

SEASONAL CLIMATE PREDICTION FOR RAIN-FED CROP
PRODUCTION PLANNING IN THE UPPER AWASH BASIN, CENTRAL
HIGH LAND OF ETHIOPIA

MSc THESIS

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AUGUST 2015

HARAMAYA UNIVERSITY, HARAMAYA

SEASONAL CLIMATE PREDICTION FOR RAIN-FED CROP
PRODUCTION PLANNING IN THE UPPER AWASH BASIN, CENTRAL
HIGH LAND OF ETHIOPIA

A Thesis Submitted to the Postgraduate Program Directorate
(School of Natural Resource Management and Environmental Sciences)
Program of Agro-Meteorology and Natural Risk Management

HARAMAYA UNIVERSITY

In Partial Fulfillment for the Requirement of the Degree of
MASTER OF SCIENCE IN AGRO-METEOROLOGY AND NATURAL RISK
MANAGEMENT

By
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August, 2015
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DEDICATION

Dedicated to my beloved God and family

STATEMENT OF THE AUTHOR

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ACRONYMS AND ABBREVIATION

CCA	Canonical Correlation Analysis
CDFs	Cumulative Density Functions
CV	Coefficient of Variation
EATAL	East Atlantic
ENSO	El Niño Southern Oscillation
EOFs	Estimating Empirical Orthogonal Functions
EOS	End of Season
EQAT	Equatorial Atlantic
EQPA	Equatorial Pacific
ETo	Reference Evapotranspiration
FAO	Food and Agriculture Organization of the United Nations
FMAM	February March April May
FSD	First Stochastic Dominance
GCM	Global Circulation Model
HS	Hit Score
HSS	Hit Skill Score
IOD	Indian Ocean Dipole
ITCZ	Inter-Tropical Convergence Zone
JJAS	June July August September
LGP	Length of Growing Period
MJO	Madden-Julian Oscillation
NAO	North Atlantic Oscillation
NAT	North Atlantic
NCEP	National Center of Environmental Protection
NMSA	National Meteorological Service Agency
NOAA	National Oceanic and Atmospheric Administration
NRD	Number of Rainy Days
PCA	Principal Component Analysis
RSCZ	Red Sea Convergence Zone
SAT	South Atlantic

SCF	Seasonal Climate Forecast
SD	Stochastic Dominance
SIN	South Indian
SMLR	Statistical Multiple Linear Regression
SOI	Southern Oscillation Index
SOS	Starts of Season
SPA	South Pacific
SSD	Second Stochastic Dominance
SST	Sea Surface Temperature
UAB	Upper Awash Basin
WMO	World Meteorological Organization
WPA	West Pacific

BIOGRAPHICAL SKETCH

The author, Abdisa Alemu Tolossa, was born in Dawo Woreda, Southwest Shawa Zone of Oromiya Regional State, and Ethiopia in November 12, 1982. He began his education at Busa Elementary and Junior Secondary School and completed his high school at Tullu Bolo Yehibrate Free Senior Secondary School in September 14, 2002. He joined Arba Minch University in December 14, 2002 and graduated with Bachelor of Science Degree in Meteorology Sciences in July 22, 2006.

As soon as his graduation from the University, he joined and served as meteorologist in National Meteorological Agency of Ethiopia. He joined Haramaya University, Postgraduate Program to pursue his MSc Degree study in Agrometeorology and Natural Risk Management in October, 2013 and graduated in October, 2015.

AKNOWLEDGEMENT

I take the advantage of this special occasion to express my sincere gratitude and appreciation to my major and co-advisors Dr. Diriba Korecha and Dr. Muktar Mohammad, respectively, for their boundless, insightful and professional advice that they provided me from the day I was about to write a proposal, to the very last moments I barely remember. Had it not been for their commitment careful through and conscience reading of the manuscript unlimited guidance and follow up as well as provision of comments and suggestions this piece of work would not have been achieved.

I would like to express my appreciation to the National Meteorological Agency of Ethiopia (NMA) for giving me the chance to pursue my study; and RUFORUM through Haramaya University for granting me the research fund and Ethiopian Meteorological society to assist me fund for field work. I do not know how I would return the favor that my friend Badasa Ragasa and Tamiru Kebede assist me data collection and entry as well as offering me Software training. Last but not least, I honor the lord, for giving me such a caring, lovely and beloved family with whom I am always peaceful and healthy and my soul praises God for all his wills upon me.

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ABSTRACT

This study was designed to use of local level seasonal climate prediction for rain feed crop production planning by providing valuable support for decision-making strategies in the Upper Awash Basin (UAB). A rainfall data recorded over 24 well-distributed rain-gauge stations confined within UAB covering time period of 1980 to 2014 were used for regionalization of homogeneous rainfall pattern. Principal component analysis was used to classify the study area into different homogenous rainfall regions with seasonal rainfall characteristics and spatial continuity. The first four leading rotated principal components (RPCs) explained Belg rainfall variability from 25% to 80% and for kiremt ranges from 18% to 53% of variance, respectively. According to the finding, three climatological sub-divisions were found in the Upper Awash Basin. On the other hand from 1970 to 2014 years of daily rainfall data of eight selected stations from UAB were analyzed to identify variation of rainfall characteristics such as onset and cessation dates, probability of dry spell frequency, seasonal rainfall amount and its temporal as well as spatial distribution. Besides, the risk of dry spells with varying number of days was computed using first-order Markov chain model. The result indicates that zone three has a relatively higher dry spell risk as compared to the other zones. April is start of small rainy season while September is the cessation of main rainy season. The small rainy season has higher dry spell risk and onset variability than main rainy season. The major seasonal predictors for the study area were found to be the Nino regions and Indian Ocean dipole phase (IOD). Due to variability of ENSO phases, rainfall amounts in the major rainy season were high in La Niña but low in El Niño years. By using weighted average rainfall from homogenous zones and zonal crop yield data of major crops obtained for the periods of 1995 to 2013, the rainfall- crop relationship result generated from this study revealed that, excess rainfall would reduce crop yield in zone one while relatively better for zone three. Hence, use of seasonal climate prediction is enable to maximize agricultural rain feed crop productivity while minimizing the crop risk associated with seasonal rainfall. Crop yield risk analysis compared to the ENSO-based approach using cumulative density function refers that, during normal ENSO phase has resulted in preferable yield value and less crop risk by first stochastic dominance and second stochastic dominance senses. Hence, Normal phase is found to have the best risk efficient set identified for each three Zones crop productions planning. Therefore, users in the study area can take comparisons based on alternate ENSO forecasts for further insight to crop risk planning and management strategies. This research therefore had given attention to the response farming activities with scientific seasonal climate prediction information respect to ENSO phase. It is customary to note that seasonal climate prediction provides the best opportunity for farmers to adjusting time of sowing date, cultivar selection in the rain feed crop production.

Key words: Dry spell risk, ENSO, Principal component, Prediction and rainfall variability.

1. INTRODUCTION

WMO (2005) stated that, seasonal climate prediction systems should be considered for crop risk management and risk assessment approach. Seasonal climate prediction is climatic pattern of forthcoming seasons and in particular the extent to which the expected climate differs from the climatological conditions. The distribution of possible outcomes is expected to match what has been observed in the past. However, the climate is often perturbed in predictable ways by various factors, which make these perturbations to the distribution of possible outcomes which are the basis for and target of seasonal forecasting (Stockdale *et al.*, 2010). An important source of seasonal predictability comes from the El Niño-Southern Oscillation (ENSO), a quasi-regular variation in the atmosphere and ocean in the tropical eastern Pacific (Goddard *et al.*, 2003).

The seasonal climate information that can be provided to reduce climate related crop risk or to assist in planning and decisions making in tropics is well known that rainfall is one of the most important climatic element for rain feed crop production (Baigorria, 2008). From an analysis of recent rainfall conditions, rain feed agricultural crop production has direct relationship with inter-seasonal to seasonal rainfall and it is the sectors most vulnerable to seasonal climate variability. The impact is even stronger in Africa, where rain feed agriculture is important for the daily subsistence, and where adaptive capacity is low (Nuhu *et al.*, 2007; Cooper *et al.*, 2006). Particularly, the seasonal climate variability is a major source of crop production risks (Harwood *et al.*, 1999). Hence, seasonal climate prediction has the potential benefits on the decision making process in agricultural crop production planning (Stern and Easterling, 1999; Jones *et al.*, 2000; Hansen, 2002). In accordance with this, seasonal climate forecasting (SCF) can increase the confidence of the decision-makers and be perceived as having insurance value by a risk-averse manager (Washington *et al.*, 2004). When this information must be made available and accessible at the right time and place and demands on crop risk management skill and adjusts possibly many interrelated decisions (Shin *et al.*, 2009).

The seasonal climate forecast should capture the high-frequency modes of weather/climate variability (e.g., wet/dry spell sequences) properly to use it in a crop model for a reliable crop yield risk analysis, the yield risk forecast is based on location and ENSO-based seasonal

climate (Fraisie *et al.*, 2006). The frequency of rainfall within a season exhibits higher predictability than the seasonal total rainfall (Robertson *et al.*, 2008). In Ethiopia the degree of yield variability over time is changed not only by the amount of seasonal rainfall, but also by the pattern and frequency of the rainfall cycle (Adugna, 2005). Hence, Farmers are more concerned about within-season characteristics (onset, cessation, and likelihood and severity of mid-season dry spells) of rain than total seasonal rainfall, which will help farmers for plan properly in terms of timing of planting to avoids the crops reaching the critical stages at times when there are high probability of dry spells (Elijah *et al.*, 2007). Reliable prediction of rainfall characteristics, especially onset date of the rain, is needed to determine a less risky planting date or planting method, or sowing of less risky types/varieties of crops in responsive farming (Stewart, 1991).

Annual variation of the onset, intensity, duration and cessation of the rainfall has negative impacts on socio-economic, agricultural crop and environmental development (Elijah *et al.*, 2007). Particularly in areas where rainfall variability is frequently befallen during sowing and crop growing period, seasonal rainfall prediction is substantial for rain-fed agricultural activities and natural risk monitoring. Hence, the amount of water available for crops strongly depends on the rainy season's onset, length, and cessation, temporal and spatial distribution that can directly indicate the climatic suitability of the crop and its chances of success or failure in a season. Therefore, local level based seasonal climate prediction is very important for crop production and decreasing crop risk that are associated with seasonal climate.

The Upper Awash River rises from the high plateau of central Ethiopia near *Ginchi* town, west of Addis Ababa extends Koka dam and based on physical and socio-economic factors the UAB is part of lands where all digital elevation map are located about 1500 m above sea level (Taddese *et al.*, 1998). The rainfall type of UAB is bimodal type one, which are two rainy season and one dry season, namely *belg* and *kiremt* are rainy season, while *bega* is dry season (NMSA, 1996). Based on FAO (1998) the dominant soil types are Cambisols and Vertisols. The chief agricultural crops of Upper Awash River Basin are cereal crops, pulse and oil seeds. Cereal crops are Teff, Barley, Wheat, Maize and Sorghum. Out of Oil seed *Nueg* is commonly grown and other crops accustomed in the region are Pulses such as broad Beans, Horse beans, Chickpeas, Peas, lentils and *Guaya*, which are widely grown in rotation with grain crops and

Oil seeds (CSA, 2014). *Enset*, a banana-like plant, is grown on the high land of almost all types of fertile soils of the basin.

There is a significant gap between the information needed to support farm decision making which are routinely available given by forecasting center at the study area. By using homogenous rainfall zones data and agricultural crop production data of major cereal crops of UAB, to attempts to show patterns of rainfall and provides insight into the preparation of an early warning system in the UAB. Therefore the concept of "response farming" can be apply according to seasonal climate outlooks to assists farmers to use scientific seasonal climate prediction for improving their traditional farming practices.

In different pocket areas of UAB, rainfall related crop risks like prolonged dry spells, wet spells, untimely rainfall, rainfall variability, flash flood in plain areas and outbreak of crop pests are the challenges which affect crop production. Delay in sowing period due to rainfall variability can cause severe reduction in yield or entirely expose to loss of crop production. This is mainly because of inexistence of optional crops to sow on their farm land after the sowing period of Teff has been elapsed. Therefore the derived rainfall regimes and local level seasonal climate prediction would have useful in the planning and management of rainfall dependent agricultural crop planning activities in the sub basin. This thesis research involves activities according to seasonal rainfall performance and reducing climate variability impacts on crop risk to improve crop yield production. Hence, this study has a general objective of characterizing and predicting seasonal rainfall for supporting rain-fed crop production risk management. Specifically, the research study was conducted with the following objectives:

- To identify homogenous seasonal rainfall regime
- To characterize seasonal climate pattern at local level;
- To examine local level seasonal rainfall predictions for crop yield risk management;
- To identify seasonal crop planning decision supporting strategies in the study area.

2. LITERATURE REVIEW

2.1. Ethiopian Seasonal Climate Characteristics

Though in the tropics there are only wet and dry seasons, in Ethiopia the types of the season are categorically divided in to four distinct parts based on rainfall pattern. According to National Meteorological Agency of Ethiopia NMSA (1996) season classification varies with spatial location, i.e. Central, northeastern and eastern Ethiopia have three seasons: namely, main rainy season (*Kiremt*) from June to September, dry season (*Bega*) from October to January and small rainy season (*Belg*) from February to May. While frost occurs during October to December season mainly over north eastern, central, eastern and southern high lands the country. Thus, the lowest minimum temperature measured during October to December. As a result, the occurrence of extreme minimum of night and early morning temperatures favors for frost occurrence.

The first rains of the *belg* and major *kiremt* rainy seasons occur in early March and June over the middle and Upper Awash catchment, respectively. The weakening and strengthening of the *kiremt* rains are associated with a shifting in the location of (ITCZ), cross equatorial flows and monsoon troughs wide spread rains that usually accompanied by heavy falls, covering much of the catchment when cross equatorial flows are strong enough to pump abundant moisture into the high grounds of the central and north eastern Ethiopia and hence lifts up ITCZ to the northern highlands (Korecha, 2002).

2.1.2. Use of identifying homogenous rainfall regime

In order to get local based climate pattern and best seasonal climate prediction information, it is very important to identify the region into different homogenous rainfall zones. The principal components analysis (PCA) introduced by Pearson (1901) and developed by Hotelling (1933) which is a statistical technique used to examine the interrelations among a set of variables in order to identify the underlying structure of those variables. Therefore regional local level rainfall variability has been analyzed so that, the local climate patterns can be well characterized.

2.1.3. Weather producing systems during different seasons

a. *Bega*: - This is generally the dry season that covers the period from October to January. However, there is occasionally untimely rain over various parts of the country. During this season, most part of the country predominantly falls under the influence of dry and cool north-easterly winds. These dry air masses originate either from the Saharan anticyclone and /or from the ridge of high pressure extending into Ethiopia from Arabian land and from the large high surface pressure over central Asia and, Siberia (NMSA, 1996; Gonfa, 1996).

b. *Belg*: - *Belg* is small rainy season that covers the period from mid-February to mid-May. However, the rainfall is highly characterized by inter annual and inter seasonal variation. Major systems during the *Belg* season are the following:-development of thermal low over South Sudan, generation and propagation of disturbances over the Mediterranean Sea, sometimes coupled with easterly waves, development of high pressure over the Arabian Sea, Some of the interaction between mid-latitude depressions and tropical systems accompanied by troughs and the subtropical jet and occasional development of the Red Sea convergence zone(RSCZ) (NMSA, 1996; Gonfa, 1996).

c. *Kiremt*: - *Kiremt* is the main rainy season that covers the period from June to September. Major rain producing systems during *Kiremt* season includes; Northward migration of ITCZ, development and persistence of the Arabian and South Sudan thermal low along 20°N latitude, development of quasi-permanent high pressure systems over south Atlantic and south Indian Oceans, development of tropical easterly jet and the generation of low level Somali jet that enhance low level south westerly flow (Tadesse, 1994; NMSA, 1996; Segale and Lamb, 2005).

2.2. Use of Inter-seasonal to Seasonal Climate Prediction for Crop Risk Management

According to WMO (2005) stated that, climate forecast systems should be considered for crop risk management and risk assessment approach. Disaster risk managers use seasonal climate information to develop appropriate crop risk management strategies (Hellmuth *et al.*, 2011). However, decision making in agricultural production is a complex process in which many risk need to be considered for an informed decision to made. Farmers face many types of risks

related to production-marketing, legal, social and human aspects (Sivakumar *et al.*, 2007). However, decision makers often desire more detailed prediction information in the form of number of dry days, rainy days, onset date, length of season, possible long dry spell within the season, and locally specific information. Seasonal climate forecasts are being increasingly used to benefit decision-making in more climate-sensitive agricultural sector, where climatic variations, experiences frequent droughts resulting in massive food shortages (Reddy and Kidane, 1993).

Seasonal climate forecast (SCF) is one of the tools, which can help farmers and decision makers better prepare for seasonal rainfall variability, on the proper choice of crop, cropping schedule, levels of input and use of mitigating measures (Celia *et al.*, 2009). Since rain-fed agriculture is practiced in 80% of the world's physical agricultural area and generates 62% of the world's staple food (FAOSTAT, 2005) and most food for poor communities in developing countries is produced in rain-fed agriculture, which is 93% of farm land is rain-fed in Sub-Saharan Africa (Nuhu *et al.*, 2007). The role that climate information can play in risk reduction, early warning and early action (Haile, 2005; GIZ, 2007; IFRC, 2009), for preparedness measures, such as prepositioning and resource planning, and to inform agricultural management decisions such as crop or variety choice (Haile, 2005; Patt *et al.*, 2005; Hellmuth *et al.*, 2007). Farmers are the major group of potential users and they have identified more confident use of forecasts as a priority for research (White, 2000). Therefore the importance of examining climate variability is to the sustenance of life, whether that variability is expressed in the form of droughts and floods. Coping strategies developed to handle the consequences of climate variability, help to ensure mankind's survival (Harrison *et al.*, 2007).

2.3. Inter Seasonal to seasonal rainfall prediction for response farming

Response farming is a multi-layered decision system incorporating timing seasonal rainfall onset dates, close monitoring of actual rainfall, being able to adjust plant numbers and the forecast guides the farmer either in adjusting fertilizer use upward through top dressing (high rainfall), or in thinning plant population with low rainfall (Stewart, 1998). According to Stewart (1995), response farming is a flexible system of farming in which key decisions affecting crop water utilization and crop yield are modified each season in response to pre-

season and early season predictions of season rainfall parameters. Due to spatial and temporal climatic variation, experience in a wide range of contexts reveals that farmers can best respond to forecast information when it:-(a) seasonal climate prediction is interpreted locally; (b) includes information about growing season weather beyond the seasonal average; (c) expresses accuracy in transparent, probabilistic terms; and (d) is interpreted in terms of agricultural impacts and management implications (Ngugi, 2002; Klopper *et al.*, 2006).

The actions which should be taken when below normal seasonal rainfall is expected are staggering planting dates, implement soil-water conservation techniques, increase plant spacing to reduce competition for nutrients and seasonal available water to maximize production in seasonal wet lands and when above normal rainfall is expected, planting early with the first rains, early plant more high yielding varieties, diversification of crop mix with some commercial crops, staggering planting of selected varieties to minimize risks like water logging improve field drainage applications as risk of leaching and optimum use of fertilizers (Elijah *et al.*, 2007). Hence the need of SCF information and disseminate enable to maximize agricultural rain feed crop productivity while minimizing the risk and hazards associated with annual and inter-annual climate variations, to identified and quantified rainfall related risks and guides strategies for addressing them at farm level (Stewart, 1995).

2.4. Prediction of Seasonal Rainfall Variability for Soil Water Management

The method used to translate the climate predictions to “on the ground” soil moisture storage follows the climate predictions in essence relies upon routine (dekadal, monthly and seasonal standard operating procedures). So that, in African countries and parts of India private infrastructure provide water storage to mitigate the rainfall variability impacts on crop growth, to increase the control of water resources is a direct method for managing the risk associated with climate variability and water storage is the most common approach to increasing water control (Brown and Hansen 2008). During dry season soil and water conservation or in-situ water harvesting systems form the logical entry point for improved water management in rain-fed agriculture and during wet season strengthen terraces and making channel in field to reduce the effects of water logging (Nuhu *et al.*, 2007).

2.5. The Influences of SST on Seasonal Climate Pattern

The statistical behavior of weather, that is the time or space averages, may be predictable over time scales of a season or longer due to the interaction between the atmosphere and the slowly varying lower boundary including ocean and land surface properties (Shukla, 1998; Wang et al., 2009). The most important surface condition affecting seasonal climate is sea surface temperature (SST). The SST in the tropical zones anomalies are particularly slow to change because of the high heat capacity of water relative to the atmosphere, because of its higher density and its anomalies extend to tens of meters beneath the ocean surface. Slowness in the variations of SST implies that significant departures from normal (i.e., anomalies) of the currently observed SST are likely to persist into the coming several months (Quan *et al.*, 2004). Therefore, the most important initial conditions for the seasonal forecast range are likely to be the state of the ocean, and the upper two to three hundred meters of sufficient wind system.

