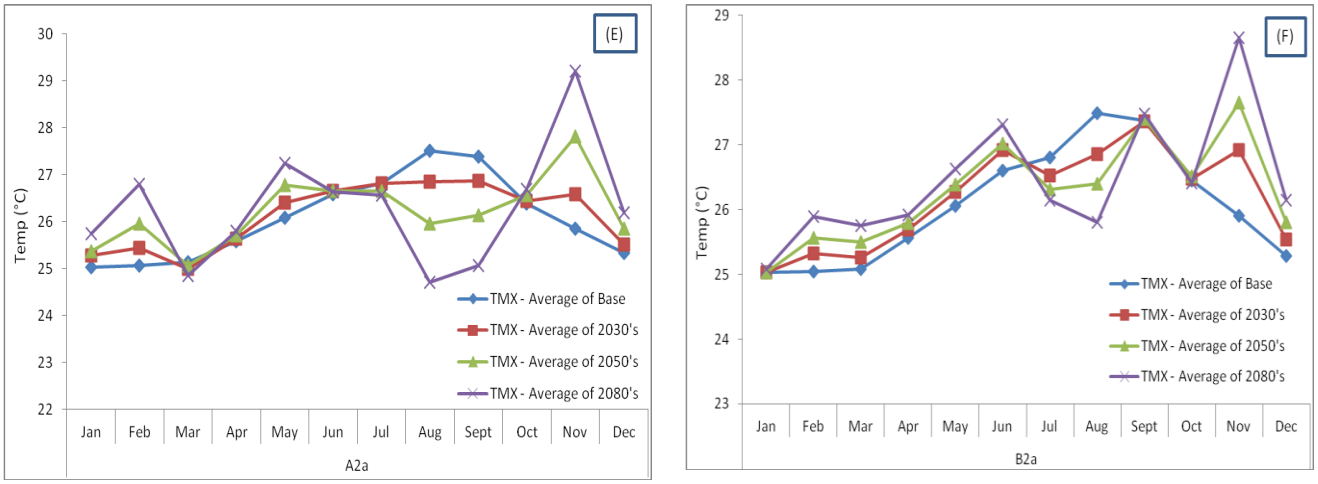

Figure 21. General trends for maximum temperature at Debre Zeit corresponding to a climate change with A2 (E) and B2 (F) scenarios

Therefore, the result revealed a warming trend. The study area is located within a town and the release of industrial byproducts (carbon dioxide) might affect the concentration of the atmospheric composition, which in turn affects temperature.

The present study implies increasing trend of heat wave occurrence in the study area, which may affect durum wheat production in many ways. For instance, increased heating leads to greater evaporation, and thus surface drying. If not offset by adequate moisture, this will increase the intensity and duration of drought, thereby resulting in failure of durum wheat production. Heat stress induces flower abortion and poor grain filling of wheat. This might affect the number of grain per plant and subsequently the yield per unit area. In line with the current result, NMA (2007), Zeray (2006), Yemenu and Chemeda (2010) and Tamiru *et al* (2011) reported that minimum and maximum temperature in Ethiopia would increase. IPCC (2014a) indicated that large scale increase in average temperature is very likely in the mid- and late-21st century under both low and high emissions scenarios. The change in average temperature is projected to be greater over northern Africa. Under a low-emissions scenario, average temperature rises across Africa are projected to be less than 2°C by both the mid- and late-21st century. All seasons are expected to warm which may results in more frequent heat waves as indicated by IPCC.

Therefore, this analysis has shown that A2a and B2a scenarios defined in the same GCM (HadCM3) sources can give different outputs for future rainfall and temperatures characteristics. This is because the scenario data are also based on a set of assumptions on international geopolitics, economic and population growth rate, and technical development. These assumptions are dependent on the local dynamics of the system that cannot be accurately described (IPCC, 2007b).

As the interest of this study was more in the relative variation of the climatic variables rather than in the absolute values, the results interpretation can be considered as appropriate. As noticed IPCC (2014a), projections for rainfall are less certain than projections for temperatures, the same remark has been noticed in this study.

4.3. Impact assessment on Durum Wheat Production

4.3.1. Model calibration and performance

Results of model calibrations and the derived parameters are presented in Table 20 for Ude and Yerer cultivars and statistical indicators of model performance are shown in Table 19 for both cultivars.

For grain yield, the data indicates that the simulated grain yield values reasonably matched the observed values, with values above critical value of agreement index (d-statistic) of 0.5 for both cultivars. The more d-statistic values close to 1 are regarded as better simulations (Wilmott *et al.,* 1985 cited by Musongaleli *et al.,* 2014). The CERES-Wheat model simulated yield with acceptable accuracy, with a Wilmott index (d-Statistic) of agreement of 0.58 and for Ude and of 0.98 for Yerer. The predicted wheat yield by the model also showed difference of 53.54 kg/ha for Ude and 254.8 kg/ha for Yerer. Compared to the observed data, a high correlation was obtained for Ude and Yerer between simulated and observed grain yields. This difference may be due to inability of the models to capture the effects of biotic stresses such as pests, diseases and weeds, inaccuracies in defining the initial conditions. However, the simulated long-term yields reflected the trends in the yields reported on farm and on station fairly well in all scenarios. The coefficients of correlation are 65.1 and 61.6 % for Ude and Yerer

respectively (Table 19). Similar results were found by Valizadeh (*et al.*, 2013) and Ludwig and Asseng, (2005) when assessing climate change impacts on wheat production in India and in Western Australian Wheat Cropping Systems respectively.

Moreover, the crop growth simulation runs resulted in low RMSE values the difference between predicted and observed data was low for anthesis and maturity stage. This is indicative of the high ability of this model in the prediction of these traits. Predicted values for the traits of days to anthesis and days to maturity were estimated respectively by the model with the difference of 6.91 % and 4.69 % for Ude and 5.53 % and 3.12 % for Yerer of the measured data which is the appropriate amount for the validity of crop's growth simulation model (Table 19). Also a good correlation was observed between predicted and measured values for days to anthesis and days to physiological maturity with a correlation coefficient of 71 % and 60 % respectively for Ude and a correlation coefficient of 78 % and 95 % respectively for Yerer (Figures 26 and 27).

Table 19. Statistical indicators of model performance

Crop parameters	Statistical parameters		
	R-Squared	RMSE	d-Statistics
	Ude		
Grain Yield	0.65	53.54	0.58
Days to physiological maturity	0.60	4.69	0.77
	Yerer		
Grain Yield	0.616	254.8	0.998
Days to physiological maturity	0.9565	3.12	0.62

The model was run first to fix the genetic coefficients (cultivar parameters) that influence physiological parameters. The GLUE program made 3,000 runs for phenology coefficient such P1V, P1D and P5, and then 3,000 runs for growth coefficients such as G1, G2, G3 and PHINT. We have found that the generated genetic coefficient would somewhat simulate the exact conditions of wheat production under the recommended management

options for Ude and Yerer cultivars at Ada'a (Figures 22 and 23). The value for each coefficient and for the two cultivars is shown in Table 20.