2.6. The Impacts of *La Niña* and *El Niño* Phenomenon on Seasonal Climate

Monthly spatially SST averaged as anomaly and the index values of each month was considered over the tropical Pacific region of 5° S–5° N and 150° W–90°W. If the SST index values are 0.5°C or greater, between -0.5 °C and 0.5 °C, and -0.5 °C or less for five consecutive months over central and eastern and pacific ocean, ENSO phase is categorized as El Niño, Neutral and La Niña respectively (Goddard *et al.*, 2001). During *La Niña* events, the equatorial trade winds strengthen, resulting in colder water being brought up from the ocean's floor, in the other hand when SST warmer than the normal condition is referred to as *El Niño* phase, and Neutral is the term for when neither *El Niño* nor *La Niña* are present in the Pacific (Trenberth, 1997). Under neutral conditions, trade winds blow from east to west near the Equator in the Pacific Ocean. *El Niño* is the overall dominant influence in regional seasonal climate variability worldwide, though other modes of sea-surface temperature variability can be more important in some regions (Folland *et al.*, 1991). The most important feature of sea surface temperature variability that can cause large scale weather disruptions is El Niño and its counterpart La Niña, a near basin-wide warming and cooling of the equatorial Pacific Ocean, known as ENSO (Goddard *et al.*, 2001). Many authors have documented how ENSO events have strongly linked with various atmospheric system and rainfall distribution

over Ethiopia like (Korecha and Barnston, 2007). The principal cause of drought in Ethiopia is asserted to be the fluctuation of the global atmospheric circulation, which is triggered by sea surface temperature (SST) anomalies, occurred according to ENSO events. The phenomena have significant impact on displacement and weakening of the rain producing mechanisms on seasons. ENSO episodes and other regional systems have impact on seasonal rainfall performance and rainfall variability over Ethiopia is due to remote teleconnections system (NMSA, 1996; Tsegay, 1998; 2001; Gissila, 2001; Korecha, 2002; Korecha and Barnston, 2007).

2.7. Source of Predictability for Seasonal Climate Pattern

NMA identified the regional factors which affects the inter-seasonal to seasonal climate patterns of Ethiopian seasons. Such factors are surface pressure system over southwest Indian Ocean, north Indian Ocean, Mediterranean Sea, Read Sea, north Atlantic Ocean, Positive or negative phase of IOD, southern and eastern Atlantic Ocean (NMSA, 1996; Gonfa, 1996; Shanko and Camberlin, 1998; Gissila *et al.*, 2004).

Topography itself has a profound effect on spatial patterns of precipitation both globally and regionally. Mountains influence the flow of air and disturb the vertical stratification of the atmosphere by acting as physical barriers and as sources or sinks of heat (Barros and Lettenmaier, 1994). At the scale of entire mountain ranges (hundreds of km) the rain shadow effect has a well-documented and significant influence on precipitation patterns. On the leeward side of mountains, dry climates can exist due to the dry air caused by compressional heating. Enhanced precipitation on the windward side of mountain ranges has been recognized in the geological community as a long-term control on landscape evolution and the geotectonic development of mountain ranges (Willett, 1999). Therefore, climate of a certain local depends on many factors including the amount of sunlight it receives, its height above sea level, the shape of the land, and how close it is to oceans, land coverage, topographic and local wind pattern can cause the spatial rainfall variability of the local area.

2.8. Mechanisms of Seasonal Climate Prediction

Predictable signal always co-exists with unpredictable noise in the seasonal forecasts, due to the effects of synoptic activity and/or other sources of unpredictability (Stockdale *et al.*, 2010). Seasonal forecasts are typically provided as probabilistic outlooks for precipitation totals and monthly mean temperature. The seasonal climate information should be first generation of useful climate predictions, second, translation of that information into forms useful for decision makers and third, dissemination and communication of the results (Beller-Simms *et al.*, 2008). These variables have been cited as useful indicators in many applications (Lisa *et al.*, 2009). Seasonal rainfall and temperature forecasts issued at least a month in advance, by providing probabilities as to the chances of below, near, or above-normal conditions. Therefore, the mechanisms that implicit in complex coupled atmosphere–land–ocean models offer the possibility of a predictable signal on seasonal timescales.

2.8.1. Modeling seasonal climate

In the past few decades, climate scientists have made tremendous advances in understanding and modeling the variability and predictability of the seasonal climate system. As a result, prediction of seasonal to inter-annual climate variations and the associated uncertainties using multiple regression equation and dynamical models have become operational for decision making (Palmer *et al.*, 2004). Most statistical model is based on multiple linear regressions, which provides the “best guess” forecast. The primary problems with linear regression are multiplicity and multi co-linearity as well as non-normality of the predictands. Multiplicity refers to the effects of having a large number of candidate predictors (Harrison *et al.*, 2007). Extensive use has been made of correlation and regression methods in attempting to establish evidence of “teleconnections” (Nicholls, 1991).

2.8.2. Analogue years seasonal climate prediction technique

Historical climate records as a tool for decision making, the “analogue year” approach – still often held as the benchmark to be beaten by GCM based methods - has been successfully used in some regions based on a range of different climate indicators such as SOI (Stone *et al.*, 1996), SST or MJO predictions based on upper level wind and outgoing long wave radiation

anomalies (Wheeler *et al.*, 2009). Yet, for some regions MJO-based forecasts are showing considerable promise at this intra-seasonal time scale (Wheeler *et al.*, 2009). Similarly a strong ENSO phase that has strong influence on the start of the Northern Australian wet season (Lo *et al.*, 2007). The idea behind analogue forecasting is a simple one, i.e. given current meteorological conditions, searching back through pre-seasonal SST and quasi-regular variation in the atmospheric phenomena used as a basis for analogue method application on seasonal climate prediction the data record for the closest match. This approach is based on identifying SOI phases, which has also been discussed by Casey (1995).

2.9. The Impacts of Soil properties and Rainfall variability on Crop Yield

The clay soil is assumed to be at field capacity of 100mm on the last day of rain that is greater than 0.5 PET provided that the date is not preceded by a dry spell (less than 1mm daily rainfall) or more than five days (Stern *et al.* 1982). It is assumed that the depletion of available soil moisture below 40% of its field capacity will cause rapid reduction in water availability to crops. The factors which affect crop yield production are soil fertility, soil structure, soil acidity, soil salinity, soil type and organic matter content of the soil. Andrew (1995) described that a decline in crop yield production is due to decline in soil fertility and uneven distribution of seasonal rainfall. Even in the more humid areas, the seasonal distribution of rainfall described earlier is an important determining factor for crop growth, which in turn depends on the depth, organic matter content, structure, and texture of the soil, particularly the clay content, time of planting and crop-growth duration need to be closely fitted to the expected moisture supply for the rainy season (Andrew, 1995). Therefore inter-seasonal to seasonal rainfall prediction is an important source of information to determine soil water holding capacity, dry spell resistivity and soil water management in rain-fed farming system and better crop production planning strategies in the study area.

2.10. Use of Cumulative Density Functions and Stochastic Dominance (SD) Analyses

A stochastic dominance criterion is a decision rule that provides a partial ordering of risky alternatives for decision makers, whose preferences conform to specified conditions about their utility functions (preferences for consequences). Although specific risk preferences can vary from individual to individual, the cumulative density function (CDF's) can be used to

identify the treatments that would be preferred by individuals within a range of preferences using stochastic dominance analysis developed by (Meyer, 1977) as described in (Hardaker *et al.*, 1998) is first-degree stochastic dominance (FSD). According to Anderson and Dillon (1992) 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 for risk assessment. FSD analysis requires the pair wise comparison of all the pairs of distributions with the provision that once an alternative has been found to be dominated by another, then the dominated one can be dismissed from all further considerations (Hardaker *et al.*, 1998; Mamo, 2005).

3. MATERIALS AND METHODS

3.1. Description of the Study Area

This study was conducted in the Upper part of the Awash River Basin in Ethiopia, which is located between 8°16'N - 9° 18' N and 37° 57'E - 39°17'E. It covers about 7240 km² and all topographic lands lie between 1500 m to 3419m above sea level. The physical settings of the study area are characterized by the heterogeneity of the large natural systems such as orographic groups, the high plains, mountains and plateaus (Figure 1). Based on physical and socio-economic factors the Upper Awash Basin is topographic level of all lands above 1500 m (Taddese *et al.*, 1998).

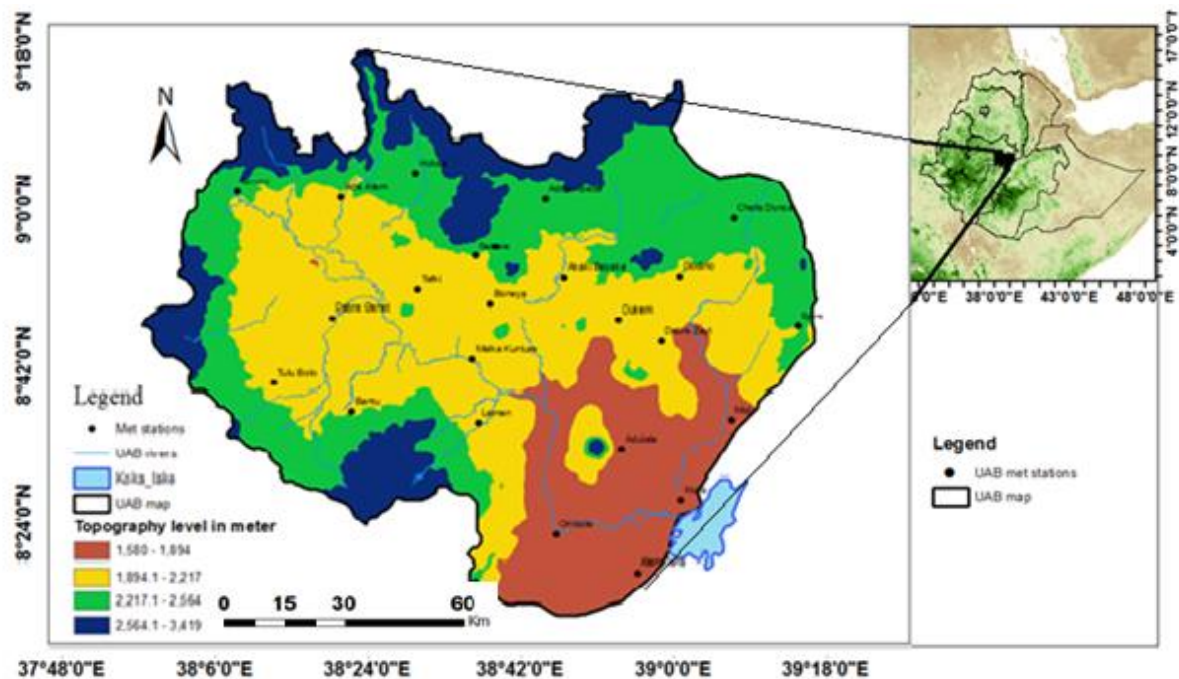


Figure 1: The Study Area of Upper Awash River Basin and its Topographic features

The land use pattern of UAB consists mainly of cultivated agricultural land, grass land and shrub land, which cover 93.2% of the total area; about 3.6% is covered by sparse trees and the remaining 3.2% comes from the other land cover types (Mussa, 2011). According to Koei (1996) and FAO (1998) soil classification, the UAB soil types are pellic vertisol, vertic cambisol, Chromic luvisols, luvic phaeozems and lithosols. However, the dominant soil types are Cambisols and Vertisols. Hence, Vertisols are unique group of soils, often described as

black cotton soils and heavy, usually dark colored, clay soils that form deep cracks when they dry out, and difficult to cultivate when dry, and become very sticky when wet Andrew (1995; Deckers *et al.*, 2001).

3.2. Types and Sources of Data and Methods of Data Collection

Various types of data were obtained from different sources in order to analyze and examine seasonal climate predictions for decision making process supporting at farm level in the study area. Daily rain gauge data and surface temperature from 1970 to 2014 were obtained from National Meteorological Agency (NMA) of Ethiopia; Missing data were filled with gridded data. Global and regional SST data and atmospheric indices for instance SOI, IOD and NAO were taken from NOAA-CIRES climate diagnostics center (<http://www.cdc.noaa.gov/>). SST over Nino regions data were taken from CPC <http://www.esrl.noaa.gov/psd/data/climateindices/list/>.

The surface observed reanalysis wind data of extreme season were obtained from http://iridl.ldeo.columbia.edu/maproom/Global/Atm_Circulation/Wind_SST_Anom.html

Major crop yield data were obtained from Central Statistical Agency (CSA).

3.3. Methods of Data Analysis

There are numbers of standard climatic data analysis methods for crop production planning and decision supporting in relation to seasonal climate prediction. Characteristics of areal rainfall character analysis, rainfall pattern analysis and prediction for the coming season. The seasonal and annual spatial rainfall distributions were computed based on historical rainfall data using various spatial analysis tools in ArcGIS software version 10.1 and presented spatially. The study assesses regionalization of rainfall, onset of rains, cessation of rains, duration of rainy season and seasonal rainfall at different probability levels. Seasonal characteristics of rainfall such as the onset and intra-seasonal rainfall distribution can be used to promote good crop yields products. Rainfall zoning system was discussed at UAB based on seasonality, quantity of rainfall, climate and geographic division.

3.3.1. Classification of homogenous rainfall regime in the UAB

In order to amalgamate the stations into homogenous rainfall regions, empirical orthogonal function (EOF) analysis was applied, followed by varimax rotation. Principal Component Analysis is a very powerful method to explore the structure of a large number of quantitative observed stations rainfall data to classify into homogeneous rainfall pattern as described by (Murata 1990; Basalirwa 1995; Malmgren *et al.*, 1999; Stathis, 2009). Therefore, Principal Component Analysis (PCA) as described by (Comrie and Glenn, 1988) was employed to delineate the UAB into distinct homogenous rainfall regime. A rainfall data recorded over 24 well-distributed rain-gauge stations confined within UAB covering time period of 1980 to 2014 were used for regionalization of homogeneous rainfall pattern. PCA arises as a method of estimating Empirical Orthogonal Functions (EOFs). It allows to reducing a set of observed variables into a smaller set of variables called principal components. Analysis of climatological rainfall data of *belg* and *kiremt* has been taken into account separately their multi-dimensional character and reveals existence of connections between their components and Varimax rotation is the most widely used. Reliable PCA of rainfall characteristics has been done by using SPSS software version 20 (Karl, 2012).

$$Var(X) = \frac{\sum (X_i - \bar{X})^2}{n-1} \quad \text{and} \quad Cov(X, Y) = \frac{\sum (X_i - \bar{X}) * (Y_i - \bar{Y})}{n-1} \quad (1)$$

The covariance is always measured between two dimensions (Equation 1). If there are data sets with more than two dimensions, there is more than one covariance measurement that PC value can be calculated by:

$$C_n = b_{11}(X_1) + b_{12}(X_2) + \dots + b_{1p}(X_p) \quad (2)$$

Where C_n = the subject's score on principal component n (the first component extracted)

b_{1p} = the regression coefficient (or weight) for observed variable p , as used in creating principal component one and X_p = the subject's score on observed variable p .

This method was considered to the physical reality of the spatial patterns of the delineated zones of rainfall network in describing the climatological rainfall patterns of Upper Awash Basin. PCA allows highlighting the similarities and differences in terms of temporal

variability of seasonal rainfall units. The component loadings can tell us how much of the variation in a variable is explained by the component. Extraction method for the PCA with Rotation Method Varimax with Kaiser Normalization was taken. For a large number of variables, it is possible to compress the amount of explained variation to just a few components. The multivariate analysis is one of the most widely used techniques in the regionalization of rainfall patterns. Therefore, the PCA with rotated dominant PCA modes was one of the method deliberated to delineate the temporal rainfall characteristics into homogeneous spatial regions, which was employed in the case of Upper Awash Basin to determining climatological homogeneous rainfall regions and as well as to define appropriate climate indices.

The eigenvalues of the covariance matrix and Principal component values are calculated by (SPSS) software version 20. With this approach, retaining and interpret any component that displays an eigenvalue greater than one were analyzed and scree plot elbow is accounting for a greater amount of variance than by others variables were contributed. To determine the appropriate number of components, just look for an "elbow" in the scree plot and component number which were taken to be the point at, which the remaining eigenvalues are relatively small and all about the same size. The cumulative proportion of the variance accounted by the current and all preceding principal components. Extraction of significant modes is based on through which only the first few components were selected. In this case the first four components containing Rotation Sums of Squared Loadings variation of the 24 station rainfall variables were taken.

The higher the component loadings, the more important that variable is to the component, Combinations of positive and negative loadings are interpreted as 'mixed'. Then the result outputs from SPSS software of the first four PC values were analyzed spatially by using Arc GIS software version 10.1 and area were uniform pattern on each of the first four PC value map was delineated into one homogenous rainfall regime. In this case, UAB was classified into different homogenous rainfall régimes. Regional local level rainfall variability has been analyzed so that, the local climate patterns can be well characterized. R_k , which is zonal rainfall anomaly for k^{th} homogeneous rainfall zone calculated by the (Equation 3). This computation was made for each of the three homogenous rainfall regime of UAB during the

belg and *kiremt* seasons that enabled to show the degree of long term temporal Zonal rainfall variability. Regional rainfall index R_k is calculated using the following formula:

$$R_k = \sum_i^m W_i \times \left(\frac{R_{k,i} - \bar{m}}{SD} \right) \quad (3)$$

Where R_k is regional rain fall index, W_i is a weighted applied to the i^{th} of n stations, $R_{k,i}$ is the rainfall at i^{th} station during year k , and $\bar{m}$ and SD are the average and standard deviation of the station's rainfall. If R_k is more than 0.5, between -0.5 and 0.5 and less than -0.5 are meteorologically the zonal seasonal pattern is wet, normal and dry season respectively.

3.3.2. Determining the onset and cessation date of the rainy season

Based on a quantitative study of this thesis research, daily rainfall data observed from 1970 to 2014 on eight stations were taken, the mean onset and cessation dates, and dry spell risk were analyzed. For the purposes of this study, the onset of rainy season is defined as the first occasion from the first of April that records 20mm of rainfall amount or more over a 3-day period, and will not be followed by a period of more than 10 consecutive dry days in the following 30 days (Stern *et al.*, 2003; Segale *et al.*, 2005). The condition of having no dry spells of more than 10 days after start of rainy season eliminates the possibility of a false start of the season. A period of 30 days is the average length for the initial growth stage of most crops (Allen *et al.*, 1998). The end of season is computed using first-order Markov chain modeling by considering maximum daily Evapotranspiration of 5mm and soil available water holding capacity of 100mm. Given with the above definitions, Instat Statistical program (Version 3.36 was used to analyze the daily rainfall data for start and end of rainy. The onset of rainfall and dry spell risk are very crucial to farmers as it answers the vital question “when to plant? And what will be frequency of dry spell expectation for the forthcoming season?

3.3.3. Inter-seasonal to seasonal climate variability analysis

kiremt rainfall data from 1980 to 2014 of two meteorological station which, are Busa and Addis Ababa have been selected from the Upper Awash Basin in order to show monthly

rainfall anomaly using (Equation 5) for main rainy season. The coefficient of variation of seasonal rainfall variability was analyzed by:

$$CV = \left(\frac{SD}{\bar{X}} \right) * 100 \text{ where } \bar{X} = \frac{\sum Xi}{N} \text{ and } SD = \frac{\sqrt{(Xi - \bar{X})^2}}{N - 1} \quad (4)$$

And seasonal rainfall anomaly during *kiremt* season can be analyzed by:

$$RA_i = \frac{Xi - \bar{X}}{SD} \quad (5)$$

Where SD is standard deviation $\bar{X}$ is long year mean and N is total number of year during observations were held for specific site SD is standard deviation, X_i is rainfall of each month and RA_i is rainfall anomaly of each month. If RA_i is more than 0.5 between -0.5 and 0.5 and less than -0.5 is meteorologically the month is wet, normal and dry respectively.

3.3.4. Dry spell analysis

The probability of dry spell frequency has been done by daily rainfall data of Busa ,Akaki and Alemtena had been taken from 1970 to 2014. To provide a viable decision aid to various practitioners, different dry spell lengths (number of consecutive dry days) were examined. Accordingly, given a condition that the first of month is a potential for planting date, the probability of dry spells longer than 3, 5, 7, 10 and 15 days were analyzed using INSTAT software by first-order Markov chain modeling. The risk of dry spells for varying number of days following the planting period is computed using first-order Markov chain modeling in which case analysis has to be done from the very beginning with the daily long year's raw data. Dry spell can be defined as a sequence of dry days including days with less than a 1mm value of rainfall. The analysis of the historical occurrence of dry spell and its probability of recurrence is important for planning time of minimum dry spell risks in the day of the year (DOY).