Table 20. Genetic coefficients used to calibrate and validate the CERES-Wheat model for simulation of Wheat var. Ude and YERER in Ada'a, Central Rift Valley

Symbols	Definitions	Coefficients	
		Ude	Yerer
P1V	Days, Optimum vernalizing temperature, required for vernalization	5.80	5.10
P1D	Photoperiod response (% reduction in rate/10h drop in pp)	45.22	84.50
P5	Grain filling (excluding lag) phase duration (oC.d)	740.70	700.80
G1	Kernel number per unit canopy weight at anthesis (#/g)	40.00	35.00
G2	Standard kernel size under optimum condition (mg)	50.00	45.00
G3	Standard non stressed mature tiller wt (incl grain) (g dwt)	1.00	1.00
PHINT	Interval between successive tip appearance (oC.d)	60.00	60.00

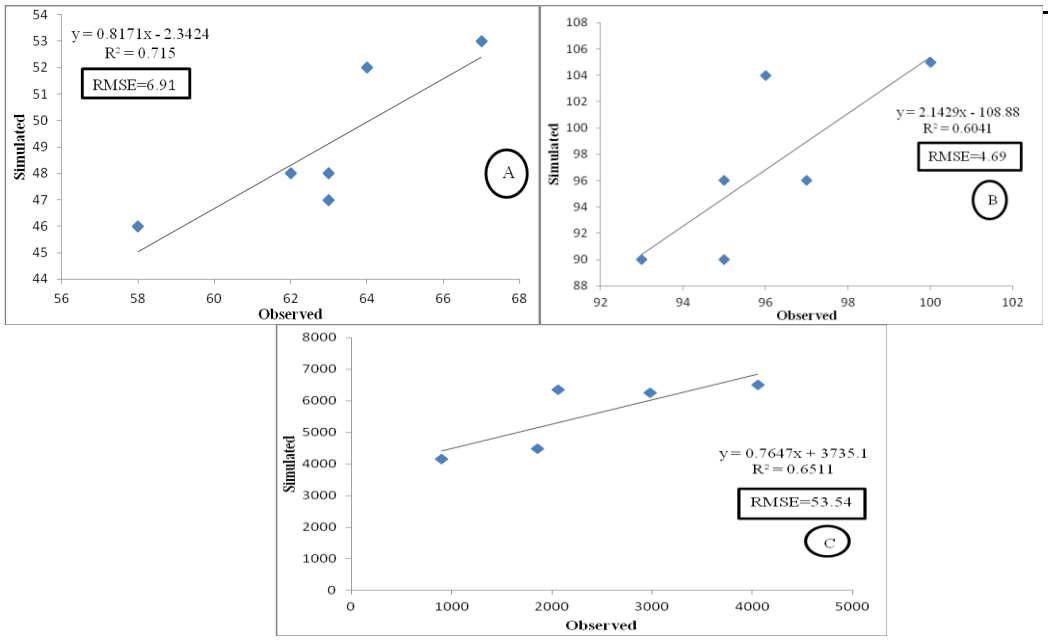

Figure 22. CERES-wheat simulation model calibrations for Ude wheat variety: A) days to anthesis, B) Days to maturity C) Grain yield

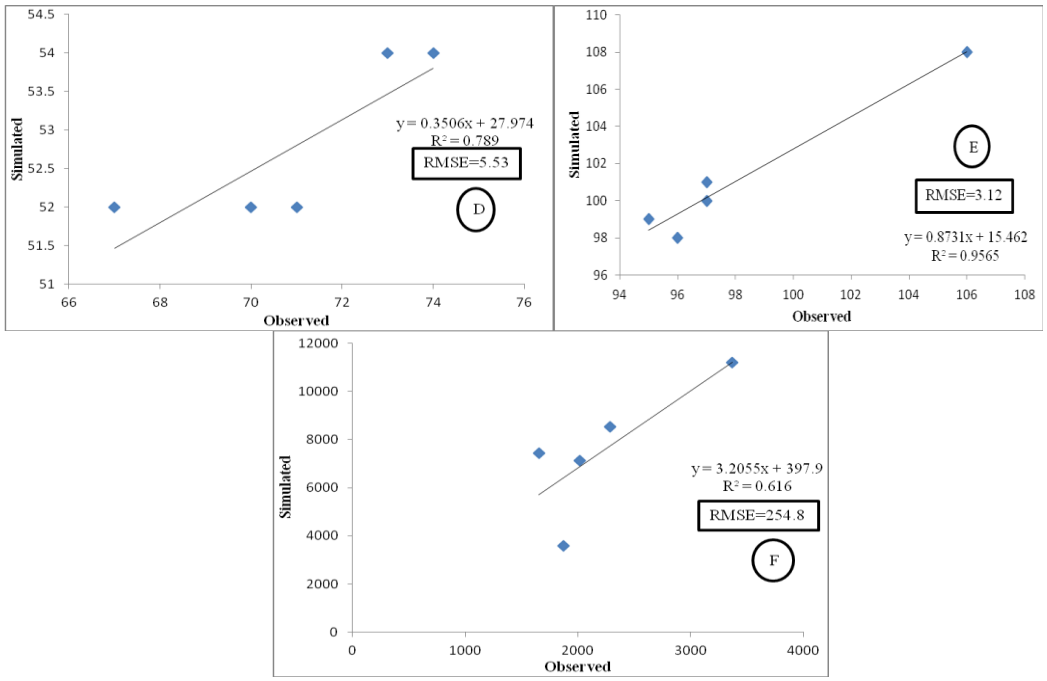

Figure 23. CERES-wheat simulation model calibrations for Yerer wheat variety: D) days to anthesis, E) Days to maturity F) Grain yield

4.3.2. Impact of climate change on durum wheat yield

The projected future climate change has a positive impact on Ude and Yerer grain yield in the study area in both scenarios by 2050's and 2080's periods while it shows a negative impact by 2030s period for Yerer only under both scenarios. The two cultivars have responded differently for future climate change. Comparing the two scenarios, the results in Figures 24 and 25 revealed that the A2 has resulted in reducing yield than the B2 scenario. In other words, the cultivars have favourable condition under the B2 scenarios than A2 scenarios.

For Ude, Figure 24 shows an increasing of grain yield under both scenario from the baseline condition (the future without climate change), the variation of grain yield oscillate between 11.89 and 30.25 % for A2 scenario while the variation oscillate between 38.20 up to 49.58 % for B2 scenario.

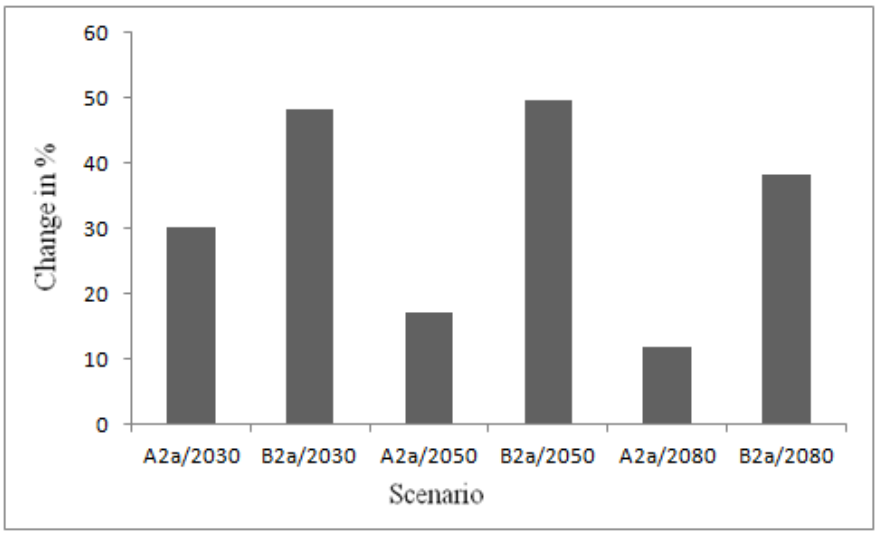

Figure 24. Change in percentage of yield from baseline period for Ude

For Yerer, the increasing of grain yield from the baseline condition has been observed by 2050s and 2080s under both scenarios and then, the variation of grain yield oscillates between 0.21 and 1.90 % for A2 scenario while the variation oscillate between 4.59 and 10.75 % for B2 scenario. However there is a declining trend of grain yield from baseline of 1.78 and 3.6 % in 2030s for A2a and B2a (Figure 25).

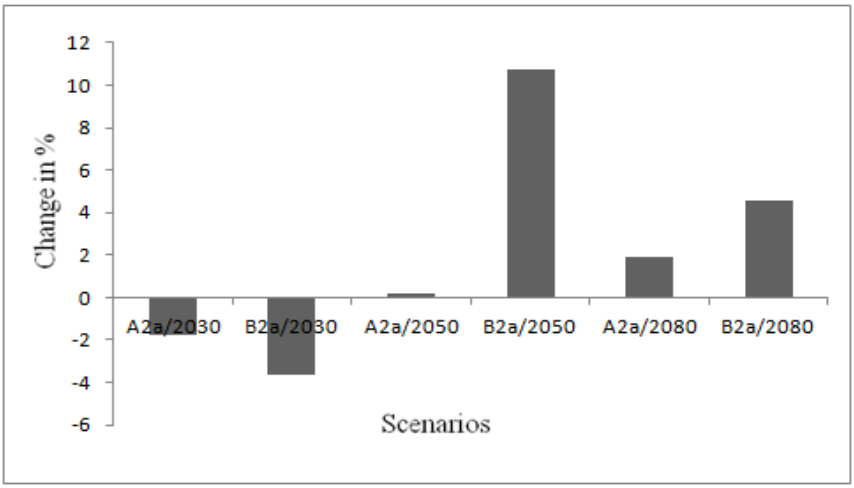

Figure 25. Change in percentage of yield from baseline period for Yerer

For this study, the substantial increase in durum wheat production should be affected on increasing amount of CO_2 than any other climatic parameters. However, CO_2 effect is

more pronounced in elevated temperature which explains negative impact by 2030. In other words, high temperature enhances the effect of elevated CO_2. This increases photosynthesis, thereby increasing the carbohydrate pools of leaves and stems and has its greatest effect during vegetative and reproductive development when the additional carbohydrates produced in CO_2-enriched plants may well determine the developmental pattern of the meristematic tissues (Attri and Rathore, 2003). For example, an abundance of assimilate allows young tillers and grain primordia to survive thereby providing an explanation for the increased tiller survival and grain number per ear as can be deduced in the present study.

In other words, this positive impact is estimated assuming beneficial effects of CO_2 for C_3 crops as stated in literature review above as stomatal conductance declines with increasing CO_2 concentration for C_3 plants which seems to benefit in terms of dry matter production from a higher CO_2 level due to higher leaf expansion (Warrick *et al*., 1986). Thus, the difference can be explained by slight temperature and CO_2 increases in the latter periods.

However, the positive relationship between grain yield and increasing atmospheric CO_2 concentration was non-linear response under 710 ppm for Yerer. The underlying reason may be due to the fact that Yerer is a cultivar that performs well in waterlogging condition. And then, at 12.77 % (Table 9) where future reduction of rainfall has not been considered as yield limiting factor. In fact, as Mulholland et al. (1997) and WMO (2010) noted that at some point water limited conditions, CO_2-induced stomatal regulation is desirable trait even though actual rate of CO_2-exchange may be lower than without regulation during periods when sufficient moisture is available. In other words, in the case of 17.68 and 19.76 % (Table 9) reduction of rainfall by 2050s and 2080s respectively may be considered as a limiting factor, and then the productivity has increased under elevated CO_2 under water limiting condition than under watered conditions. In practice it means that an increase in water saving, due to partial closure of leaf stomata is beneficial effect that is expected when water resource is limiting factor.

However, furthermore, the changes in yield are shown as reduction from yield on station (Table 2). As Tables 21 and 22 for Ude and Yerer show respectively, the potential variation in Ada'a compared to the on station yield. This means that crop management options may have a positive impact to increase yield at its potential of production under future climate change.

Hence, the disparities in wheat yields at Ada'a are going to be observed probably at different rate than has been found from similar studies in Ethiopia and particularly in Oromia region. In fact, the results reported by Kelbore (2012) showed that due to climate change, wheat production in Oromia region of Ethiopia may be reduced at 7.26 % by 2050s and 9.59 % by 2100, while at national level, it may be reduced at 6.21 % by 2050s and 11.03 % by 2100. This is included in the line with Parry (*et al.*, 2003) who showed that the SRES scenarios result in crop yield decreases in developing countries with significance in Africa.

4.3.3. Risk analysis using probability of non exceedence

The outputs of risk analyses using probabilistic approach for two cultivars by three time slices are presented in Figures 26 and 27.

The results reveal that for instance, for Ude A2/2080 was dominant in second degree stochastic dominant sense giving a yield of 3000 kg per ha with 40 % risk (Figure 26 (left panel) and less, while B2/2030s and B2/2050s will be dominant in the second degree stochastic dominant sense giving a yield of 4500 kg per ha with 50 % risk and less (Figure 26 (right panel)). In other words, it can also be deduced from the same Figure that, a farmer targeting 4000 kg per ha by 2030s and 2050s could achieve the desired quantity, but the associated risk level will go up to 55 %. In such a targeted yield analyses, any decision maker should therefore be able to increase the soil water content and crop water use efficiency.

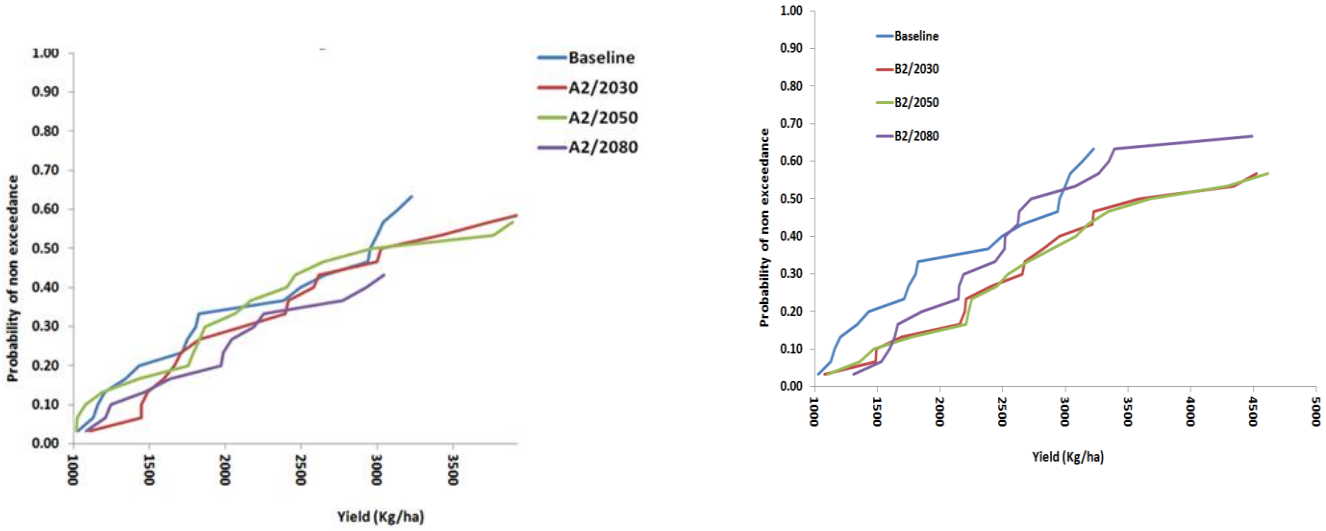

Figure 26. The Probability of non exceedence in yield of Ude with A2 scenario (left panel) and B2 scenario (right panel)