3.4. Methods of Seasonal Climate prediction

Identifying the relationship between zonal rainfall anomaly and SSTs which, is the most predictive skill comes from information contained in the initial states of the coupled ocean–atmospheric system, for ocean initialization the emphasis is on the initialization of the upper ocean thermal structure, particularly inscribed tropical area, where observational information about SST is essential. Local based regional rainfall index of each homogenous rainfall regime was evaluated and canonical correlation analysis (CCA) technique was used to relate patterns with monthly SSTs anomaly of the pre seasonal months, which was used as predictors and observed rainfall anomalies each regime as predictand. CCA uses linear statistical techniques to find optimum relationships among multivariate sets of independent and dependent variables, which is an extension of a multiple regression technique to the case of the vector-valued predictor-predictand relationship (Landman and Goddard, 2002). Canonical correlation is calculated by.

$$C = R_{yy}^{-1} R_{yx} R_{xx}^{-1} R_{xy} \quad (6)$$

Where: C = matrix of singular value decomposition

R_{yy} = Correlations between Y variables

R_{yx} = Correlations between Y and X variables

R_{xx} = Correlations between X variables

R_{xy} = Correlations between X and Y variables

The most important pattern of correlation between mean December and January Ocean SST anomalies in tropical region of 40 N to 40 S degree extensions with *belg* rainfall index and mean of April and May Ocean SST correlation with *Kiremt* regional rainfall index for each homogenous rainfall Zone across UAB respectively. Hence, seasonal (FMAM) and (JJAS) rainfall within each homogenous rainfall Zone with the global oceanic SST's of the pre seasonal months, mean of April and May as well as December and January, respectively. Parts of the oceanic surface having good correlation with the delineated zones were then identified. The predictors which have significant correlation with seasonal rainfall anomaly has been identified by those oceanic areas having a strong relationship with the respective rainfall zones for a target month, in which a threshold correlation (r) value of $\geq |0.3|$ has been taken into

account, which amounts to a minimum 10% of the variance being explained (Tanco and Berri, 2000). Using R-Gui software version 2.10.1 estimated patterns of correlation between Ocean fields and homogenous rainfall regimes have been derived. The Zonal rainfall index was described in equation (4), from each homogenous rainfall régimes (R_k), which is regional rainfall index, is correlated with global SST as established by (Landman and Goddard, 2002) to monitor the parts of the ocean, which have more specific site for each rainfall regimes. Therefore, in this section long year's regional rainfall index is correlated with pre-seasonal and zero lead time SST data.

3.4.1. Statistical multiple linear regression model for seasonal climate

Simple multiple regression model established with potential selected predictions with training period from 1980 to 2004 and hind cast period of 2005 to 2015. After the classification of homogenous rainfall regime had been made, regional rainfall index of each regime was replaced with all selected potential predictors. Predictor values having an F-ratio with 95%, P value of less than 0.05, R and $R^2 \geq 50\%$ significant levels were chosen to develop the models. Finally, the selected predictors have been taken as candidate, which normally to be tested for inclusion in the model that should be used to make predictions. The standard approach is to include only those predictors in the final regression equation that contribute to a significant reduction in the size of the errors by using Systat software with ANOVA test. The developed models constructed to predict JJAS and FMAM rainfall pattern over Upper Awash Basin.

Real-time seasonal forecasts need to be complemented by an extensive set of retrospective forecasts (often referred to as hind casts). First, seasonal forecasts require an estimate of skill and reliability of the forecast system, and hind casts are necessary to provide such skill assessments. Secondly, hind casts also provide a way to calibrate forecasts against the observations, and remove biases that are often part of the dynamical prediction systems. However, calibration can be a challenging problem in a non-stationary climate. Then, statistical multiple linear regression model is specified as (Equation 6) using systat software version 8.0 stepwise options of forward method.

$$Y = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \dots + \beta_n x_n + \varepsilon \quad (7)$$

Where Y =Zonal Rain fall anomaly, $x_1, x_2, \dots, x_n$ are best selected predictors from global indices, β_i , $i=1,2,3, \dots, n$ are regression coefficients, ϵ is the error of estimate and α is intercept. Regression coefficients and intercept are estimated from historical data set using List Square Estimation Method.

3.4.2. Evaluating statistical multiple linear regression model

The ultimate aim is to support better decision-making process using climate prediction model as a support tool, which is subjected to skill verification/performance evaluation. Prediction skill evaluation is the process of determining the quality of forecasts. Any prediction evaluation method involves comparison between matched pairs of predicted and observations to which they pertain. The goodness of fit of each SMLR model was tested by 3x3 contingency table. The structure to classify the status of forecast is determined with the help of rainfall anomalies and the hit score, which is given as (Equation 8).

$$HS = \frac{(a + e + i) * 100}{p} \quad (8)$$

Where “a” is the number of correct forecasts of below normal rainfall (B); “e” is the number of correct forecast of near normal rainfall (N); “i” is the number of correct forecast of above normal rainfall (A) and “p” is the total count of forecasting occasions. Accordingly, regional rainfall index (Rk_i) score below -0.5, between -0.5 and 0.5 and more than 0.5 is classified below, normal and above normal, respectively. Hit Score (HS) receives the score of 1 for perfect prediction, while the forecasts equivalent to the reference forecast receives 0 score (Wilks, 1995). This computation is done based on retroactive validation method, while the model is being trained sequentially using only the first few years of the data, and a prediction is made for the year immediately after the end of the training period. Then making 3x3 contingency table has been formed in the following ways (Appendix Table 1), from which HSS is computed using formula stated in

$$HSS = \frac{\text{Number of correct forecast} - \text{Number of forecast expected correct}}{\text{Total number of forecast} - \text{Number of forecasts expected correct}}$$

$$HSS = \frac{(a + e + i) - \frac{(mj + nk + lo)}{p}}{p - \frac{(mj + nk + lo)}{p}} \quad (9)$$

Where: j = total number of forecasts but observed was 'below normal'

k = total number of forecasts but observed was 'near normal'

l = total number of forecasts but observed was 'above normal'.

m = total number of observed when forecast was 'below normal'.

n = total number of observed when forecast was 'near normal'.

o = total number of observed when forecast was 'above normal'

HSS= is Hit Skill Score.

According to Lee and Wang, (2012) method of forecast quality measure for SMLR model Skill score ranges from 0 (no skill at all) to 1 (for perfect forecast) method was used to measure the quality of forecast.

3.4.3. Seasonal climate prediction using analogue year approach

The analogue year is defined by the comparison of SST indices currently observed with historical incidences. Analogue year method is the principle of the archive-based sufficient past record of observations and selection of analogous sequences of meteorological processes within three to five month interval proceeding the month of forecast. Hence, many meteorological institutions around the world either still use analogue forecasts or have done until recently (WMO, 2002). Therefore Analogue year' approach – still often held as the benchmark to be beaten by GCM based methods. The idea behind analogue forecasting is a simple one: given current meteorological conditions such as Nino regions situation and searching for back through the data record for the closest match. This forecasting technique was particularly validated for Ethiopia by Korecha and Sorteberg, (2013). Based on the weekly cumulative rainfall curves, the current global SSTs and the predicted products lead forecaster to choose the best three analogue years. Nino 3.4 region has been taken to find best analogue years for next season. The weekly cumulative rainfall for the coming season for Addis Ababa with respect to selected analogue years recorded rainfall data has been evaluated

and analogue can well extrapolated to the next season rainfall expectation as well as determining the onset by point of positive curvature and cessation by negative curvature of the forthcoming season.

3.5. Linear Relationship between Crop Yield with Seasonal Rainfall

In homogeneous zones, detections of potential trends analysis, In this regard, Rainfall data of 1980 to 2014 have been preliminarily tested for rainfall homogeneity and consequently grouped into classes of different Zones. Therefore, zonal seasonal total rainfall was taken from homogenous rainfall zone to establish correlation with Zonal agricultural crop yield of Teff and wheat from Zone one and three. To analysis the existence of any linear relationship between crop yield and Regional whited average seasonal rainfall for zone one and two, Hence, it might be interesting to examine the relationship between precipitation and yield. The linear relationship between Yields with seasonal rainfall was determined by

$$RF_{av} = \sum_{i=1}^n w_i x(RF_i) = \alpha + \beta_1 x_1 \quad (10)$$

Where RF_{av} =Homogenous zonal rain fall weighted average, x_1 is crop yield and β_i is regression coefficient, 'n' is number of rainfall stations in each homogenous zone and W_i weighted average given for each rainfall station and RF_i is the rainfall received at each station for each year of major rainy season.

3.6. Cumulative Density Functions (CDFs) and Stochastic Dominance (SD) Analyses

Stochastic dominance (SD) 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 (Hardaker *et al.*, 1998; Mamo, 2005). For instance, a CDF 'A' lies entirely below and to the right of another CDF 'B', then 'A' dominates 'B' in the first-degree sense (FSD). 'A' would be preferred by any individual who prefers more of the performance measure to less, regardless of whether they are risk averse. On the other hand, decisions are more difficult to resolve by FSD when the CDFs interact (cross-over) such as 'A' cross 'B'. Second degree stochastic dominance is applied based on the area under the CDF. If the area under CDF of

‘A’ is less the area under CDF ‘B’ at every point along the x-axis, under such circumstances, neither of them totally dominates in the sense of FSD, indicating the limited discriminatory power of the FSD (McCarl, 1996). Then ‘A’ is said to dominate ‘B’ in the second-degree sense. Activity ‘A’ would be preferred by any individual who is risk-averse for all values of the performance measure (Levy 1992, 1998). Cross-over implies that one strategy could dominate the other at the lower points (bottom tail) of the distribution, but could be dominated at the upper values (top tail) in the distribution or vice versa.

Crop yield and associated rainfall values for UAB were incorporated into a simple tool that allows users to customize the output to their specific situations. Expected impacts of changes on crops types were then computed based on ENSO forecast. Average Zonal crop yields for their specific fields with *Kiremt* homogenous Zonal rainfall data for the period from 1995 to 2013 were classified into three ENSO episodes, namely El Niño, La Niña and Neutral, based on ENSO phase classification as documented by Korecha and Barnston, (2007). This tools contains applications that allow a user to examine the rainfall forecast for individual Zone based on the ENSO phase and to evaluate crops yield risk analysis. SD analysis of Teff, Wheat, Maize and Sorghum cereal crop with different ENSO Phase like *El Niño*, *La Niña* and normal phenomena were analyzed for risk analysis and to answer which ENSO phase has contribute for better yield performance.

Stochastic dominance rules assume that farmers must decide whether to invest crop production during *La Niña*, *f*, or an alternatively *El Niño* events, *g*, and normal condition, *h*, with crop yield cumulative density functions given by $F(x)$, $G(x)$ and $H(x)$ respectively. Then by taking those three SST phase such as *La Niña*, *El Niño* and normal phase year with corresponding crop yield alternatively analyzed by first and second -order stochastic dominance (FSD) or SSD sense. Using a statistical technique known as (CDF) as stated in (Equation 12), by R-Gui software version 2.10.1, used for stochastic dominance rules that assume farmers should decide whether to invest crop production during *La Niña* phase “F” or an alternative *El Niño* phase “G” and Normal phase. Similarly, Rainfall risk analysis using different ENSO phase as $F(x)$ during *La Niña* phase “F” or an alternative *El Niño* phase “G” and Normal phase “H” of seasonal total rainfall analyzed for each rainfall regime to identify the more risk zone at each ENSO phase. Decision rule of First Stochastic Dominance (FSD) if and only if

$$G(x) - F(x) \geq 0 \quad \forall x \in R \quad (11)$$

And the cumulative density function can be calculated by

$$F(x), G(x), H(x) = \int_0^x f(X, \mu, \delta) dx, \text{ where } f(X, \mu, \delta) = \frac{1}{\sqrt{2\pi\delta^2}} \exp\left(-\frac{(x - \mu)^2}{2\delta^2}\right) \quad (12)$$

Where $F(x)$, $G(x)$ and $H(x)$ are crop yield cumulative density functions or Zonal seasonal rainfall given during *La Niña*, *El Niño* events and Normal phase respectively. Given 'X' represent crop yield in quintal per hector during crop yield risk analysis and *kiremt* Seasonal zonal rainfall in mm while analyzing zonal rainfall risk.

4. RESULTS AND DISCUSSION

4.1. Climate of the Study Area

Upper Awash Basin is part of Central highlands of Ethiopia, which covers areas with high potential for crop production with attributed rainfall variability. The location of meteorological gauging stations and topographic features of the studied area are shown in (Figure 1). The annual rainfall reaches 649-1222 mm of which the western mountain chains receives an annual rainfall ranging from 1000 to 1200 mm, while the southern, south eastern and central regions of UAB receive between 700 to 900 mm (Figure 4). Seasonally, 183 to 310 mm and 465 to 906 mm contribution come from small and main rainy seasons, respectively (Figures 2 and 3). The fact that the study area is characterized by the presence of hills/peaks of undulating nature implies that orography plays an important role in the rainfall distribution over the region. The quantum of rainfall is found to be highest in the western high land or Zone one and lowest in the lower altitude or zone three. Therefore the climate of UAB is influenced by undulated mountain chains and the circulatory systems that interact with Orography, cross equatorial wind system and ITCZ. Therefore, the rainfall distribution observed in the Upper Awash can be attributed to the orographic effect.

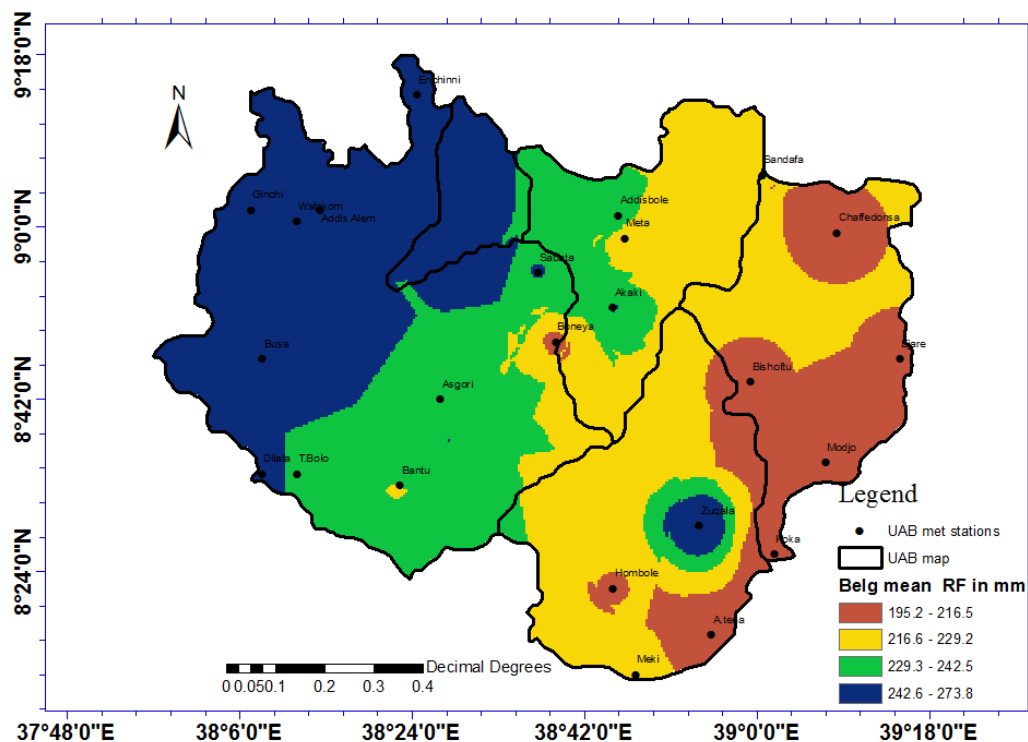


Figure 2: Spatial mean rainfall distribution of Upper Awash during *Belg* season

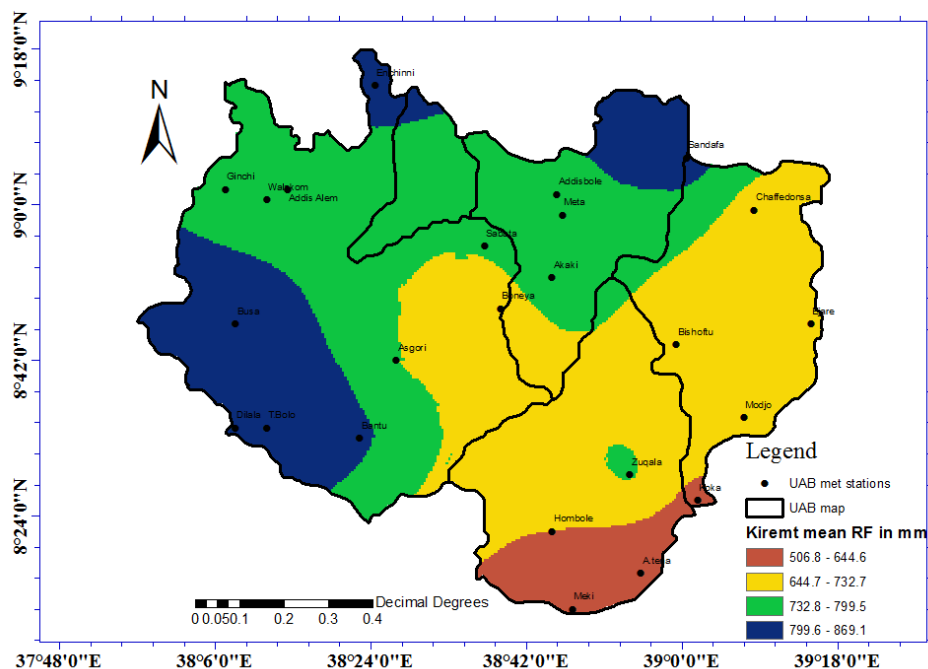


Figure 3: Spatial mean rainfall distribution of Upper Awash during *Kiremt* season

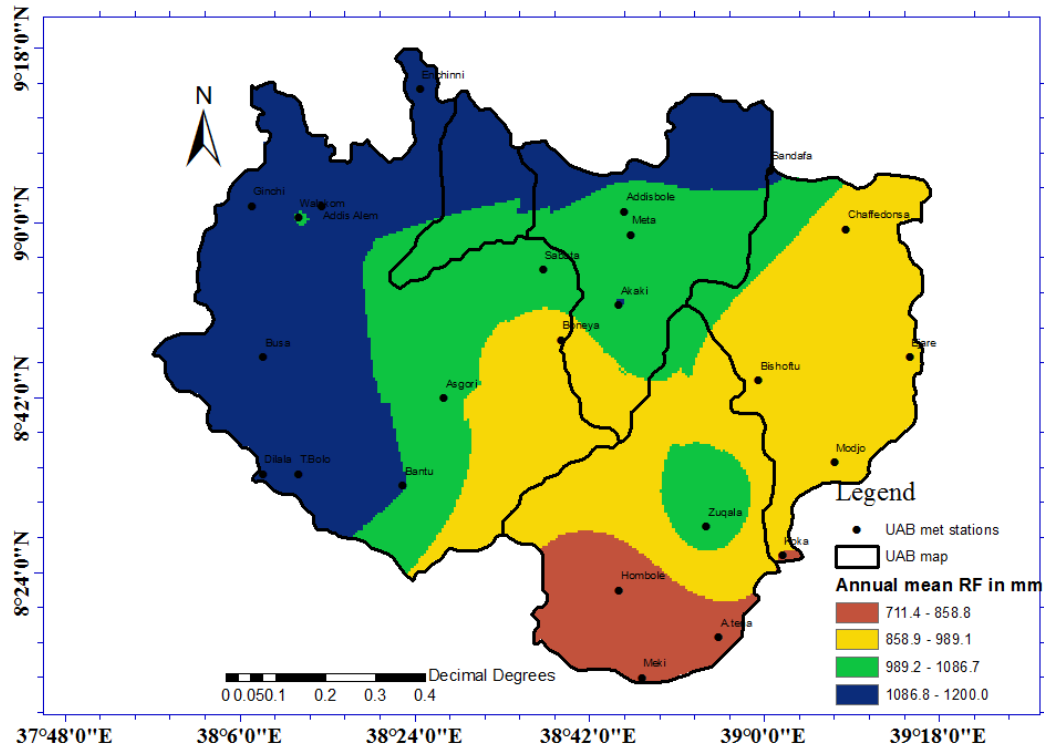


Figure 4: Mean annual rainfall distribution of Upper Awash Basin

4.2. Classification of Upper Awash Basin Rainfall into Homogenous Regimes

The regionalization of spatial variability of rainfall was studied over two distinct seasons in order to improve the quality of information for the study area. Regionalization of rainfall is necessary for various applications that include meteorological drought analysis and agricultural crop production planning to cope with dry spells that are likely be induced due to rainfall variability, forecasting rainfall and farming management. It is very essential to demarcate the quasi-homogeneous climatic zones and identify the climatic sub-regions in an observation network corresponding to specific climatic patterns, to understand the climate of the study area. These classifications are essential for in-depth understanding of the rainfall variations within each Zone to facilitate agriculture crop production planning and management. Therefore, PCA varimax rotated result shown that for climatological rainfall data based on eigenvalue more than one during *kiremt* season has eight maximum of four PCA modes accounting about 61 % of seasonal rainfall variance with Extraction Sums of Squared Loadings 25% was significant in first component (Table 2). Similarly, *belg* season has five

maximum of four PCA modes accounting about 82 % of seasonal rainfall spatial variance with Extraction Sums of Squared Loadings 58% was significant in the first component (Table 1).

the first four components containing Rotation Sums of Squared Loadings 53% of the variation of the 24 original stations variables with Component 1 explains 18 % of the variation, component 2 explains 14%, component 3 explains 11% and component 4 explains 10% and the remaining 20 components explain 47% during *kiremt* seasonal (Table 2). And the first four components contain Rotation Sums of Squared Loadings 80% of variation with Component 1 explains 25% of the variation, component 2 explains 23%, component 3 explains 20% and component 4 explains 12% and the remaining 20 components explain 20% during *Belg* season (Table 1).