For Yerer, the results reveal A2/2050s will be dominant in the second degree stochastic dominant sense and A2/2080s was dominant in third degree stochastic dominant sense yielding 2200 kg per ha with 40 % risk and 3700 kg per ha with 60 % risk respectively (Figure 27 (left panel)). On the other hand, for Yerer, the risk of getting yield of 3500 kg/ha is more than 50 % in all time slices under A2 scenario. In the same line with B2 scenario, the risk of getting yield greater than 3500 kg/ha is greater than 50 % for all time slice such 2030s, 2050s and 2080s. In other words, it can also be deduced from the same Figure that, a farmer targeting 4800 kg per ha by 2050 could achieve the desired quantity, but the associated risk level goes up to 75 %. Targeting this yield, any decision maker

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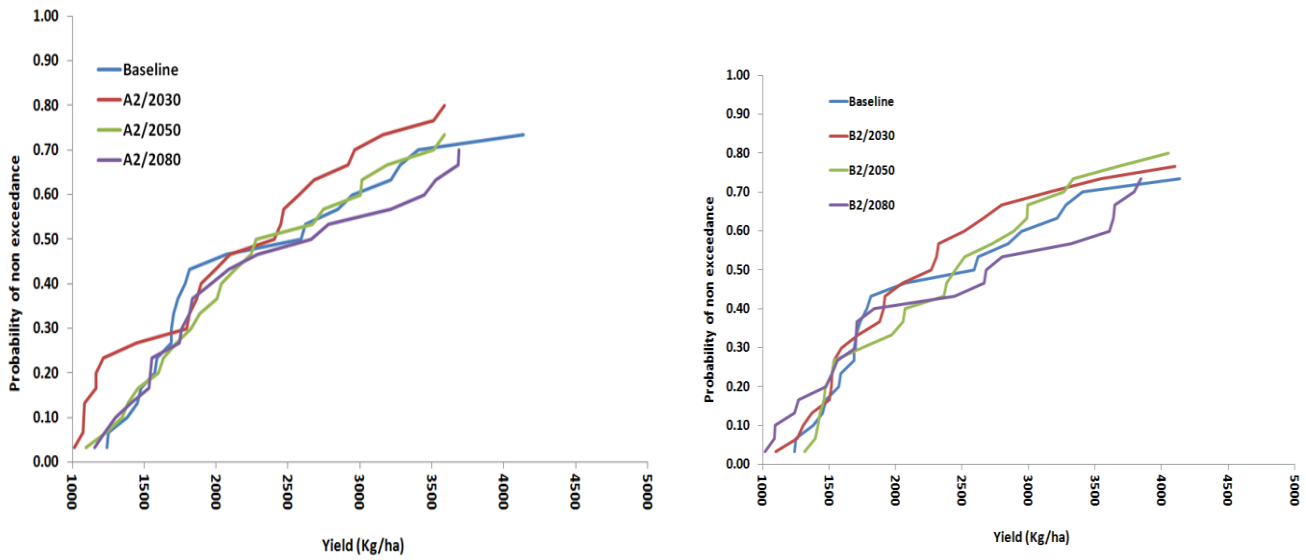

Figure 27. The Probability of non exceedence in yield of Yerer with A2 scenario (at left) and B2 scenario at right

should therefore reanalyze some crop management options such as fertilizer input, timeliness of agricultural operation, soil water content and crop water use efficiency. By comparison, therefore, it is clear that Yerer shows high potential yield with less risk associated which is greater than the one for Ude.

4.3.4. Grain yield variability from the baseline

Figures 28 and 29 show projected yield variation for Ude and Yerer due to impact of climate change at Debre Zeit under the two SRES scenarios on 2030s 2050s and 2080s. The results have been depicted in box plot using median, 25 and 75 percentile, maximum and minimum yield. The statistics are depicted in Tables 21 and 22.

For Ude, B2 scenario shows a declining medians with 26.58, 25.40 and 24.77 qt/ha under 2030s, 2050s and 2080s respectively, while the corresponding yields for A2 scenario are 22.5, 18.65 and 19.87 qt/ha (Table 21 and Figure 28). In the same figures, 32.16, 31,78 and 28.16 qt/ha of grain yield would be obtained in three out of four years for B2 scenario, while the corresponding grain yield under A2 scenarios is expected to be above 29.02, 24.61 and 22.56 qt/ha for the three time slice respectively. Whereas above 21.60, 22.11 and 18.07 qt/ha grain yield are likely in one out of four years under B2

scenario. For A2 scenario, 16.12, 14.30 and 14.68 qt/ha under the three time slices respectively with coefficient of variation of 32.4, 33.15 and 27.64 % for B2a and 37.3, 42.1 and 32.8 % for A2.

For Yerer, B2 scenario shows increment and declining medians with 19.11, 23.65 and 17.76 qt/ha through 2030s, 2050s and 2080s respectively, while the corresponding yields for A2 scenario show the same trend where the yield will likely be 19.98, 20.24 and 18.34 qt/ha (Table 22 and Figure 29). In the same figure, 24.21, 29.91 and 31.92 qt/ha of grain yield will be likely in three out of four years for B2 scenario while the corresponding grain yield under A2 scenarios is expected to be 26.83, 27.28 and 27.84 qt/ha for the three time slice respectively. Whereas above 15.23, 15.25 and 14.89 qt/ha grain yield could be obtained in one out of four years under B2 scenario while for A2 scenario, 12.15, 16.08 and 15.42 qt/ha under for different time slice respectively with coefficient of variation of 36.9, 38.8 and 44.6 % for B2a and 40.2, 34.5 and 39.2 % for A2.

Table 21. Crop Yield (kg/ha) Variability of Ude cultivar at different Scenarios and for three time slice

Statistical parameters	Baseline	A2a/2030s	B2a/2030s	A2a/2050s	B2a/2050s	A2a/2080s	B2a/2080s
Minimum	1031	1113	1078	1023	1107	1084	1535
25th %tile	1238.75	1612.5	2160	1430	2211	1468	1807.75
Median	1733	2251.5	2658	1865	2540	1987	2477
75th %tile	2244.25	2902.25	3216	2461	3178	2256	2816.5
Maximum	2940	4070	4525	3892	4617	3042	4489
Mean	1776.714	2314.2778	2631.8824	2078.94118	2657.7647	1988	2455.55
CV (%)	34.9	37.3	36.5	42.1	36.9	32.8	32.1

Table 22. Crop Yield (kg/ha) Variability of Yerer cultivar at different Scenarios and for three time slice

Statistical parameters	Baseline	A2a/2030s	B2a/2030s	A2a/2050s	B2a/2050s	A2a/2080s	B2a/2080s
Minimum	1244	1015	1101	1098	1316	1154	1020
25th percentile	1577.5	1215	1523.5	1608	1525	1542	1489.75
Median	1760.5	1998	1911	2024	2365	1834	1776.5
75th percentile	2792	2683	2421.5	2728.75	2991	2784	3192.75
Maximum	4139	3590	4100	3586	4739	3691	3844
Mean	2160.182	2121.52	2082.2609	2164.7727	2392.44	2201.333	2259.36364
CV (%)	38.2	40.2	36.9	34.5	38.8	39.2	44.6

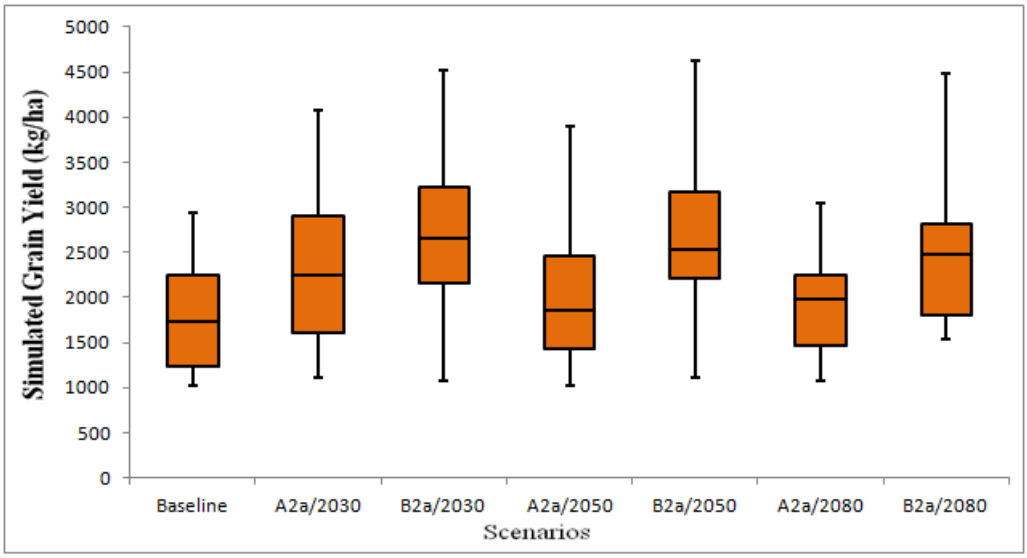

Figure 28. Box plot and whiskers, indicating variation of projected grain yield of Ude

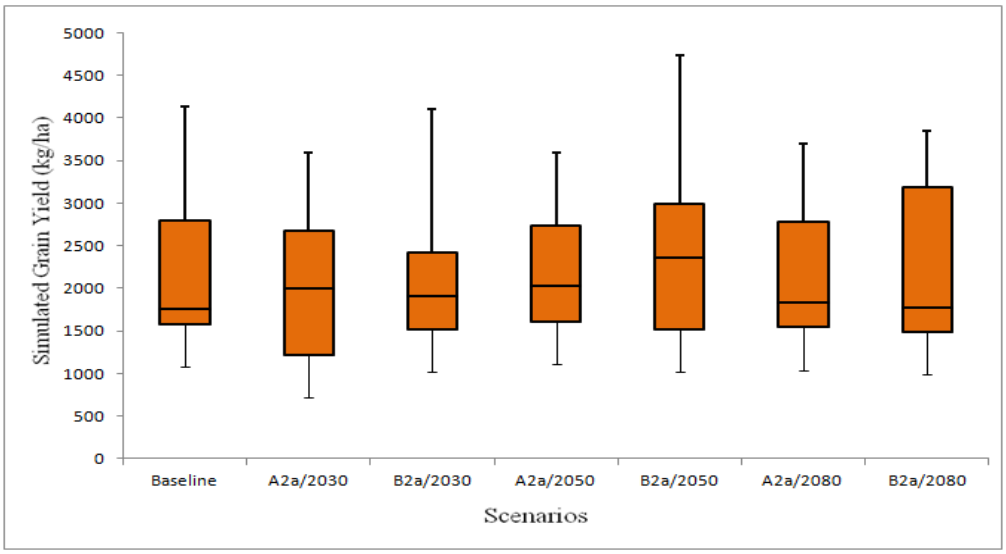

Figure 29. Box plot and whiskers, indicating variation of projected grain yield of Yerer

For Ude, the lowest mean (19.88 qt/ha) of yields is expected in 2080s for A2 which is less than the current situation in the studied area while the maximum yield may be observed at 46.17 qt/ha in 2050s followed by 45.25 qt/ha in 2030s for B2a. Those values are great than the maximum on farm yield (40 qt/ha) and less than maximum on station yield (50 qt/ha) in studied area.

For Yerer, the lowest mean (20.82 qt/ha) of yields is expected in 2030s under B2a which is slightly greater than the minimum on farm yield while the maximum yield is projected to be observed at 47.39 qt/ha in 2050s followed by 41 qt/ha in 2030s for B2a which are greater than the maximum from on farm yield (36 qt/t) and less than the maximum from on station yield (50 qt/ha).

4.3.3. Adaptation measures to the impacts projected climate change

The future adaptation measures are depicted in 36 treatments. These are shown in appendix figure 1-6. As noted in previous section of this study, negative impact of climate change on yield has been observed for Yerer in 2030s for A2 and B2. In other words, all scenarios such as A2a/2050s, B2a/2050s, A2a/2080s and B2a/2080s are benefited from projected changes in climate, but there are practices which may not help in realizing the full benefits of changes in their climatic conditions. Thus, adaptation

measures need to be developed for all scenarios at different levels of crop management options, promising technologies from the existing ones need to be carried forward. Among 36 treatments, five best bets have been picked (Table 23) and then one best adaptation measure. The figures 30 and 31 show the best treatments for Ude and Yerer.

Table 23. The five treatments representing best bet

Treatment18	Early planting	High planting density	High fertilization rate
Treatment 24	Normal planting	Medium planting density	High fertilization rate
Treatment 27	Normal planting	High planting density	High fertilization rate
Treatment 33	Late planting	Medium planting density	High fertilization rate
Treatment 36	Late planting	High planting density	High fertilization rate

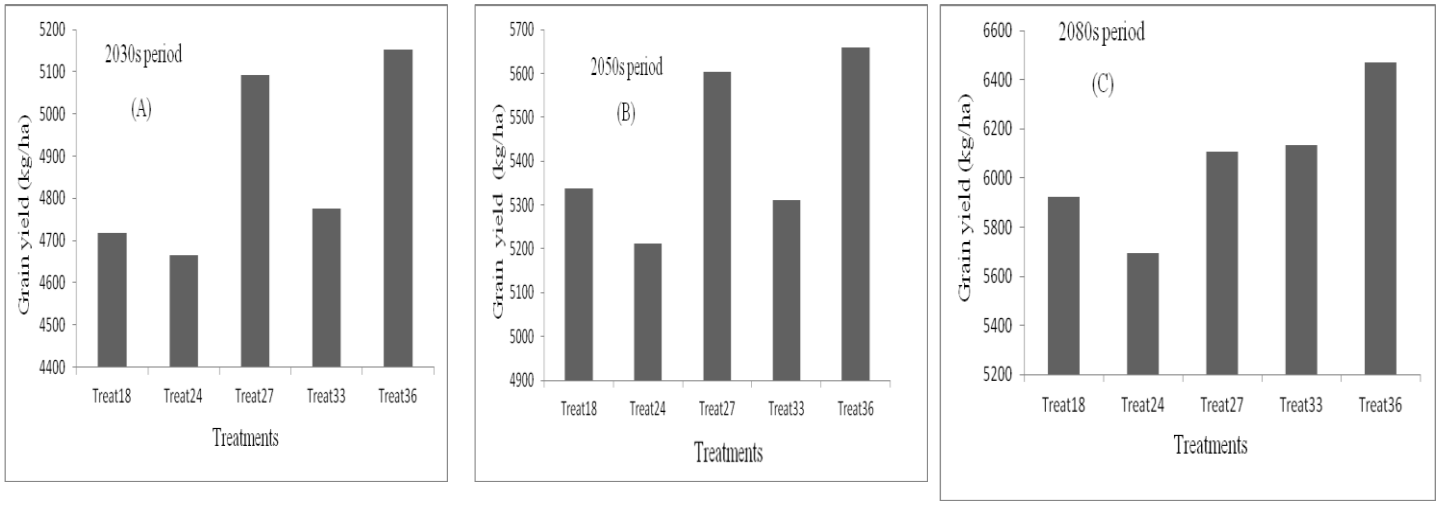

Figure 30 . Best adaptation measures for Ude at different time slices (A) 2030s, (B) 2050s, (C) 2080s

For Ude, according to figures noted above (A), (B) and (C), treatment 36 is the best and then adaptation options identified are late planting date, use of high planting density and use of high fertilization rate of nitrogen.