Table 1: *Belg* Seasonal rainfall Total variance Explained by PCA

Comp onent	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	% of			% of					
	Total	Varian ce	Cumulat ive %	Total	Varian ce	Cumula tive %	Total	% of Variance	Cumulat ive %
1	14	58	58.2	14	58	58.2	5.9	24.5	24.5
2	2.4	10	68.2	2.4	10	68.2	5.6	23.2	47.7
3	2	8.2	76.4	2	8.2	76.4	4.7	19.7	67.4
4	1.2	5.0	81.5	1.2	5.0	81.5	3.0	12.8	80.2
5	1	4.4	86	1	4.4	86	1.4	5.8	86

Table 2: *Kiremt* Seasonal total rainfall variance explained by PCA

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	% of			% of					
	Total	Variance	Cumulative %	Total	Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.986	24.940	24.940	5.986	24.940	24.940	4.262	17.760	17.760
2	3.386	14.107	39.047	3.386	14.107	39.047	3.301	13.756	31.516
3	3.318	13.825	52.871	3.318	13.825	52.871	2.733	11.387	42.904
4	1.949	8.120	60.991	1.949	8.120	60.991	2.505	10.438	53.342
5	1.790	7.459	68.450	1.790	7.459	68.450	2.133	8.889	62.231
6	1.562	6.508	74.958	1.562	6.508	74.958	1.943	8.096	70.327
7	1.450	6.040	80.998	1.450	6.040	80.998	1.860	7.750	78.078
8	1.093	4.555	85.553	1.093	4.555	85.553	1.794	7.475	85.553

The scree plot is a useful visual aid for determining an appropriate number of principal components. The scree plot graphs the eigenvalue against the component number shown on (Figure 5).

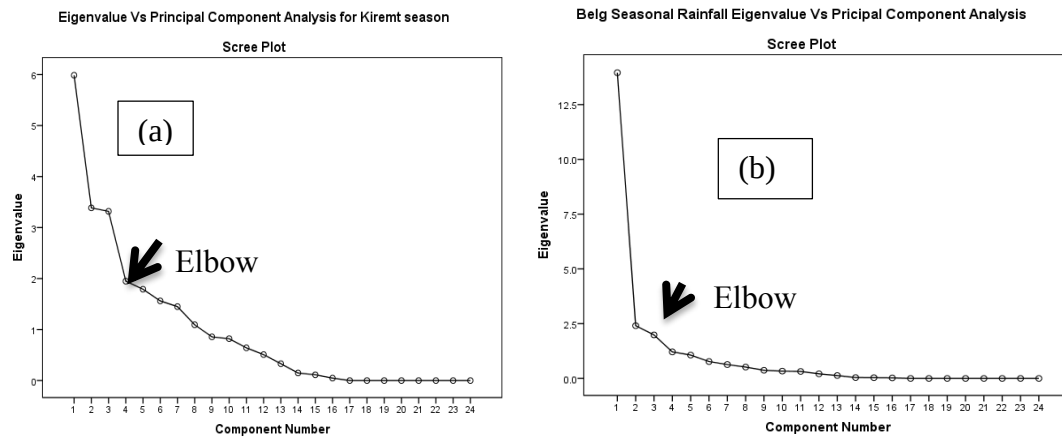


Figure 5: A scree plot graphs of variation explained by each PC

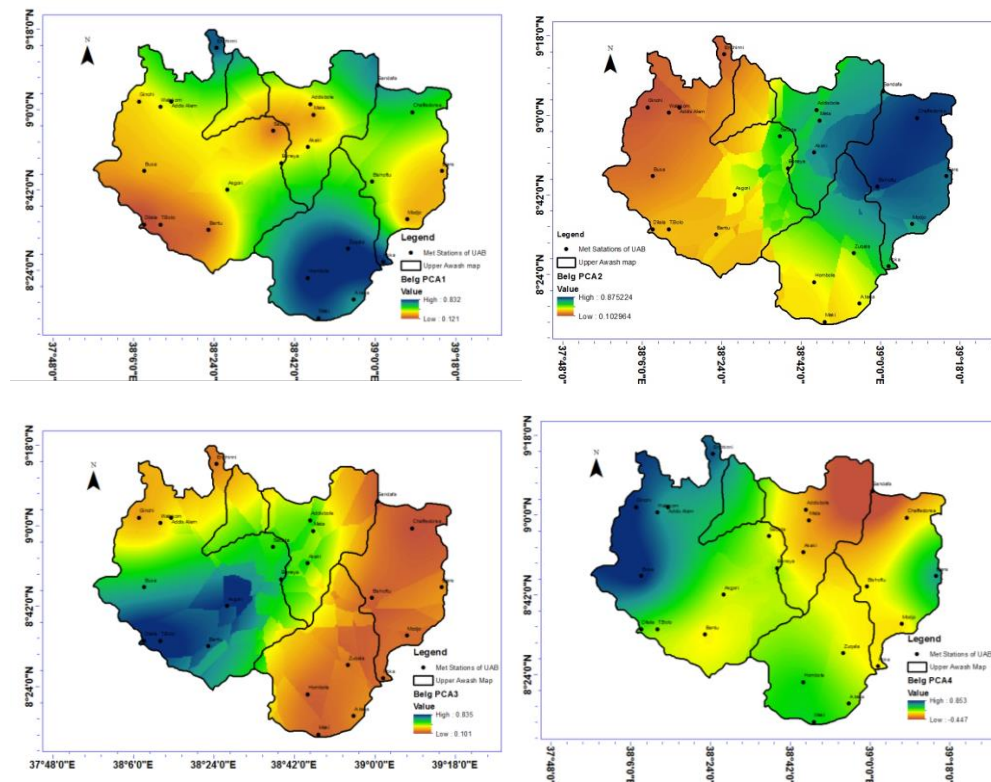


Figure 6: Belg season rainfall homogeneity graph for the first four PC value

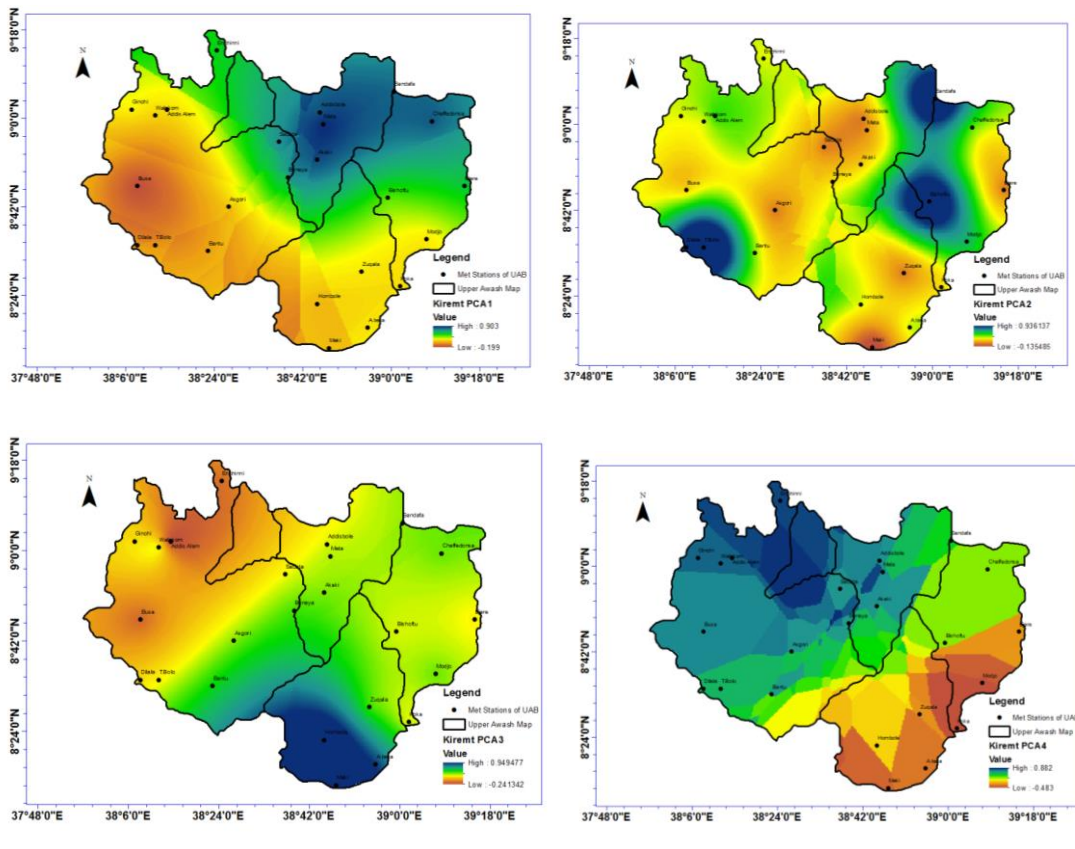


Figure 7: *Kiremt* season rainfall homogeneity graph for the first four PCA components

Based on the PCA, scree plot elbow plot and spatial PC value distribution on map, three coherent regions were identified from the rotated EOF analysis of the rainfall data, which are three climatological sub-divisions, were found in the Upper Awash Basin during *belg* and *kiremt* rainy season. Therefore, Upper Awash Basin has Regional rainfall patterns delineated into three homogeneous climatological rainfall zones during rainy season (Figure 8).

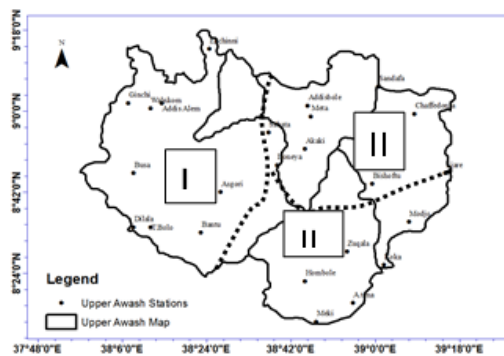


Figure 8: Homogenous rainfall regime of Upper Awash Basin during rainy season

4.3. Analysis of Seasonal and Inter-Seasonal Rainfall Variability

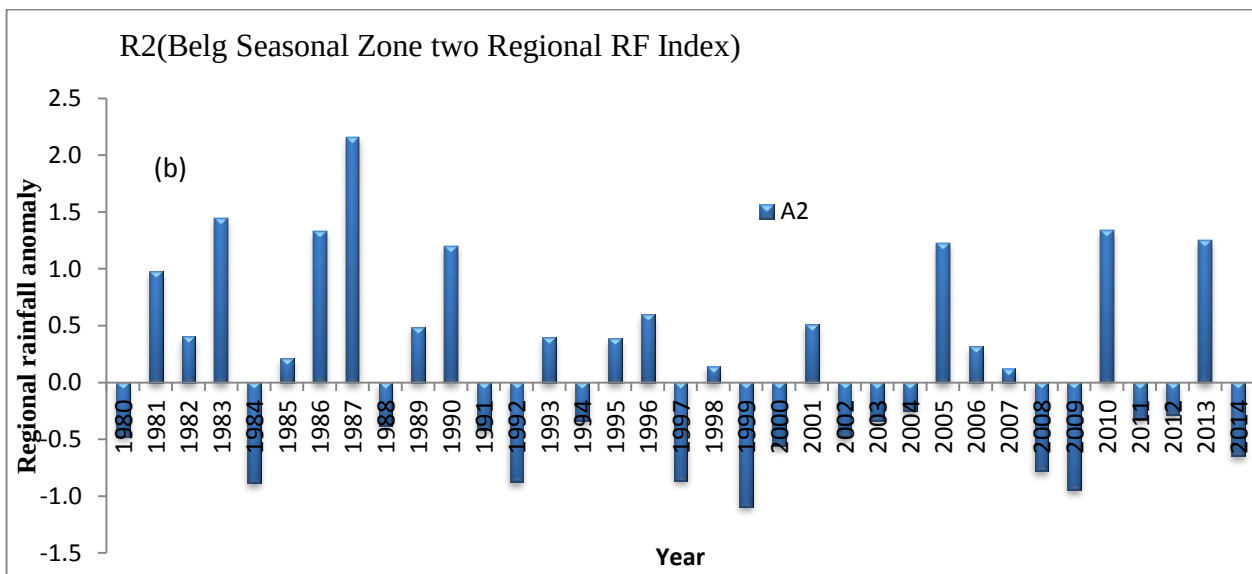
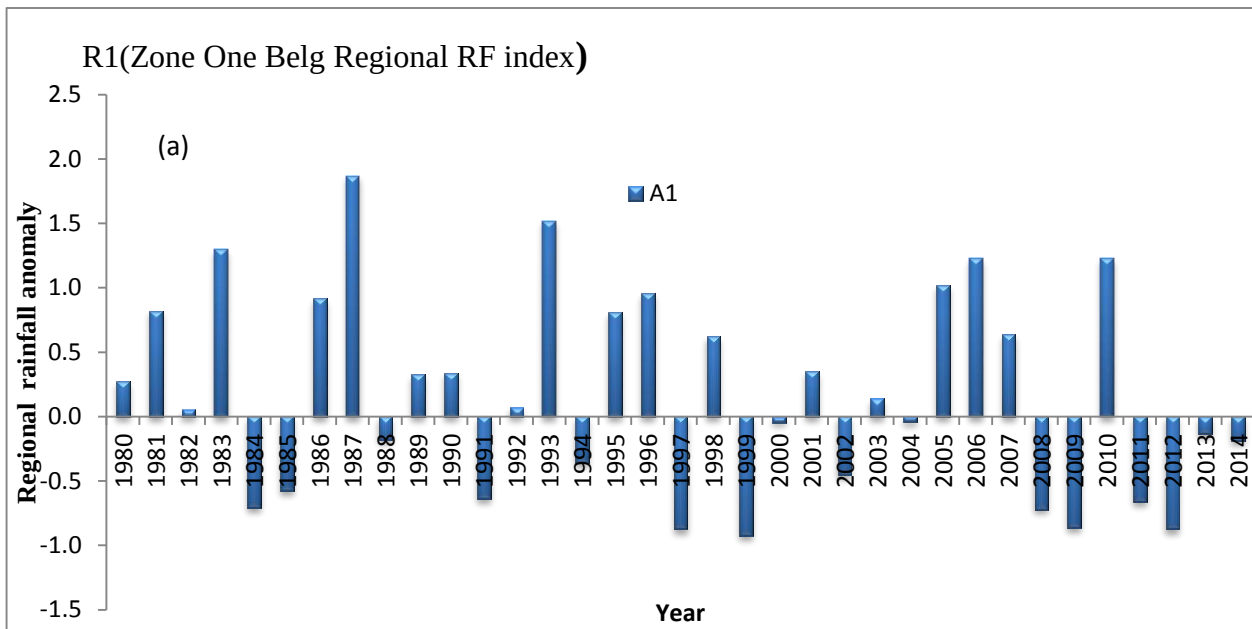
The rainfall variability resulted by coefficients of variation (CV) of inter seasonal to seasonal rainfall over UAB during *Kiremt* season and annual totals have shown that there existed less spatial and temporal variability, while monthly and *belg* season rainfall patterns have possessed high spatial and temporal variability (Table 3). Having this information of seasonal and inter-seasonal rainfall variability is very important for short and long term planning of farming system, through which cropping patterns, sowing period and selection of crop variety.

Table 3: Seasonal to inter-seasonal coefficient of variation of some selected stations

Stations	Jun CV%	July CV%	Aug CV%	Sep CV%	<i>Belg</i> CV%	<i>Kiremt</i> Cv%	Annual Cv%
Busa	42	31	38	55	55	29	28
A/Ababa bole	47	21	22	31	40	16	15
A/Tena	59	42	31	50	43	22	13
Bishoftu	48	30	28	40	55	19	19
Ginchi	35	22	25	34	43	15	16
Akaki	50	35	42	52	44	36	30

Rainfall anomaly is used to compare the long-term variation of rainfall at individual year. This gives an estimate of the degree to which rainfall recorded during the months of season is either stable or changing. Monthly rainfall anomaly characteristic was analyzed by using (Equation 5) which indicated that, whether the month is meteorological wet or dry in each individual year at station level were presented in (Appendix Figures 5), which were highly variable. Negative anomaly has shown that, the month was under meteorological dry climate while the positive anomaly indicated that the month is under wet climatic condition. Similarly, the local regional rainfall anomaly during the rainy season resulted by (equation 3) enabled to show the degree of long term temporal Zonal rainfall variability. The result of regional rainfall anomaly have shown that those extreme seasons of wet or dry season, whereas value more than 0.5 and less than -0.5 with associated years of *belg* and *kiremt* season were extreme wet and dry season respectively (Figure 9 and 10). According to Goddard *et al*, (2001) ENSO phase classification and also documented by Korecha and Barnston, (2007), the results revealed that rainfall amounts of major rainy season became very high in La Niña but low in El Niño years.

Conversely, during small rainy season, comparatively high rainfall amounts were observed when El Niño was apparently established.