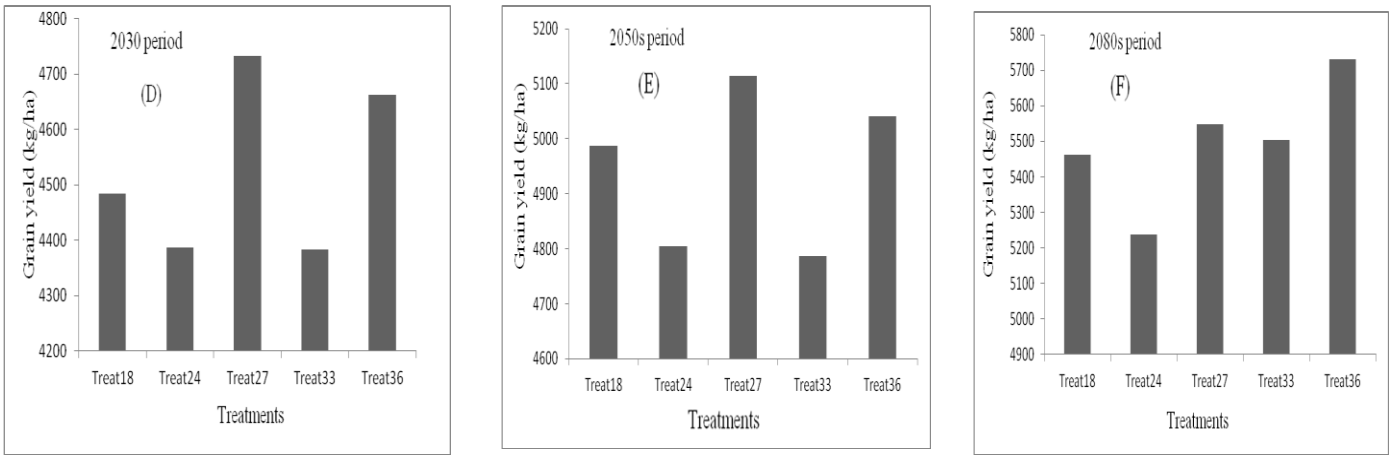

Figure 31. Best adaptation measures for Yerer at different time slices (D) 2030s, (E) 2050s, (F) 2080s

For Yerer, the figures above show that for short term and medium term ((D) and (E)), treatment 27 is the best while for long term (F), treatment 36 is appropriate. However, the difference is observed for planting date.

Therefore, Ude fits best than Yerer with adaptations measures under changing climate condition (Table 24). In fact, as noted by Challinor *et al.* (2007) choice of cultivar is an important adaptation strategy. Therefore, the adaptations measures are presented in Table 25.

Table 24. Yield comparison between Ude and Yerer under best treatments at different time slices

Time slices	2030s	2050s	2080s
Ude (kg/ha)	5152	5659.28	6469.89
Yerer (kg/ha)	4733	5113.82	5731.7

Table 25. Selected best management practices in the projected climate change

Cultivars	Planting date	Planting density	Fertilizer application rate (N)
Ude	Late	350 plants per square meter	180 kg/ha

We have noticed that adaptation measures with high yield are related to high application rate of N. The increasing rate in simulated yields was higher for Ude than Yerer (see Figures 30 and 31). The increased yield under modified climate in all the cultivars will be caused by CO_2 enrichment and higher water use efficiency and N utilization. The process of N uptake will be influenced by changes in the rate of physiological processes resulting from enhanced temperature (0.30 to 2.64°C across time slices) and CO_2 (590 to 855 ppm). In fact, as Attri and Rathore (2003) noted, owing to enhanced concentration of CO_2 in the atmosphere and, consequently, in the plant (specially, C_3), plants will tend to have higher N uptake and consequently the yield. In other words, plants will tend to maintain the C:N ratio constant for better growth and development.

One may think that, in this case, excessive N may cause some environmental consequences related to green house gases emission; particularly the emission of nitrous oxide (N_2O) through nitrification and denitrification process . Ude and Yerer have semi-dwarfing genes, and this allows higher fertilizer inputs without the associated yield loss due to lodging and disease incidence (WMO, 2010; Gerba *et al.*, 2013). But the issue of GHGs emission still remain open for further research.

Similar to our result, Luo *et al.* (2009) reported that changing the nitrogen levels from 25 to 75 kg/ha increased wheat yield under climate change in Australia, however, the projected yield increase was less than for the baseline. Similarly, Turner and Rao (2011) indicated that increasing nitrogen fertilizer rate from 20 to 80 kg/ha under a 3°C temperature rise increased yields of wheat by 15-70% in Kenya, but yields remained lower than for the baseline climate.

In addition, in line with our results, Lal *et al*. (1998) cited by WMO (2010) have also simulated a 28 % increase in wheat yield under doubling of CO_2 from the present value of 350 ppm, but they found no significant increase beyond 950 ppm. Similar findings have been reported by Cure and Acock (1986) and Rosenzweig *et al*. (1994) cited by WMO (2010), annual variations of yield were significantly higher under rainfed conditions for different cultivars.

On the other hand, Alexandrov and Hoogenboom (2000) in Bulgaria, Cuculeanu *et al*. (2002) in Romania and Tachie-Obeng *et al.* (2010) in Ghana reported an increase in wheat yields with delayed planting dates for climate change scenarios.

5. SUMMARY AND GENERAL CONCLUSIONS

Studies like this, which focus on likely future climate change scenarios and their impact on specific enterprises like wheat crop production are essential. As understanding the problem is part of the solution, grasping the level of impact is a prerequisite to propose adaptation measures that can reduce the damage. Hence, the impact of climate change on wheat production, analysis of future adaptation measures was carried out to address part of the global problem. The study involved a cascade of analysis of climate, crop and climate models and model outputs to generate an image of projected climate related to durum wheat production and to simulate the impacts of these changes on durum wheat production in specific area. Finally, adaptation measures that can serve to reduce the damages were proposed.

The main objective of this study was to characterize climate, assess its impact on durum wheat production and identify management options for future adaptation in Ada'a district of the Central Rift Valley of Ethiopia

1. To characterize the climate and identify temporal changes in precipitation and temperature

2.To assess impact of climate change on grain yield of rainfed durum wheat and identify management options for future adaptation.

In the context of the aforementioned objectives, the study, therefore, analysed four important rainfall features using two methods and based on 42 years historical climatic data in study area. These features are onset, cessation date, length of growing season and seasonal rainfall amount characteristics.

In the same line, we analyzed historical trends of climate in the study area. The seasonal rainfall at Debre Zeit exhibited a significant declining trends ($P< 0.05$) with CV=24.9 % over the period 1970-2012. There was large inter-annual variability in the length of the growing season, ranging from 83 to 147 days with Hargreaves method while the length of growing season, ranging from 129 to 206 days with INSTAT method. The magnitude of the LGP obtained in the study is less with Hargreaves's method and adequate with

INSTAT method. With this last method, the number of days is fairly enough to support both durum wheat cultivars which are commonly grown in the areas of the district that require not more than 110 days of growing period to their maturity. On the other hand, under rainfed farming, the occurrence of the intermittent dry spells also becomes critical particularly for seedling establishment during the first 30 days after planting. In fact, a dry spell of length of 5, 7 and 10 days could occur at some stage of crop growth; however, there is higher potential for damage when it coincides with the most sensitive stages such as heading and grain filling. For the study area, the probability of dry spells of longer than 5 days was found to occur even at the middle of rainy season but with risk less than 10%. This carries useful information for planting decisions by risk taking farmers who work under different capability or resource endowments.

The study confirmed as well that the Statistical DownScaling Model (SDSM) is able to simulate all, except the extreme climatic events. The model simulated minimum and maximum temperatures more accurately than rainfall. Analysis for future climate change scenarios based on one GCM (HadCM3) and two emission scenarios (SRES, A2 and B2), which were accessible at the time of analysis, suggested that the annual rainfall may change by -9.8% to -19.6 % under both scenarios, while with regard to temperature, there is clear indication for warming trends for future climate. Analysis for future climate change scenarios showed that minimum temperature may increase by 0.341˚C to 2.4˚C and maximum temperature by 0.07˚C to 2.63˚C under both scenarios by 2100.