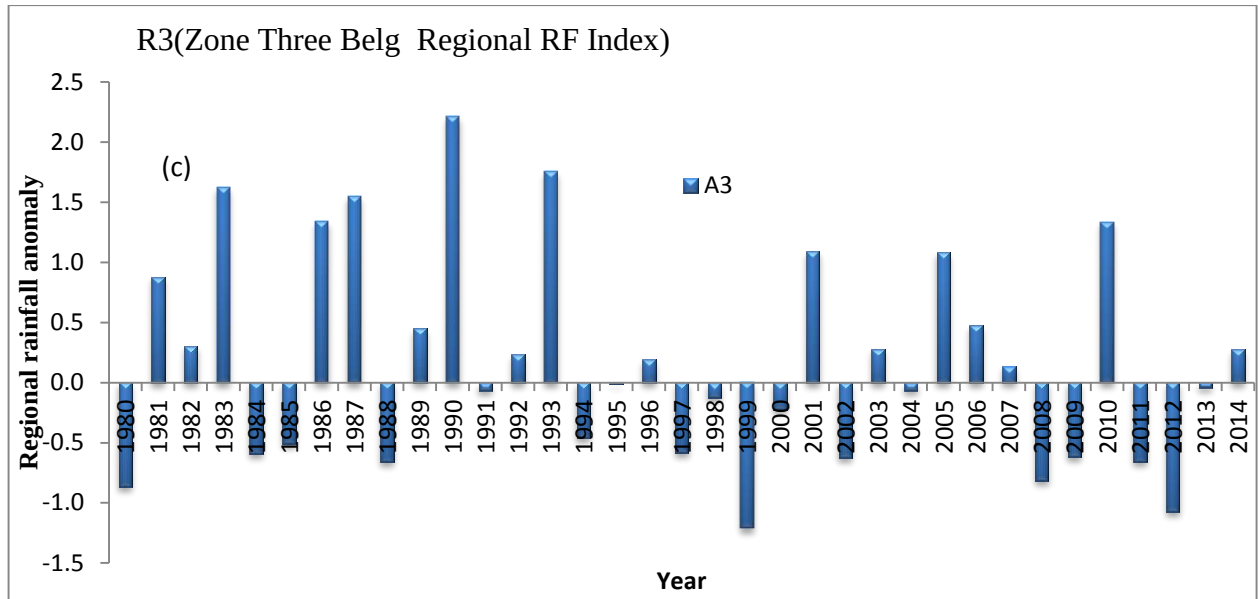


Figure 9: Zonal homogenous rainfall variability index during Belg season

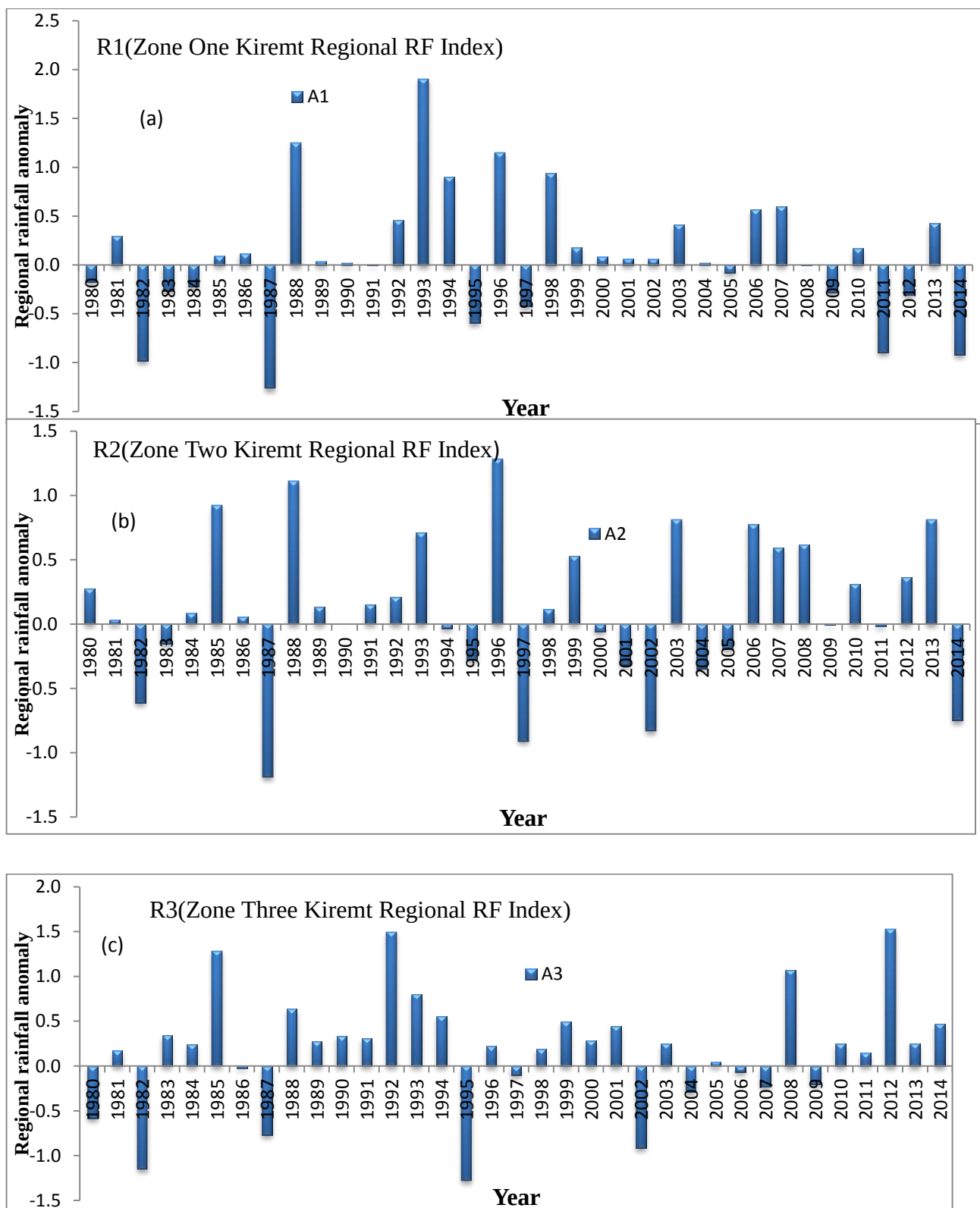


Figure 10: Zonal homogenous rainfall variability index during *kiremt* season

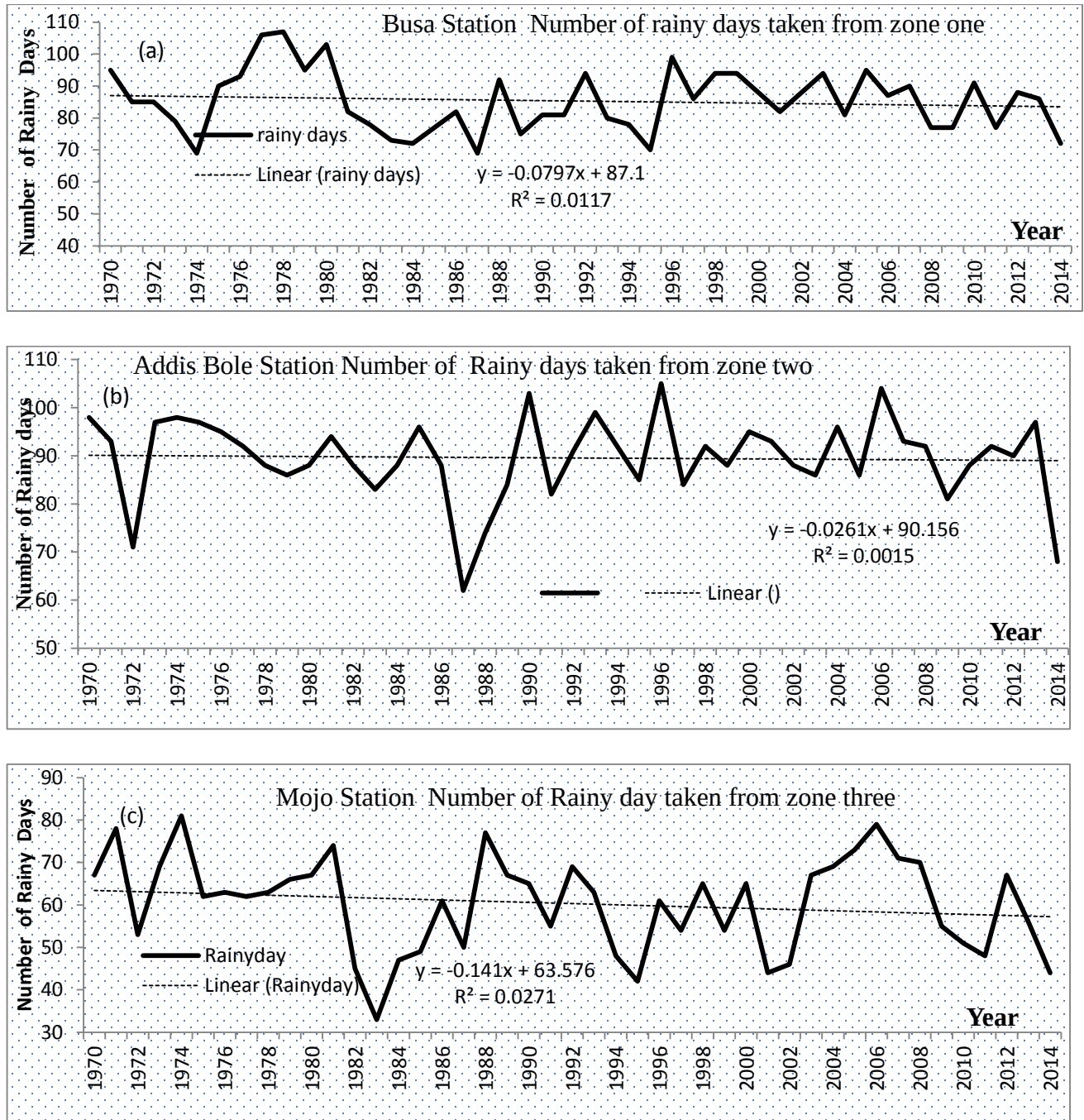


Figure 11: Time series analysis of number of rainy days during kiremt season

The trends of number of rainy days' from the time series analysis shows that, there is R^2 less than 0.027, which has no significant statistical change of number of rainy days for all selected station at each homogenous rainfall regime (Figure 11). Similarly, Coefficient of variation of mean number of rainy days (NRD) is less than 20% for selected stations, which has no significant statistical variation (Table 4).

Table 4: Mean (NRD) and their variation for selected stations during *kiremt*

Station	Mean NRD	SD of NRD	CV% of NRD
Busa	85	10	11
Addis Ababa Bole	90	9	10
Mojo	60	11	19

4.4. Onset, Cessation and Duration of Rainy Period

The patterns of rainfall onset, cessation and length of growing season were determined and subsequently establish the relationships between these characteristics. The amount of water available to plants depends on the seasonal onset, length and termination of the rainfall, as well as soil water holding capacity. The result shows that there is more variability in the onset of the rainy season than in its cessation. The highest variability in the onset was observed over the southern and eastern parts of UAB. Nevertheless, the variability of cessation dates of the rainy season is too small (Table 5).

Besides other rainfall characteristics, total amount and distribution of seasonal rainfall during this period is important in determining the types of crops that are cultivated within the basin. The onset of the rainy season is used to investigate changes in the start of the long cycle crop planting period and land preparation in study area. Regularly, the early onset of rainy season starts after 96 DOY in high land Zone one and 120 DOY in lower altitude Zone three (Table 6), which is in month of April. Even if rainfall was recorded before April it does not full fill the criteria of Markov chain, the first rainy period onset was generally earlier in the Zone one areas with at least three weeks variation to Zone three (Table 6).

Previous studies have indicated that existence of two rainfall peaks within central Ethiopia (NMSA, 1996), Upper Awash Basin which have two rainy seasons and one dry season. The minor season with high frequency of dry spell while less frequency of dry spell in major season, both rainy period are coming consecutively with small gap in between the two peaks of rainy season. The length of growing season decreased from southern to western part of the upper Awash Basin. For the period reviewed at each station, the short LGP season ranges from 90 to 134 days and long LGP season ranges from 150 to 195 Days. Cessation variation is almost two weeks and start of season variation is about one month at selected station (Table 5 and 6). According to the study area rainfall pattern and distribution, 80% probability of

exceedance, (50%) and (20%) of RF data series of *kiremt* season (Table 5) shown that dry, normal and wet season respectively. Similarly, 80% probability of exceedance data series 50% and 20% Early, normal and late onset and cessation dates (day/month) respectively and Long LGP (20% probability of exceedance), normal (50%) and short (80%) length of growing season (days) for rainy season for various stations in the study area, which is the summary of the onset and cessation dates and LGP obtained from Upper Awash Basin (Table 6).

Strong inter-seasonal variability in the timing of the onset was observed alongside an increasing number of dry days and at the onset period. Therefore April to September period is when rainfall activities has better performance and all of the rain-fed agricultural crop production activities take place in Upper Awash Basin, which is important for rain fed crop production planning is recommended for crops production under rain- fed system in this study area, which means small rainy period (*Belg*) rainfall season recommended for land preparation, sowing short cycle crop like Haricot bean and sowing long cycle crops of dry spell resistance like sorghum while *kiremt* season used for rest crop production planning activity. Hence, in relation to problems of small rainfall amount, high risk of dry spells, too small length of minor season and small gap with major season leads to none of harvesting time makes the small rainy season very difficult in the planning of all rain-fed crop production activity.

Table 5: Rainfall exceedance probability distribution and CV of SOS, EOS and LGP

Stations	RF 80%	RF 50%	RF 20%	Kiremt RFCV%	SOS CV %	EOS CV %	LGP CV%	SD of SOS	SD of EOS	SD of LGP
Busa	597	878	1167	29	22	5	21	27	14	33
Ginchi	645	772	865	15	22	3	17	26	8	28
Enchinni	768	840	965	18	24	4	21	30	11	33
Dilala	676	762	952	16	19	3	18	24	9	28
Akaki	662	763	888	36	21	3	20	28	8	30
Mojo	583	672	771	22	21	4	26	32	11	34
Chefedonsa	541	664	778	21	19	4	28	29	11	36
Alemtena	456	558	679	22	18	5	27	28	15	33

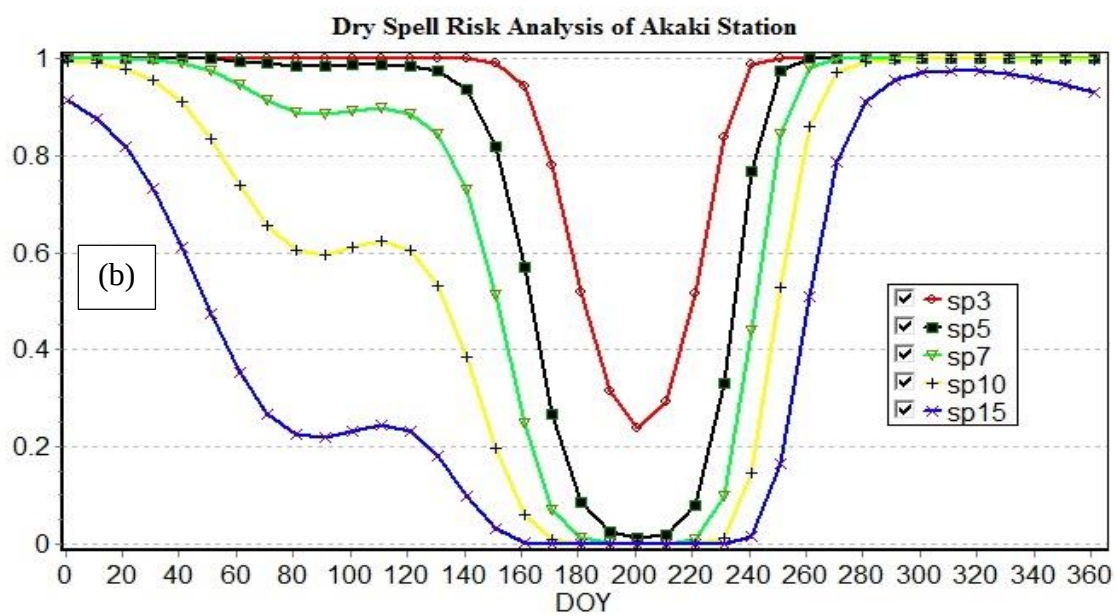
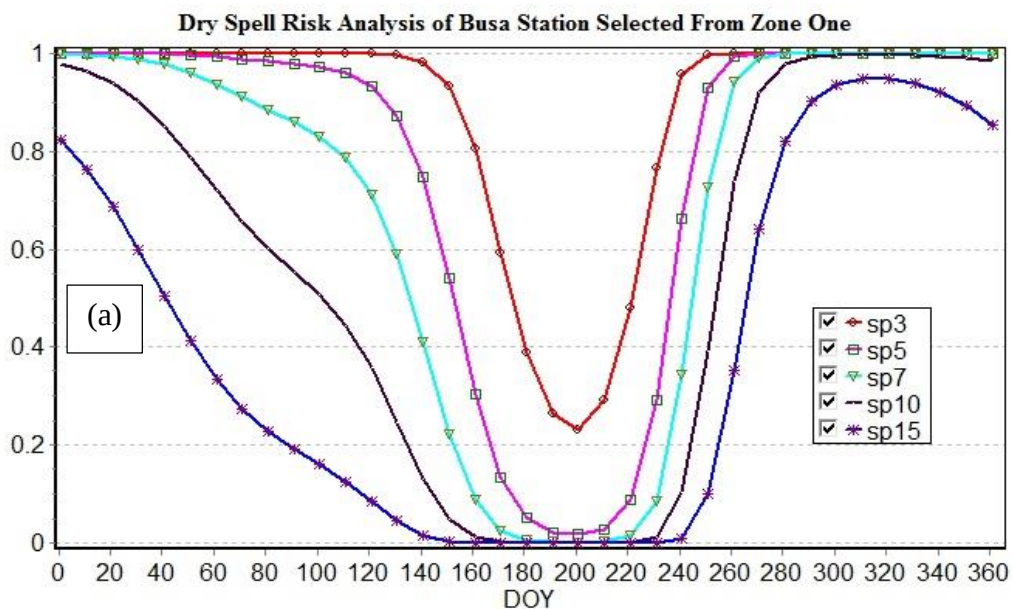
Table 6: Onset, Cessation and LGP determining by Exceedance probability

Station	Onset in DOY			Cessation in DOY			Length In Days		
	Early	Normal	Late	Early	Normal	Late	Long	Normal	Short
Busa	96	124	154	271	280	295	192	161	124
Ginchi	97	117	157	281	289	295	192	167	134
Enchinni	97	119	167	280	289	298	195	165	123
Dilala	98	128	153	278	286	292	183	155	130
Akaki	98	131	164	277	283	288	183	142	122
Chefedo	115	164	178	269	279	285	164	114	90
Mojo	115	160	176	270	278	287	162	122	99
A/tena	120	154	178	256	273	285	150	124	90

4.4.1. Seasonal dry spell risk analysis

The Risk of getting 3, 5,7,10 and 15 days of dry spells based on the fitted first order Markov chain probability values at Busa, Akaki and Alemtena stations selected from each Zones shown that, the dry spell risk of being fifteen days consecutive dry befallen at Busa,Akaki and Alemtena from April to September is less than 20%, 25% and 47%, respectively (Figure 12 a,b and c). This information is very important to farmers in the region in deciding on crop types to be cultivated and on planning sowing dates as a function of observed from the onset dates. Information on dry-spell lengths could be used in decision making with respect to selecting dry spell resistance crop and field operations within the farming system.

The dry spell effects on crop growth are related to water requirement of the crop and soil water holding capacity. Thus, whether soil has high or low water holding capacity information is extremely useful for planning and design applications for agriculture crop production. The peak rainfall period during the growing season occurs between July and August in UAB. The Risk of 5, 7, 10 and 15 days of being dry spell decreases from April to June and again there is a rapid increase in chances for experiencing dry spells after receiving rain or September, But from June to August the probabilities of the risk of a dry spell being more than 15 and 10 days are below 1%. The occurrence of dry spells longer than 15 days in a season was more widespread in Zone three of the study area than areas of Zones one and two (Figure 12 a ,b and c).Therefore, apart from the period April to September cycles of the year, the dry spell risk is too much, which is difficult to rain feed crop production planning activities.



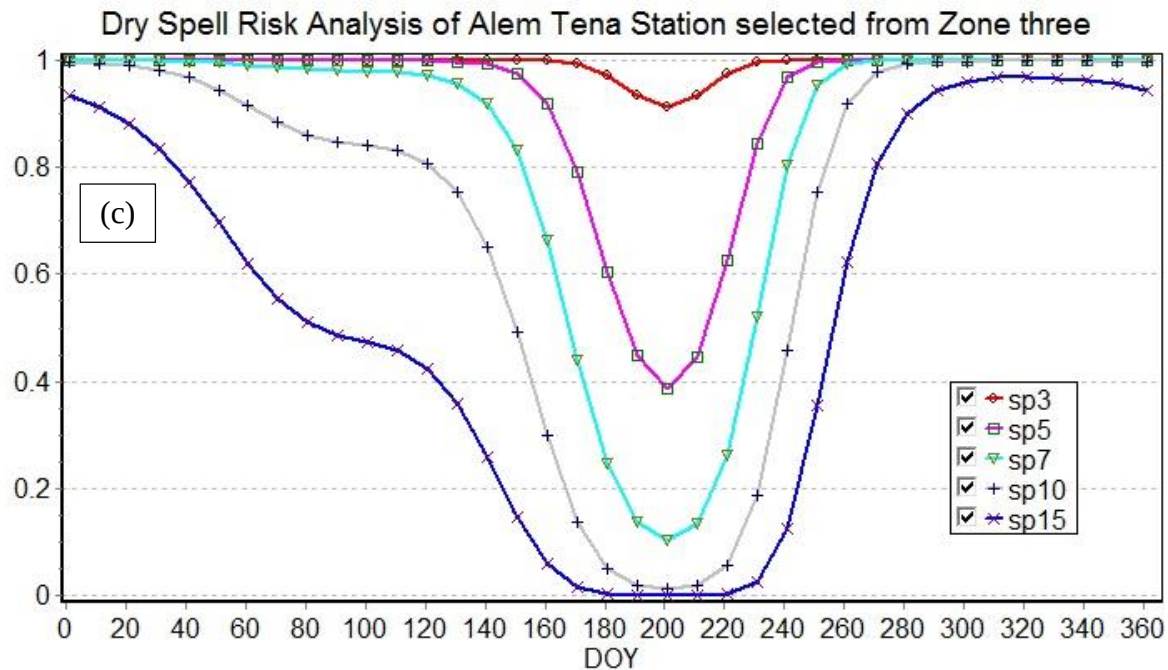


Figure 12: Dry spell risk analysis by first order Markov chain probability over each Zones

4.5. Spatial Correlation between SST and Regionalized Rainfall Index

The interpretation of regional rainfall index (R_k) value is important to consider that wetness and dryness are relative to historical average for the regional rainfall index, which was explained in (equation 3) correlations with pre-seasonal SST data results shown that, rainfall during JJAS and FMAM have strong relationship with the global SSTs and other indices such Nino regions, the Indian Ocean dipole (IOD) and south Indian Ocean (SIN). This index expresses the magnitude of excess or stress rainfall relative to normal. Therefore, applying regional rainfall index is an effective tool for a local climate risk monitoring system. The results of a statistical technique known as (CCA), which was stated in (Equation 5), with SST Anomalies over most of the Pacific Ocean tend to be inversely correlated with each homogenous rainfall Zones of UAB during *kiremt* season (Figure 14 a,b and c), while directly proportional with *belg* rainfall index (Figure 13 a,b and c).

During *belg* season, Zone one regional rainfall index correlated result with mean of December and January Spatial global sea surface temperature results shown that, relatively the best correlated area (r) value of $\geq |0.3|$ are Nino regions such as Nino 4 and Nino 3.4, part of Nino 3 and North eastern Pacific ocean and some parts of southern Atlantic and south western

Indian ocean, which are positive correlation while western Pacific and most of Eastern Indian ocean have a negative correlation with Zone One and also positive IOD has more significant with zone one (Figure 13 a). And for Zone two, best correlated area are Nino 4, north eastern pacific and parts of southern Atlantic, which are positive correlation, while west Pacific Ocean and most parts of Eastern Indian and some parts of southern Atlantic Ocean are a negative correlation with Zone two. Besides, the positive IOD has more significant with zone two (Figure 13 b). Similarly for Zone three relatively the best correlation area are, Nino regions such as Nino 4, Nino 3.4 North eastern pacific and some parts of southern Atlantic Ocean, which are positive correlation. while Eastern Indian, west and southern pacific ocean and some parts of Azores region have a negative correlation with Zone three, and positive IOD has more significant with zone three (Figure 13 c).

Kiremt regional rainfall index of Zone one correlated with mean of April and may Spatial global sea surface temperature results shown that, the best correlated area which has (r) value of $\geq |0.3|$ are some part of North eastern pacific and northern India ocean, which are positive correlation, while parts of southern India and southern Atlantic ocean are a negative correlation with Zone one (Figure 14 a). And for Zone two , relatively, the best correlation area are Nino regions such as Nino 4 Nino 3.4, Nino 3 , Nino1+2 and parts of Southern Indian are negative correlation while central Atlantic and part of north Atlantic, parts of north and west pacific and north Indian ocean ,which are positive correlation with Zone two (Figure 14 b). Similarly, for Zone three, the best correlated area are Nino regions such as Nino 4 parts of Nino 3.4 and some parts of north eastern Atlantic ocean border coast of north west Africa are negative correlation, while south east and some parts of western pacific ocean, have positive correlation with Zone three during *kiremt* season (Figure 14 c). The IOD phase has no that much significant relation with each *kiremt* zonal rainfall (Figure 14 a,b and c).