The study investigated how durum wheat production will also be affected by future climate change and what option for adaptation measures. The results revealed that the projected future climate change has a positive impact on Ude and Yerer grain yield in the study area in both scenarios by 2050 and 2080 periods while it shows a negative impact by 2030s period for Yerer only under both scenarios. The two cultivars will respond differently for future climate change and Yerer showed high potential yield with less risk associated than Ude.

In fact, for Ude, grain yield will increase by 11.89 to 49.58 % across climate change scenarios, relative to the baseline by 2100s while for Yerer grain yield will increase by 1.90 to 10.75 % relative to the baseline. A decreasing trend has been observed for 2030s under both scenarios by 1.76 and 3.6 %. With risk analysis for Ude, a farmer targeting 4000 kg per ha by 2030 and 2050 periods could achieve the desired quantity, but the associated risk level will go up to 55 %. In such a targeted yield analyses; any decision maker should therefore be able to increase the soil water content and crop water use efficiency, whereas for Yerer, a farmer targeting 4800 kg per ha by 2050 could achieve the desired quantity, but the associated risk level will go up to 75 %. Targeting this yield, any decision maker should therefore reanalyze some crop management options such as fertilizer input, timeliness of agricultural operation, soil water content and crop water use efficiency.

The study proposed future adaptation measures at different level of crop management options such as planting date, planting density, fertilizer application rate and choice of cultivar resulting in yield difference. Ude showed high potential yield than Yerer and best adaptation measures suggest combination of late planting, high planting density and high fertilizer application.

Therefore, climate change and variability are affecting at different magnitude and fluctuation durum wheat productivity in the study area. Future durum wheat yield is mostly affected by amount of carbon dioxide than any other factor. In this study, useful understanding of the climatic determinants in Ada'a district of Central Rift Valley's for wheat growing period has been gained. The study disclosed that, growing Ude cultivar under future climate condition with improved management options such as high fertilizer application rate, improved soil water and planting in third dekad of July could ensure high yields during a good rainy season. Likewise, good yield could also be observed during a poor rainy season. On the other hand, a focus could be made on Yerer also, where it showed that even without future adaptation measures under climate condition its efficiency is evident and this could be combined to synergize the yield benefits or optimize production in order to improve food security and livelihood of farmers from the

study area. This basic difference underscores the need for farmers to improve decisions making for the durum wheat cropping in the study area.

Research could play significant role by providing scientific evidence and more reliable climate information and its impacts. As recommendation, the following measures, as drawn from the gaps of this research should be given priority to enhance durum wheat crop production under changing climate in CRV of Ethiopia.

- Building institutional capacity for relevant data such as network of weather stations, soil database, crop phenological observation in order to promote soil-crop-climate research on climate change impacts and adaptations;
- Communicating projected climate change impacts and possible management strategies effectively among farmers and decision makers;
- A modelling approach that integrates the biophysical, economic, social and institutional aspects of a system under study could be helpful to assess the impact of climate change on crop production and explore more appropriate adaptation strategies for further studies. In fact, socio-economic issues such as market infrastructure, access to credit system and agricultural inputs (seed, fertilizer, pesticides) and institutional arrangements for effective extension services also need attention in research and policy for improving adaptation planning and implementation.

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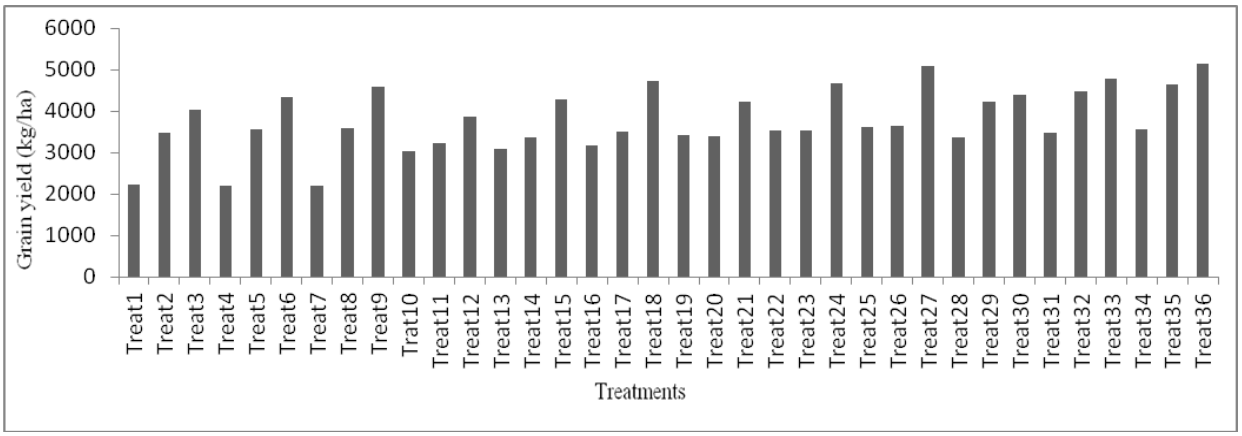
7. APPENDIX

Appendix table 1. Different treatments used for determination of adaptation measures in DSSAT

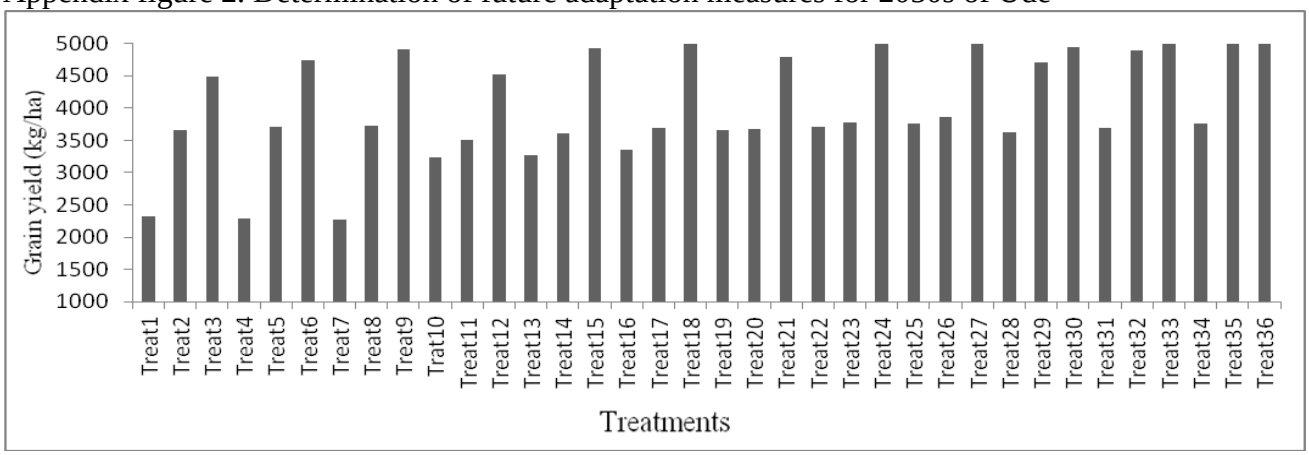
N°	Treatments	Planting date	Plant population (Plants/m^2)	N Fertilization rate (kg ha^{-1})
1	Treatments 1	Very early planting	120	60
2	Treatments 2	Very early planting	120	120
3	Treatments 3	Very early planting	120	180
4	Treatments 4	Very early planting	200	60
5	Treatments 5	Very early planting	200	120
6	Treatments 6	Very early planting	200	180
7	Treatments 7	Very early planting	350	60
8	Treatments 8	Very early planting	350	120
9	Treatments 9	Very early planting	350	180
10	Treatments 10	Early planting	120	60
11	Treatments 11	Early planting	120	120
12	Treatments 12	Early planting	120	180
13	Treatments 13	Early planting	200	60
14	Treatments 14	Early planting	200	120
15	Treatments 15	Early planting	200	180
16	Treatments 16	Early planting	350	60
17	Treatments 17	Early planting	350	120
18	Treatments 18	Early planting	350	180
19	Treatments 19	Normal planting	120	60
20	Treatments 20	Normal planting	120	120
21	Treatments 21	Normal planting	120	180
22	Treatments 22	Normal planting	200	60
23	Treatments 23	Normal planting	200	120
24	Treatments 24	Normal planting	200	180
25	Treatments 25	Normal planting	350	60
26	Treatments 26	Normal planting	350	120
27	Treatments 27	Normal planting	350	180
28	Treatments 28	Late planting	120	60
29	Treatments 29	Late planting	120	120
30	Treatments 30	Late planting	120	180
31	Treatments 31	Late planting	200	60
32	Treatments 32	Late planting	200	120
33	Treatments 33	Late planting	200	180
34	Treatments 34	Late planting	350	60
35	Treatments 35	Late planting	350	120
36	Treatments 36	Late planting	350	180

Very early planting date: June 11; Early planting date: June, 25; Normal planting date: July, 07; Late planting date: July, 21.

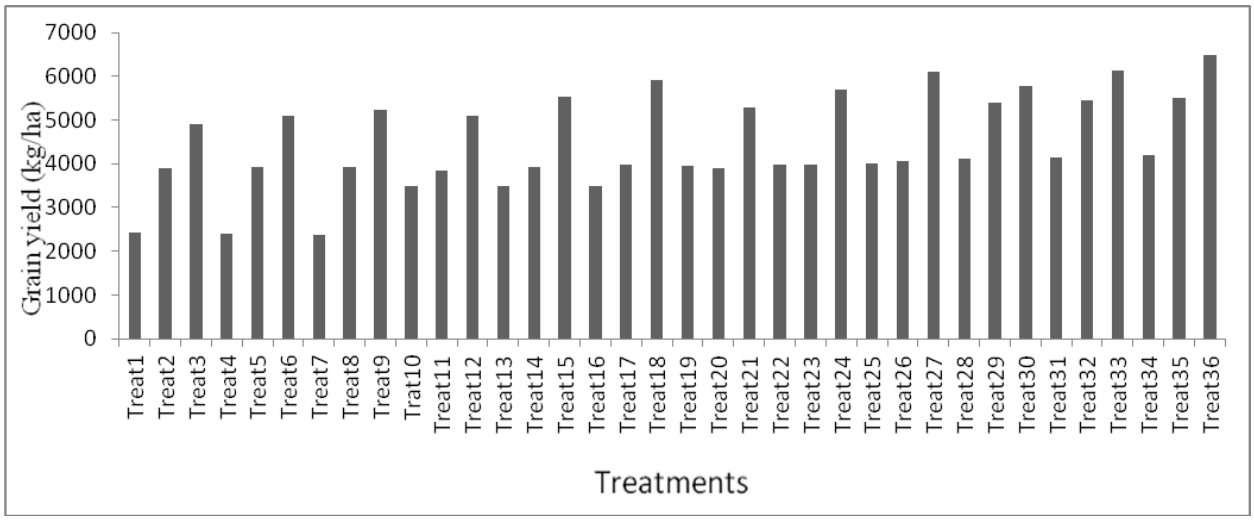
Appendix figure 1. Determination of future adaptation measures for 2030s of Ude



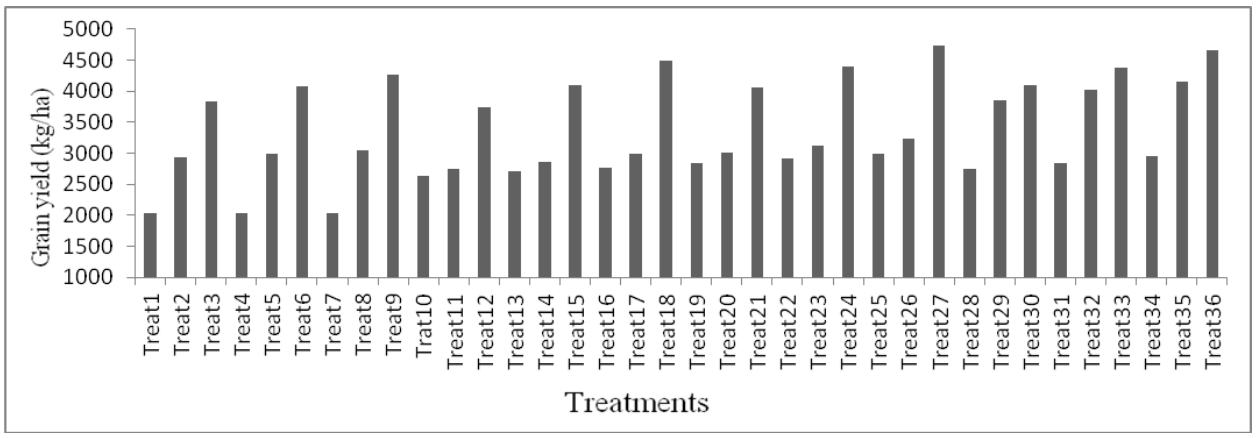
Appendix figure 2. Determination of future adaptation measures for 2050s of Ude



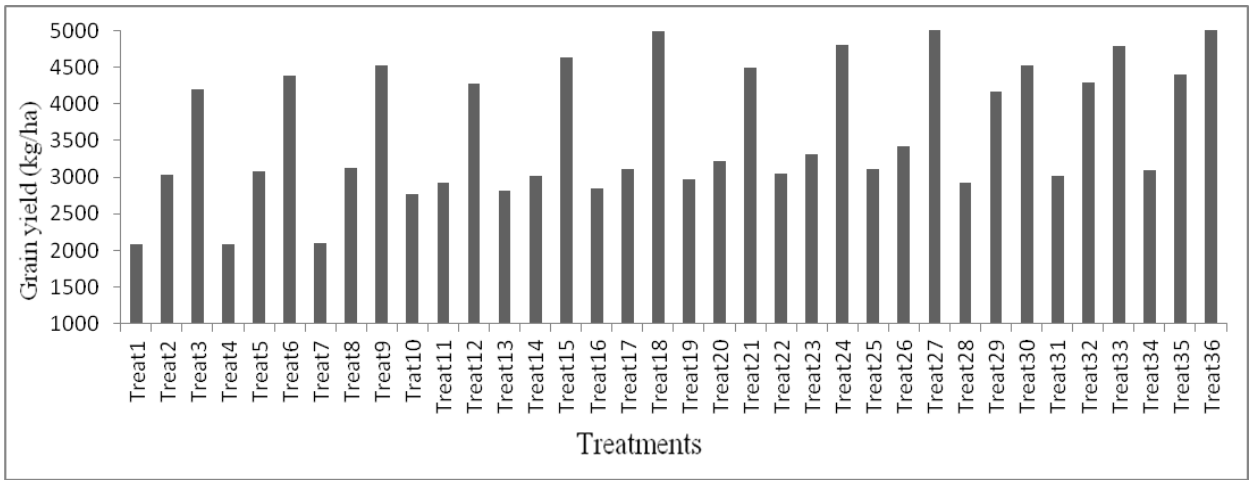
Appendix figure 3. Determination of future adaptation measures for 2080s of Ude



Appendix figure 4. Determination of future adaptation measures for 2030s of Yerer



Appendix figure 5. Determination of future adaptation measures for 2050s of Yerer



Appendix figure 6. Determination of future adaptation measures for 2080s of Yerer