In general, as described in all maps of (Figure 13 and 14), the basic points found is that, the most rainfall predictive sites for study area are the Nino region and IOD phase. Nino region is positive correlation with *belg* rainfall, which means that warming phase of Nino regions during those seasons would increase rainfall amount, on the other hand, negative correlation of Nino regions with *belg* season means that cold phase, which cause to reduce/null rainfall amount over the study regions/Zones. When Nino regions is positively correlated with *kiremt* season rainfall, which mean that warm phase of Nino regions, cause to hinders *kiremt* rainfall,

while negative correlation with *kiremt* rainfall means that cold phase of Nino region cause to increase *kiremt* rainfall amount.

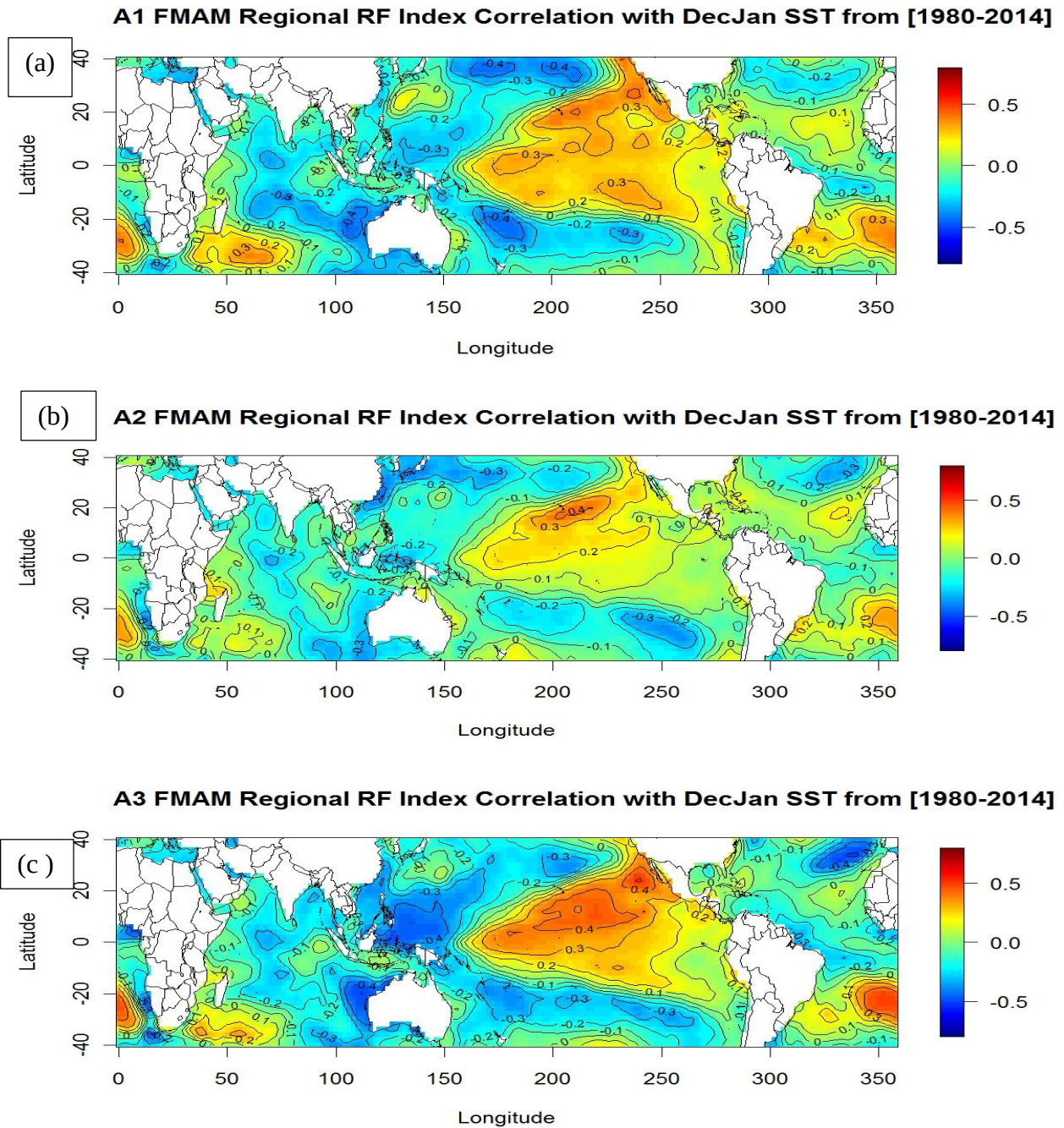


Figure 13: FMAM R_k index correlation with DecJan global spatial SSTa of each Zones

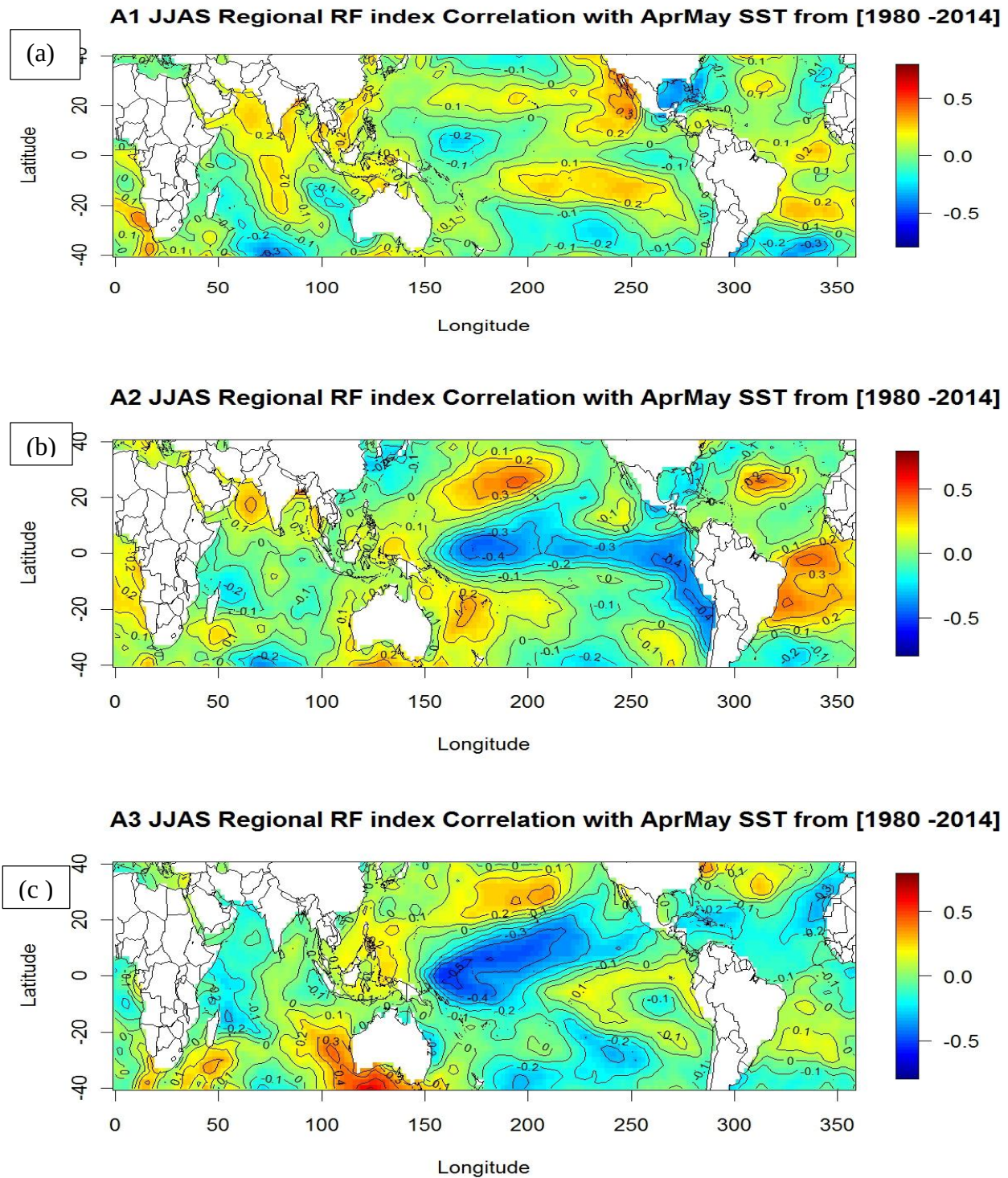


Figure 14: JJAS regional R_K index correlation with AprMay global spatial SSTa

4.6. Relationship between Zero lead time Nino regions SST with regional rainfall index

The result of zero lead time of the Nino region SST anomaly correlation with *kiremt* regional rainfall index as explained as (Table 7), all Nino regions have negative correlation with *kiremt* rainfall index, while all Nino regions have positive correlation with *belg* regional rainfall index (Table 8). Nino 3 and 3.4 SST have more significant to Zone one and two regional rainfalls, while Nino 4 and 3.4 SST have more significant correlation with Zone three *kiremt* regional rainfall index (Table 7). But Nino 3.4 and 3 regions have more significant correlation with all three regional rainfall indexes during *belg* season (Table 8).

Table 7: Zero lead time Nino region SSTa correlation with Zonal rainfall index of *Kiremt*

Correlation during <i>kiremt</i>	Correlation Matrix						
	JJAS nino4	JJAS nino3.4	JJAS nino3	JJAS nino1+2	<i>Kiremt</i> Z1	<i>Kiremt</i> Z2	<i>Kiremt</i> Z3
JJAS nino4	1.000	0.898	0.700	0.326	-0.209	-0.501	-0.341
JJAS nino3.4		1.000	0.909	0.562	-0.368	-0.610	-0.331
JJAS nino3			1.000	0.827	-0.427	-0.631	-0.251
JJAS nino1+2				1.000	-0.321	-0.502	-0.078
<i>Kiremt</i> Z1					1.000	0.695	0.390
<i>Kiremt</i> Z2						1.000	0.503
<i>Kiremt</i> Z3							1.000

Table 8: Zero lead time Nino region SSTa correlation with Zonal rainfall index of *belg*

Correlation during <i>belg</i>	Correlation Matrix						
	FMAM nino1+2	FMAM nino3.4	FMAM nino4	FMAM nino3	<i>Belg</i> Z1	<i>Belg</i> Z2	<i>Belg</i> Z3
FMAM nino1+2	1.000	0.675	0.388	0.890	0.247	0.087	0.214
FMAM nino3.4		1.000	0.869	0.894	0.474	0.312	0.429
FMAM nino4			1.000	0.613	0.380	0.245	0.350
FMAM nino3				1.000	0.427	0.268	0.407
<i>Belg</i> Z1					1.000	0.787	0.799
<i>Belg</i> Z2						1.000	0.797
<i>Belg</i> Z3							1.000

According to long years' time series analysis of Nino region SST and seasonal regional rainfall index for each Zone results shown that, the time series analysis of SST and rainfall anomaly relationship of long year observation described during *belg* season the rainfall anomaly and related Nino regions are positive correlated, while during *kiremt* season rainfall anomaly and SST are opposite sign (Figure 15). In other words positive SST anomaly is

related to increasing sea surface temperature than normal while negative SST anomaly is related to coldness of sea surface than normal condition, Which resulted to increase rainfall activity in the *kiremt* rainy season during La Niña years/cold phase as well as increased rainfall activity. These associated heavy falls can destroy crops and also cause water-logging problems during *kiremt*.

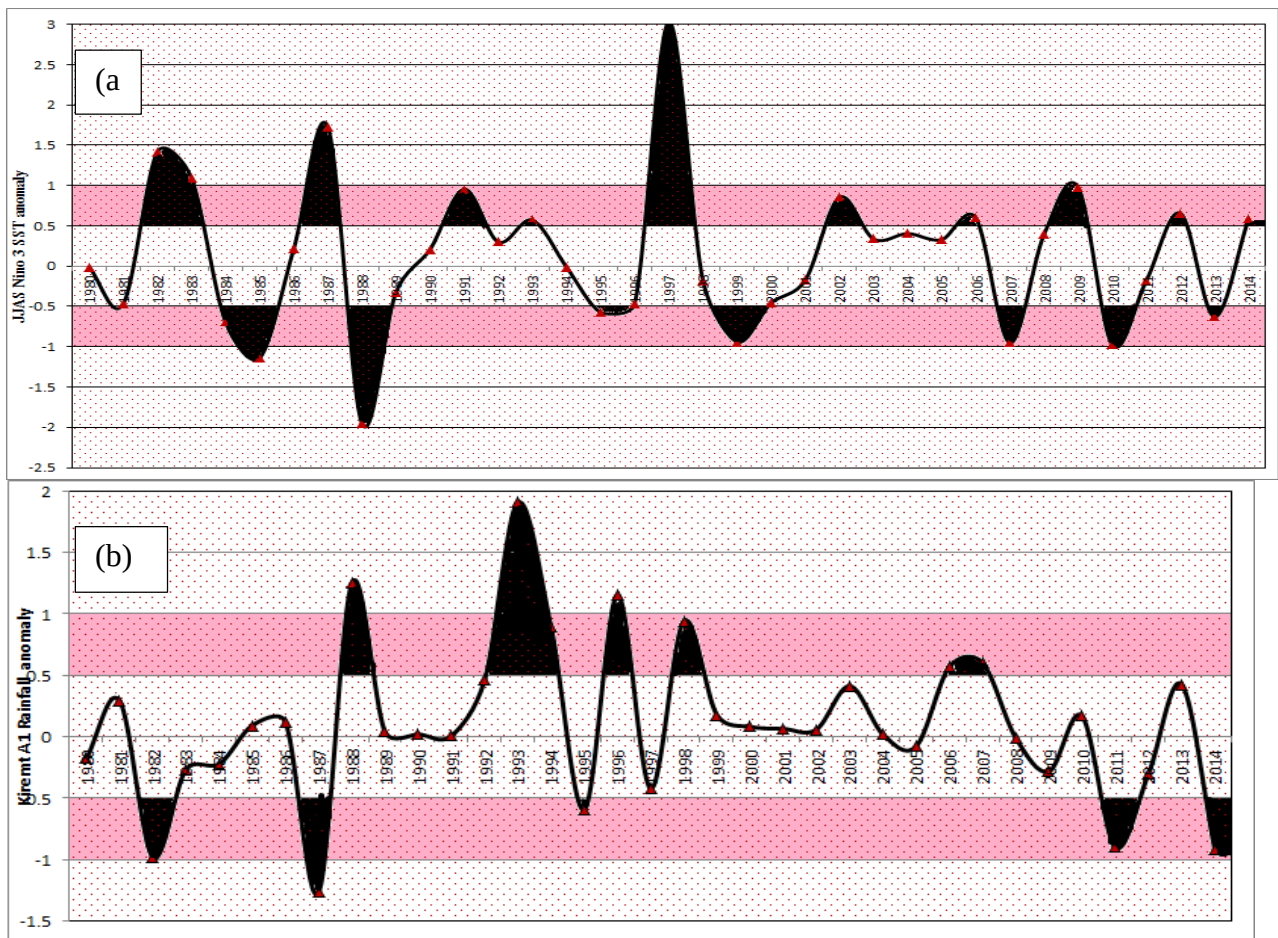


Figure 15: Time series analysis of JJAS Nino 3 SSTa and Zone one regional rainfall index

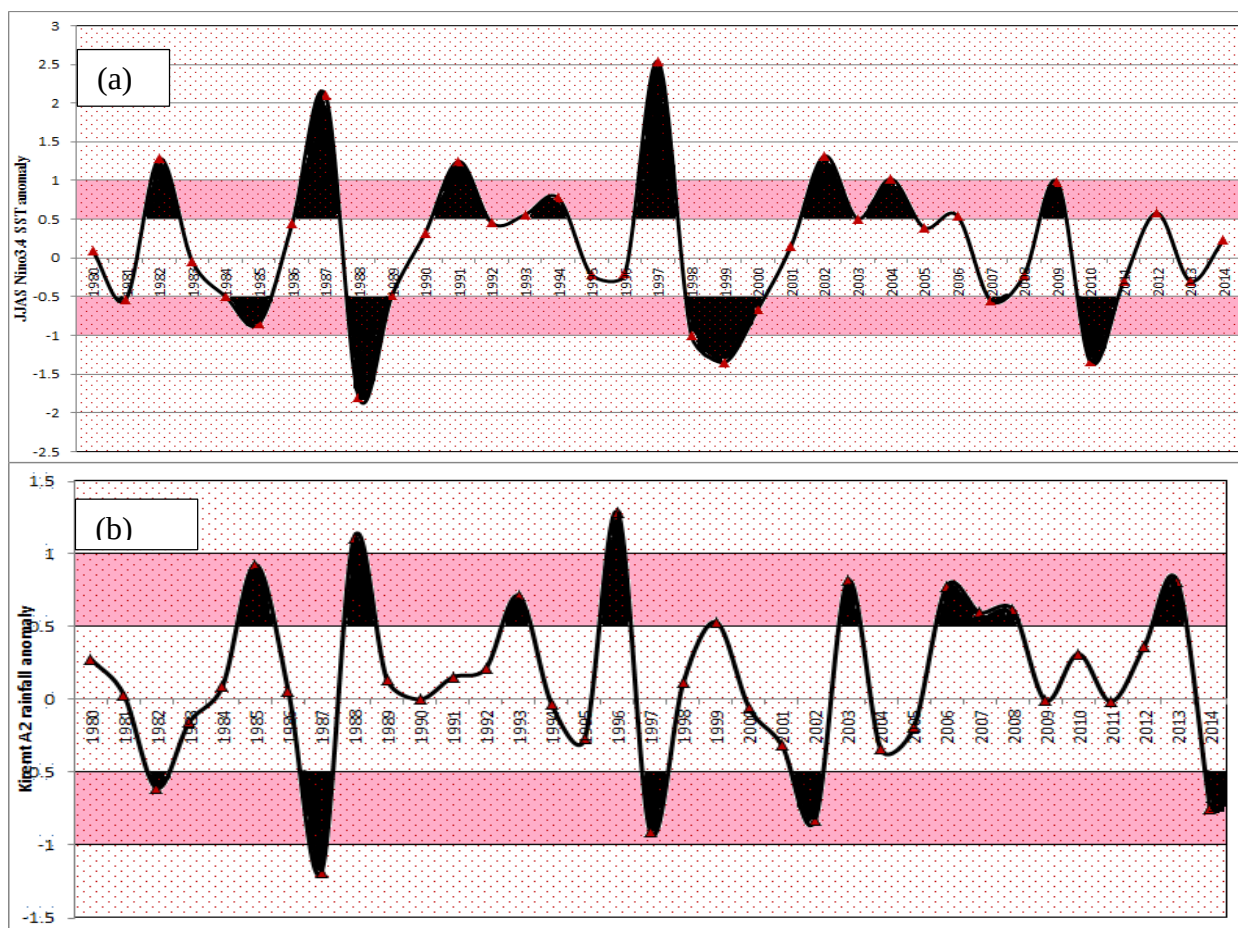
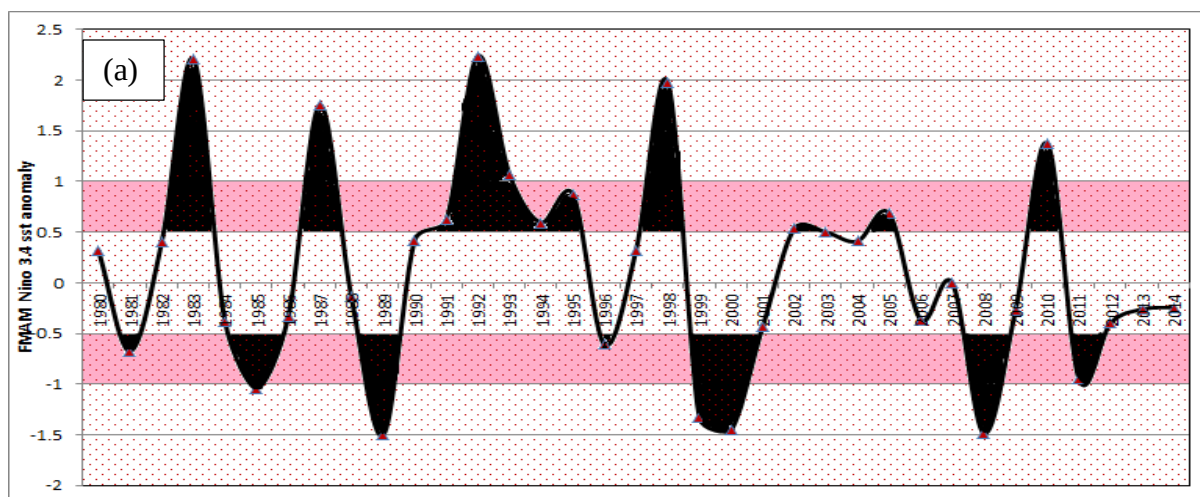


Figure 16: Time series analysis of JJAS Nino 3.4 SSTa and Zone two regional rainfall index



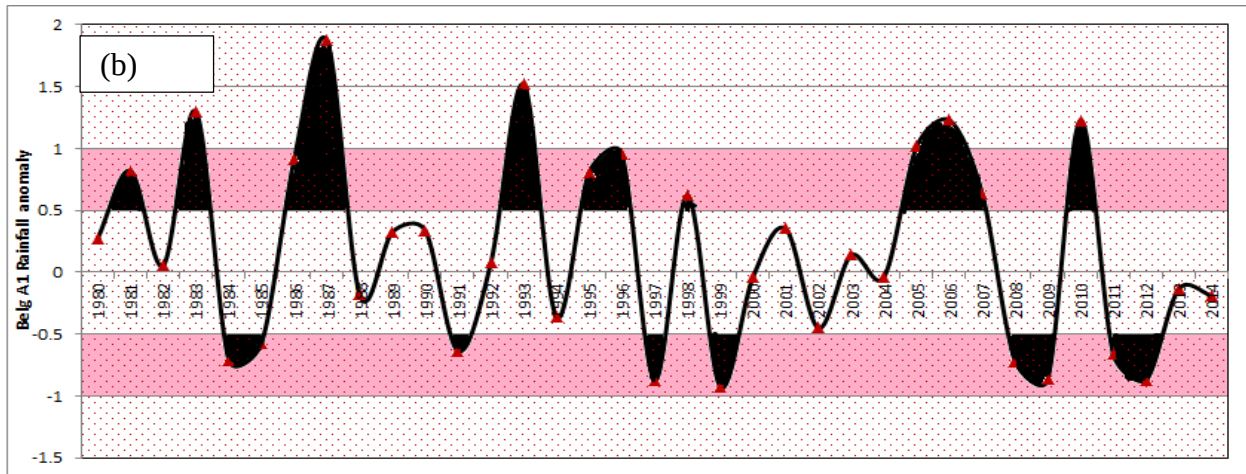
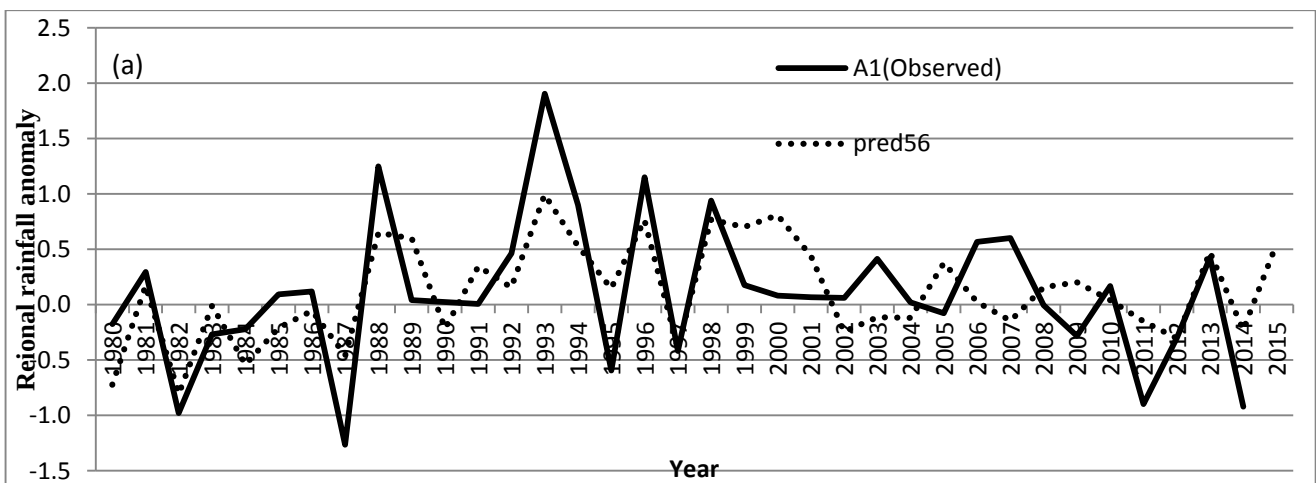


Figure 17: Time series analysis of FMAM Nino3.4 SSTa and Zone one regional rainfall index

4.7. Statistical Multiple Linear Regression Models for Seasonal RF Prediction

It is the great variability in seasonal climate, both short term and long term, which creates the never-ending demand for predictive information. As the result of statistical multiple linear correlation and regression a relation with SST and homogenous rainfall Zones have shown that, the developed model has a system that derives forecast of seasonal rainfall from very early rain occurrences given the forecast as Below normal, Normal and Above normal which, makes choices of crops and practices to conform to the seasonal expected forecasts.



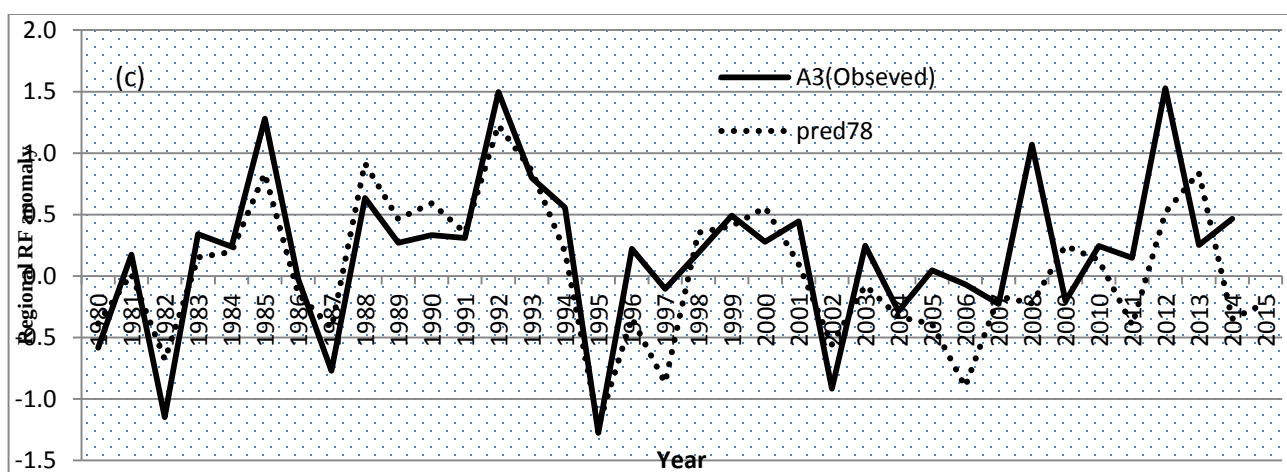
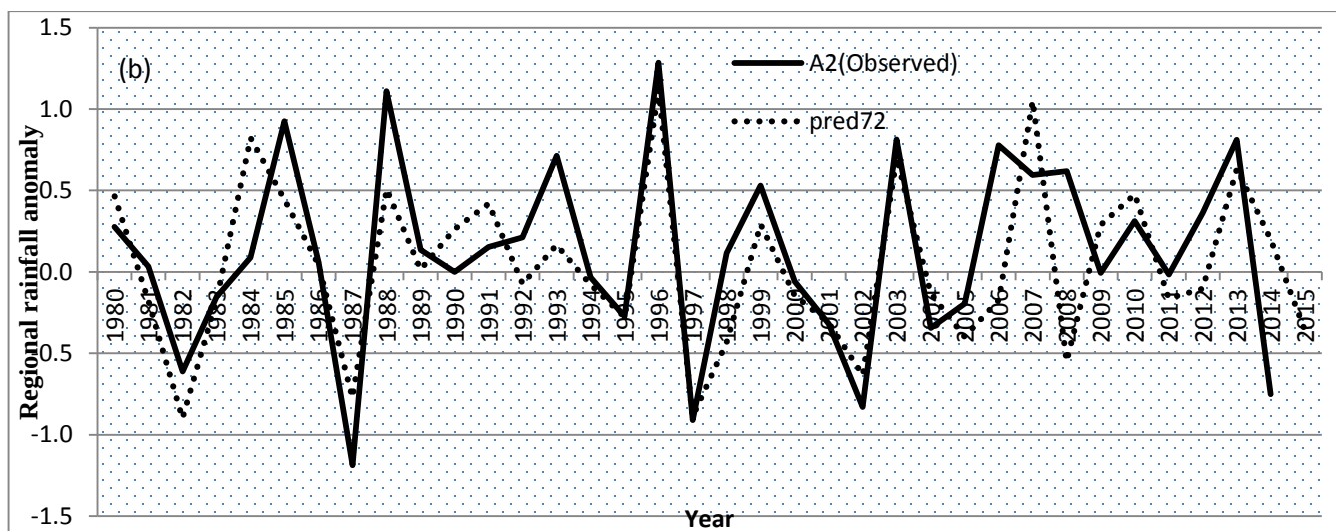
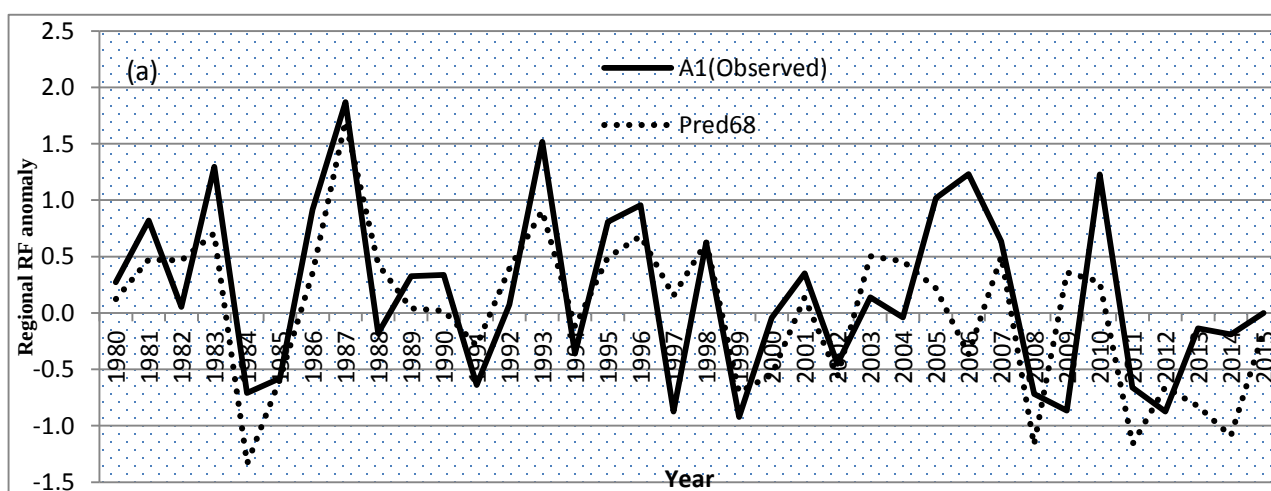


Figure 18: SMLR model For Zone one to three during *Kiremt* Season



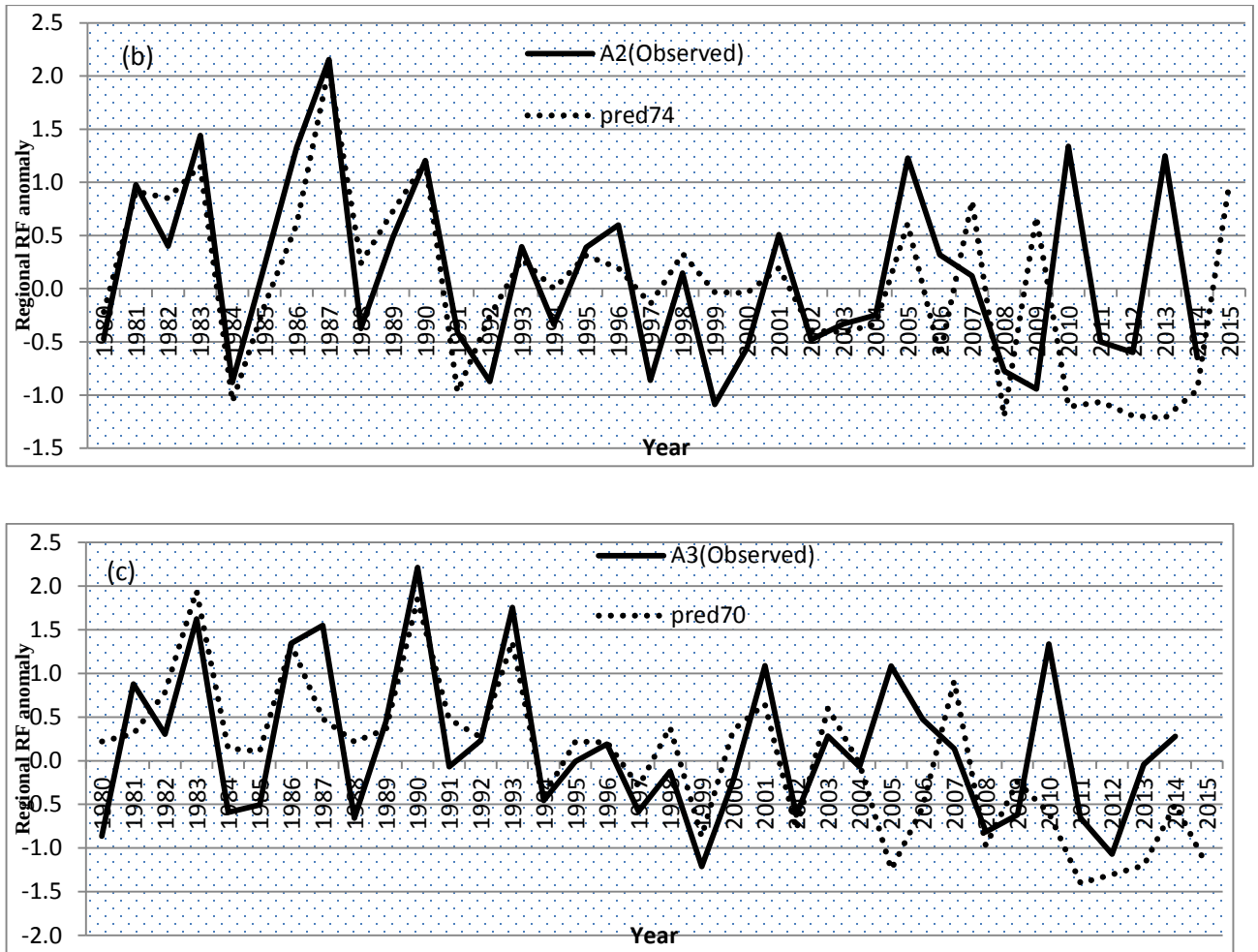


Figure 19: SMLR model For Zone one to three during *belg* Season

Table 9: Multiple linear regression model Equations of *belg* and *kiremt* seasons for UAB

Zones/season	Equations	R	R ²
<i>Belg</i>			
Zone one	$Z1_{pred69}=0.357*SIN13+0.068*INDSSTMOD3-0.151*ATLSSTMOD5$	0.83	0.69
Zone two	$Z2_{pred74}=0.331*SAT16+0.470*SIN13+0.409*SPA8-0.355*EATAL-0.130*ATLSSTMOD5$	0.85	0.74
Zone three	$Z3_{pred70}= -0.138*INDSSTMOD4+0.094*INDU850MOD3-0.220*ATLSSTMOD5+0.140*ATLSSTMOD6$	0.83	0.70
<i>Kiremt</i>			
Zone one	$Z1_{pred56}=0.317*EQAT24-0.246*NAT44-0.359*NAT124+0.123*ATLU850MOD6$	0.75	0.56
Zone two	$Z2_{pred72}=-0.360*ATB54+0.443*NAT104-0.249*SIN264-0.063*INDSSTMOD6+0.027*INDU850MOD1$	0.85	0.72
Zone three	$Z3_{pred78}=0.196*EQPA24+0.247*INB44-0.246*NAT124+0.324*SIN134+0.184*SIN164-0.587*WPAC4$	0.88	0.78

4.7.1. Performance of the statistical multiple linear regression models

The performance of each SMLR model has to be tested by contingency table is used to test the goodness of fit of the model based on model generated and observed values for the hind cast period. The approaches that have been implemented here to investigate the performance of each model is according to (Appendix Table 1) given by (Equation 8 and 9).

$$HS = \frac{(a + e + i) * 100}{p} = \frac{(3 + 19 + 5) * 100}{35} = 77\%$$

$$HSS = \frac{(a + e + i) - \frac{(mj + nk + lo)}{p}}{p - \frac{(mj + nk + lo)}{p}} = \frac{(3 + 19 + 5) - \frac{(5 * 5 + 24 * 20 + 6 * 10)}{35}}{35 - \frac{(5 * 5 + 24 * 20 + 6 * 10)}{35}} =$$

$$\frac{(27 - 16.1) * 100}{35 - 16.1} = 58\%$$

Table 10: Contingency table of SMLR evaluation for Zone two during JJAS season

Zone two Observed	Zone two JJAS Forecast			Total
	Below normal	Normal	Above normal	
Below Normal (B)	3	2	0	5
Near Normal (N)	0	19	1	20
Above Normal (A)	2	3	5	10
Total	5	24	6	35

Table 11: Contingency table of SMLR evaluation for Zone three during JJAS season

Zone three Observed	Zone three JJAS Forecast			Total
	Below normal	Normal	Above normal	
Below Normal (B)	1	0	1	2
Near Normal (N)	3	19	3	25
Above Normal (A)	0	2	6	8
Total	4	21	10	35

Table 12: Contingency table of SMLR evaluation for Zone two during FMAM season

Observed	Forecast			Total
	Below normal	Normal	Above normal	
Below Normal (B)	5	6	0	11
Near Normal (N)	2	10	3	15
Above Normal (A)	2	1	6	9
Total	9	17	9	35

Table 13: Hit Score and Hit Skill Score for Zone two and three FMAM and JJAS season

	FMAM HS%	FMAM HSS%	JJAS HS%	JJAS HSS%	JJAS SS%
Zone two	60	38	74	58	54
Zone three	57	33	74	49	56

The model evaluation result shown that, the model captured about 74% and 60 % of ground truth during *kiremt* and *belg* season respectively (Table 13). The results of the developed SMLR model have shown that, more or less the predicted and observed Rk index have similar

trends. However, the fitness may not perfect, the model can show the expected seasonal rainfall indicates as above, below or normal rainfall expectation of the season.

4.8. Seasonal Climate Prediction by Analogue Years approach

From identified previous periods that resembled the immediate past period and predicting the following month's or season's climate resulted in (Figure 20). Which are different years have shown similar behavior with current reference season by SST phase and their rainfall patterns. The occurrence of global teleconnection features such as ENSO of one year might be resembled with the others. Since central and eastern Pacific Ocean has better statistical significant correlation with Zonal rainfall of the UAB, thus Nino 3.4 region has shown the phenomena of the coming rainfall season (Figure 20). Based on the current regional and global conditions and the pre-seasonal rainfall patterns of from select analogue year's attempts from the previous years have shown, the graph of cumulative rainfall approach can be the expected weekly rainfall distribution of coming season of Addis Ababa station has been predicted as shown in (Figure 21). From this weekly cumulative rainfall distribution it is possible to identify the starts and end of rainy season, which are the points of positive curvature and negative curvature respectively. Therefore, according to this selected analogue years *kiremt* season of forthcoming rains starts from 12 June (positive curvature) and ends at 18 September (negative curvature) with total seasonal rainfall expected up to 700mm (Figure 21).

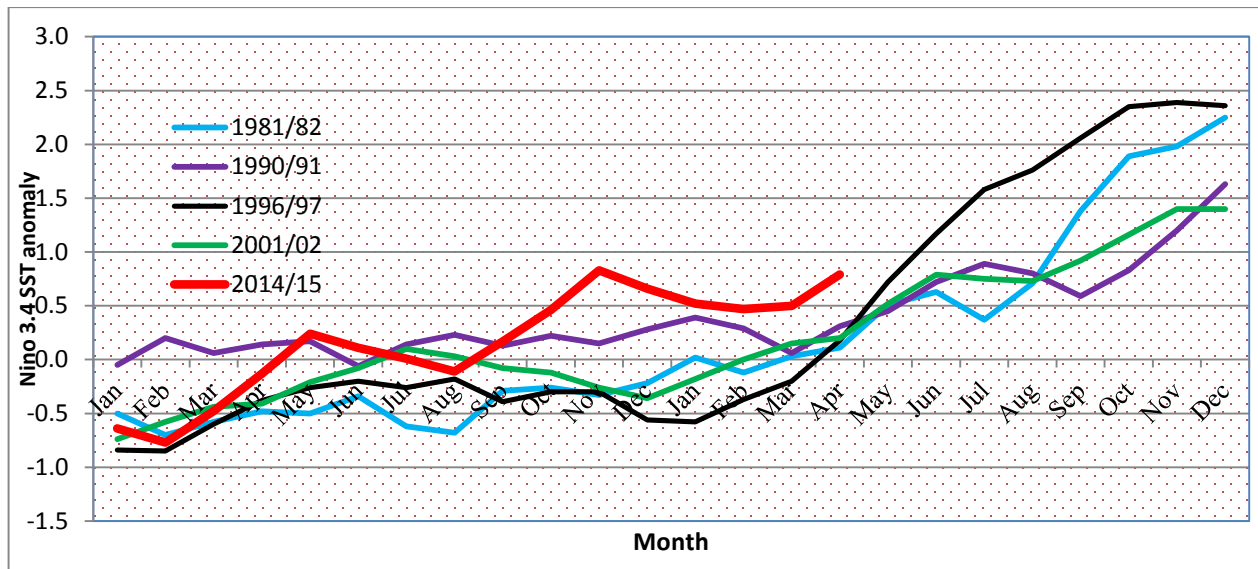


Figure 20: Selection of analogue years with respect to Niño 3.4 SST trend

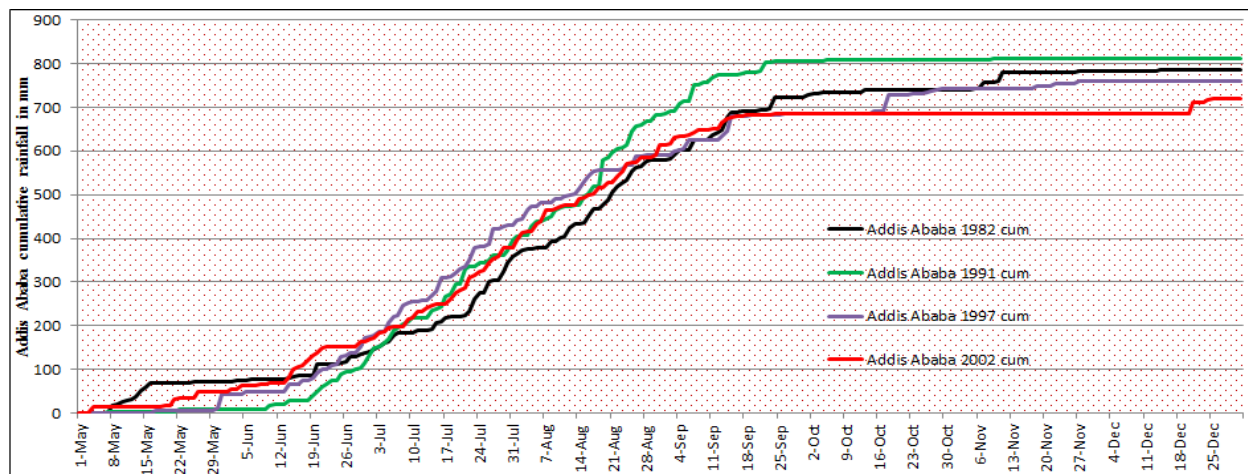
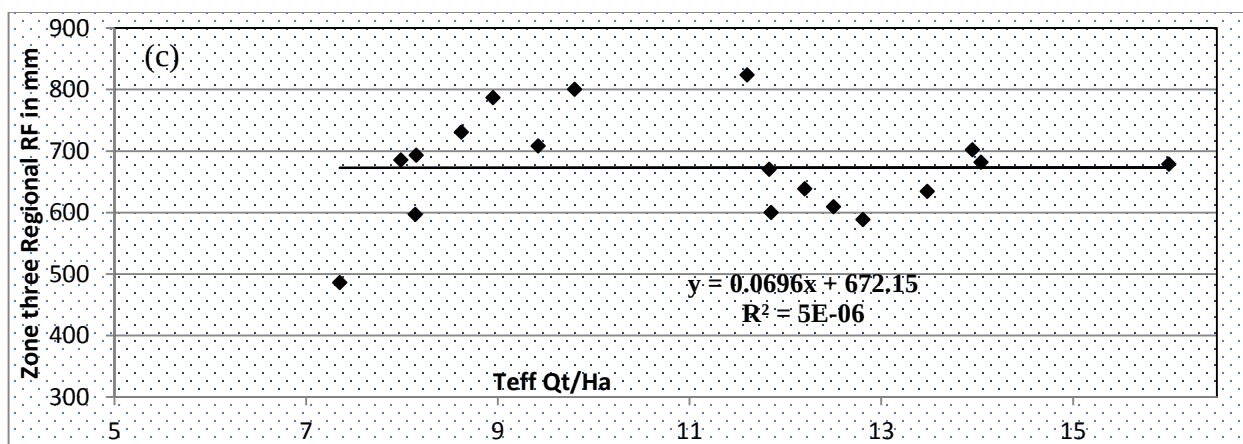
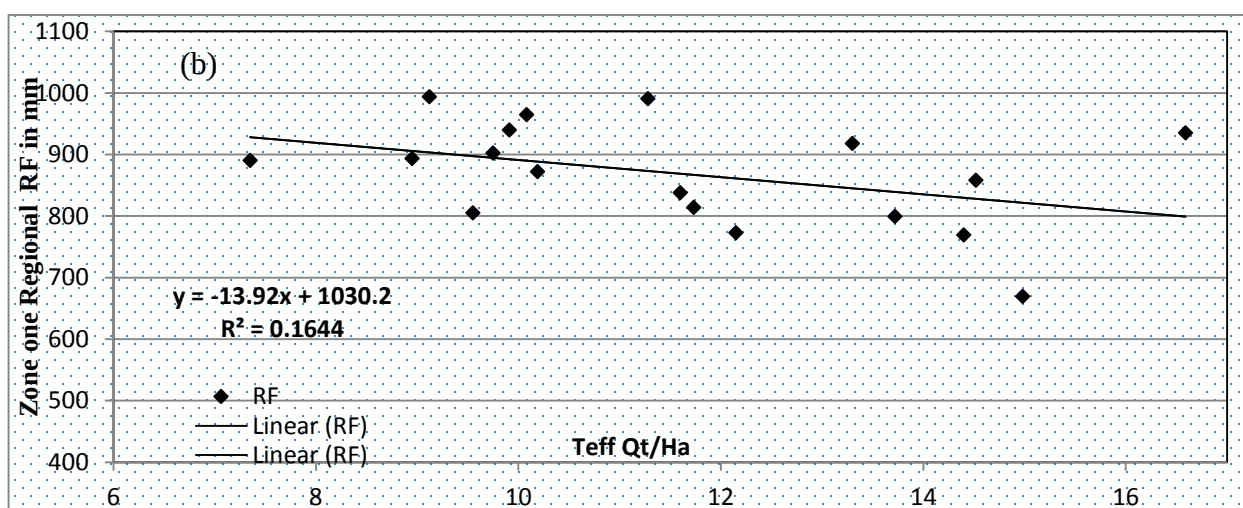
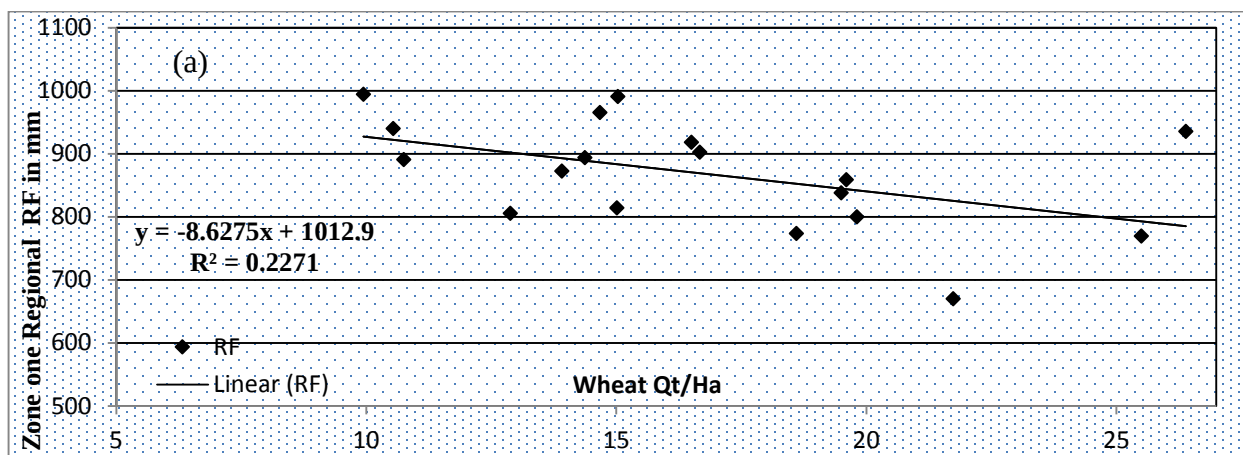


Figure 21: Cumulative dekadal rainfall analysis with respect to selected analogue year

4.9. Linear Relationship between Crop yield and Seasonal Rainfall Total

The linear relationship between Zonal rainfall with teff and wheat crop yield equation for zone one homogenous rainfall regime are Zonal RF= $-13.9x+1030$ and Zonal RF= $-8.63x+1012$ respectively. Similarly for Zone three homogenous rainfall regime Zonal RF= $0.07x+672$ and Zonal RF= $1.6x+645$ for teff and wheat crop yield respectively. Although the trend that existed between zonal rainfall totals and crop yield production has failed any statistical significance test, there seemed some valuable relationship between both parameters (Figure 22 a,b,c and d),

which mean that, Zone one teff and wheat crop yield is negatively linked to more weighted zonal rainfall (Figure 22a and b), while for Zone three teff and wheat crop yield has positive linked with zonal weighted average rainfall (Figure 22 c and d).



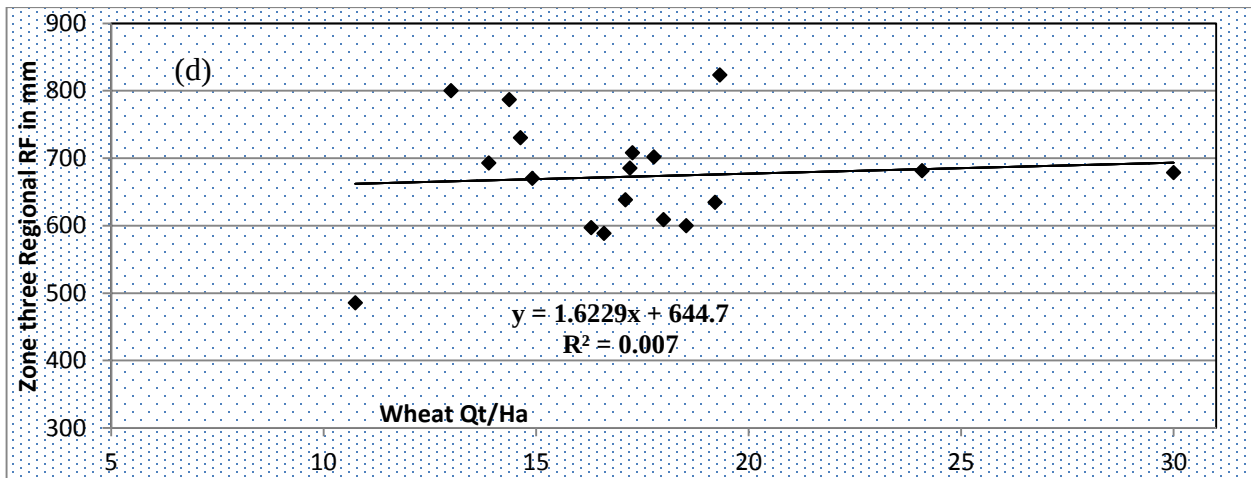


Figure 22: The linear relationship between Zonal seasonal rainfall and Zonal crop yield

4.10. Crop Yield risk Analysis by using ENSO Phase

According to crop risk analysis based on 19 years of crop data associated with seasonal ENSO phase of 4 ElNiño years, 4 La Niña years, and 11 Neutral years result, by the First order stochastic dominance (FSD) shown that, the dominating variable would be preferred by any decision maker who prefers “more” to “less”, regardless of the attitude towards risk. Normal phase is preferable, since CDF of plot of line of crop yield during normal phase is to the right of CDF plot of during El Niño phase, as described in crop yield CDF production in (Figure 23 a,b) and (Figure 24 a and c), which illustrates that, those CDFs of crop yield during ‘Normal’ SST phase and ‘La Niña’ SST phase are dominant relative to crop yield CDF of during ‘El Niño’ SST phase in the FSD sense. This means that for every risk percentile point on the Y axis, a farmer gets at least x amount of more crop yield from CDF of ‘Normal’ or ‘La Niña’ SST phase as compared to the yield obtained from CDF during ‘El Niño’ SST phase. At Zone one during ‘El Niño’ phase has better wheat crop yield production than during La Niña’ by FSD sense (Figure 23b). The seasonal climate information may further support in the selection of crop variety/types, field allocation and other strategic management activities with respect to less crop risks.

The cross-over between CDF during ‘la Niña’ phase and CDF during ‘Normal’ phase implies in (Figure 24 b), that curves meet the requirements for Second order stochastic dominance (SSD) and the comparison should be handled using the higher order stochastic dominance

techniques to be the first choice as described by (McCarl, 1996). Wheat crop yield CDF during 'Normal phase' lies to the left of CDF during 'La Niña' at the lower level of the yield data series, meaning that the during 'La Niña phase' alternative is better choice in this range of the yield data distribution, while CDF during 'La Niña' lies to the left of CDF during 'Normal' at the upper tail of the series, meaning that during 'Normal' phase is a better and less risky choice in the upper range of the wheat yield at Zone three(Figure 24b).

Comparing the total area under the CDF of (Figure 24b), during 'Normal' phase is bigger than CDF during 'La Niña' phase at upper percentile points. SSD requires that the area under the cumulative density function during normal SST phase at lower tail is smaller than the area under the cumulative density function for the during La Niña phase at upper tail as described in (Figure 24b).Therefore, during 'Normal' phase standard algorithms for identifying stochastic dominance utilize pair-wise area comparisons of wheat yield sorted series of net revenue distributions CDF during 'La Niña' and 'Normal' phase for wheat production yield at Zone three has better performance. Every risk-averse, farmer therefore prefers Normal phase alternative that dominated by SSD. Therefore, Normal phase is found to have the best risk efficient set identified for each three Zones crop productions planning. Crop yield has good performance during Normal SST phase than El Niño and La Niña phase; users can make comparisons based on alternate ENSO forecasts for further insight for crop risk planning and management strategy. For instance, it can also be deduced from the same curve that, a farmer targeting 12Qt/ ha of Teff crop yield at Zone three cropping seasons could achieve the desired quantity, but the associated risk level is of the highest order of 40% as described in resulted from (Figure 24 a).

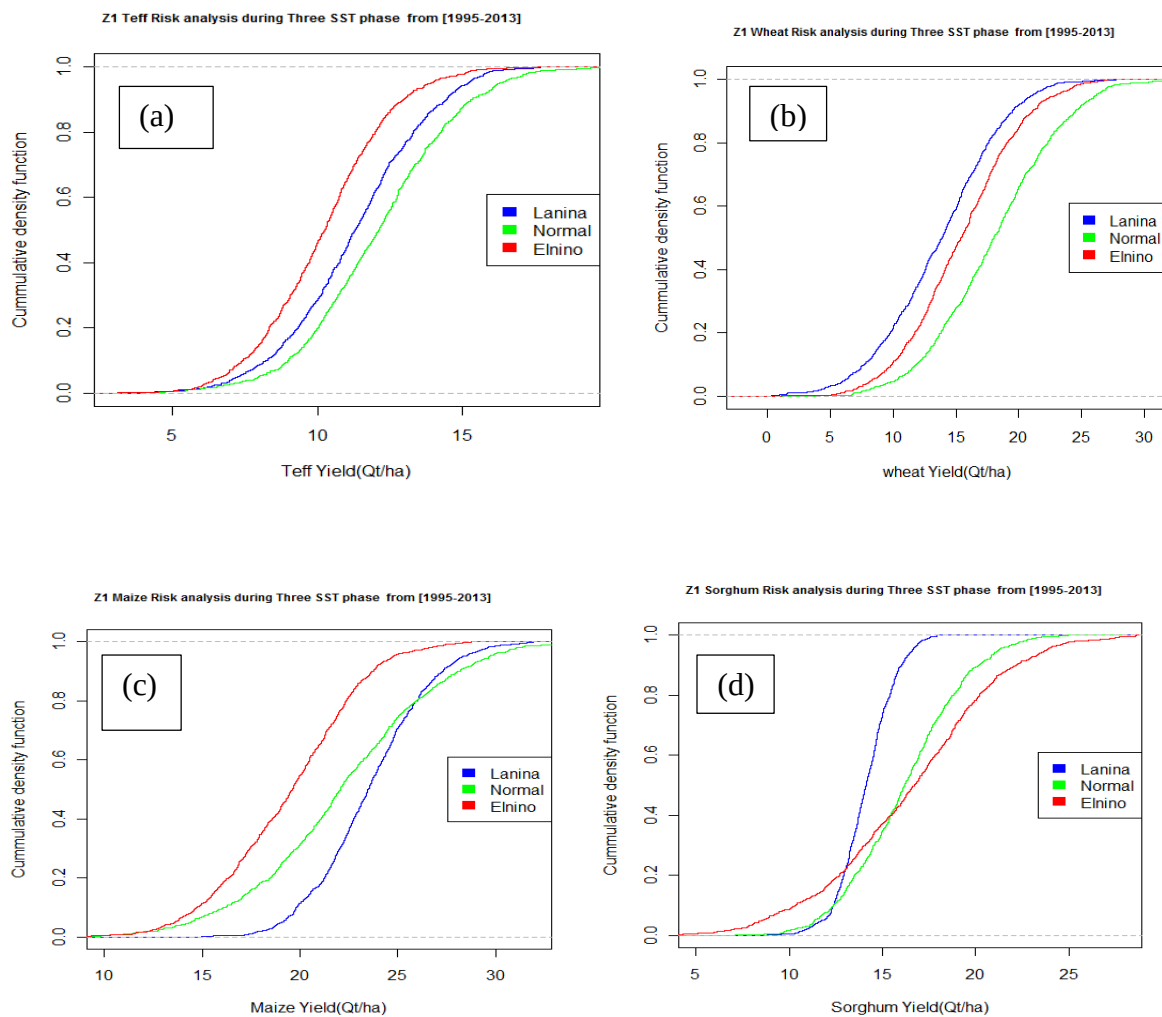
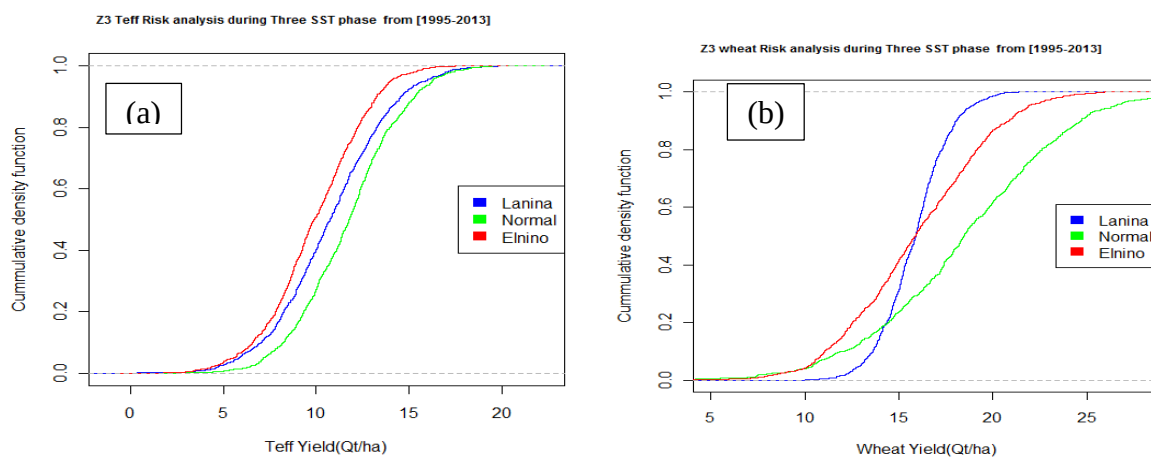


Figure 23: Cumulative Density function for cereal crops of Zone one at three SST phase



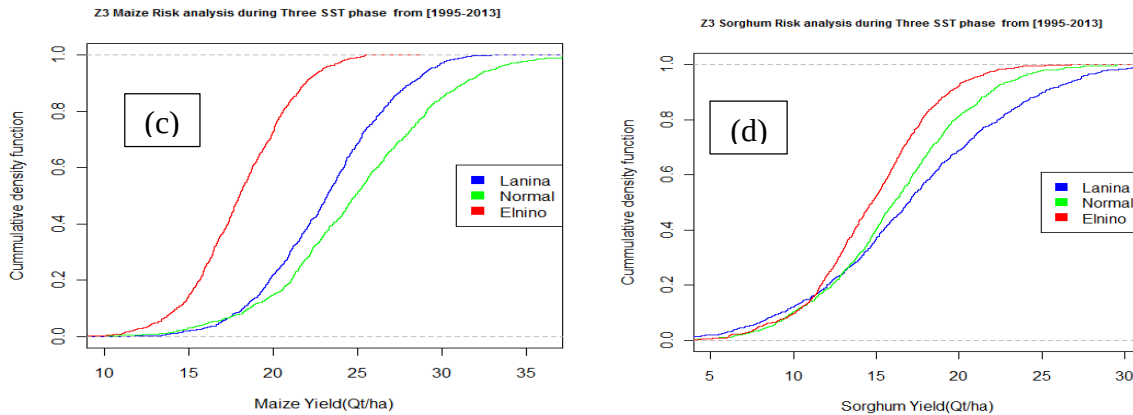


Figure 24: Cumulative Density function for crops yield of Zone three at three SST phase

4.11. Zonal Rainfall risk analysis using different ENSO phase

A key issue for agriculture in this regard is seasonal variability of rainfall due to ENSO phase. Both deficient and excess rainfall periods can create serious problems on crop production. Onset relationships for the approaching season, to quantify possible ranges of rainfall behavior and probabilities within the ranges, expected seasonal rainfall characteristics is no longer confined to long term rainfall probabilities. Responding to rainfall predictions, alternative farm management decisions should be taken. As SD of rainfall risk analysis for each homogenous Zone result shown that, during La Niña' phase all Zones have less rainfall distribution risk than the others ENSO phase(Figure 25d,e and f) and Zone one has better rainfall distribution by First stochastic dominance senses at each of ENSO phase as described in (Figure 25a,b and c). Those CDFs of rainfall during 'La Niña' SST phase and 'Normal' SST phase are dominant relative to CDF during 'El Niño' SST phase in the FSD sense (Figure 25). Relatively rainfall amounts in the major season were high in La Niña but low in El Niño years While, rainfall during Neutral years of ENSO phase shown that characteristics is in-between la Niña and El Niño.

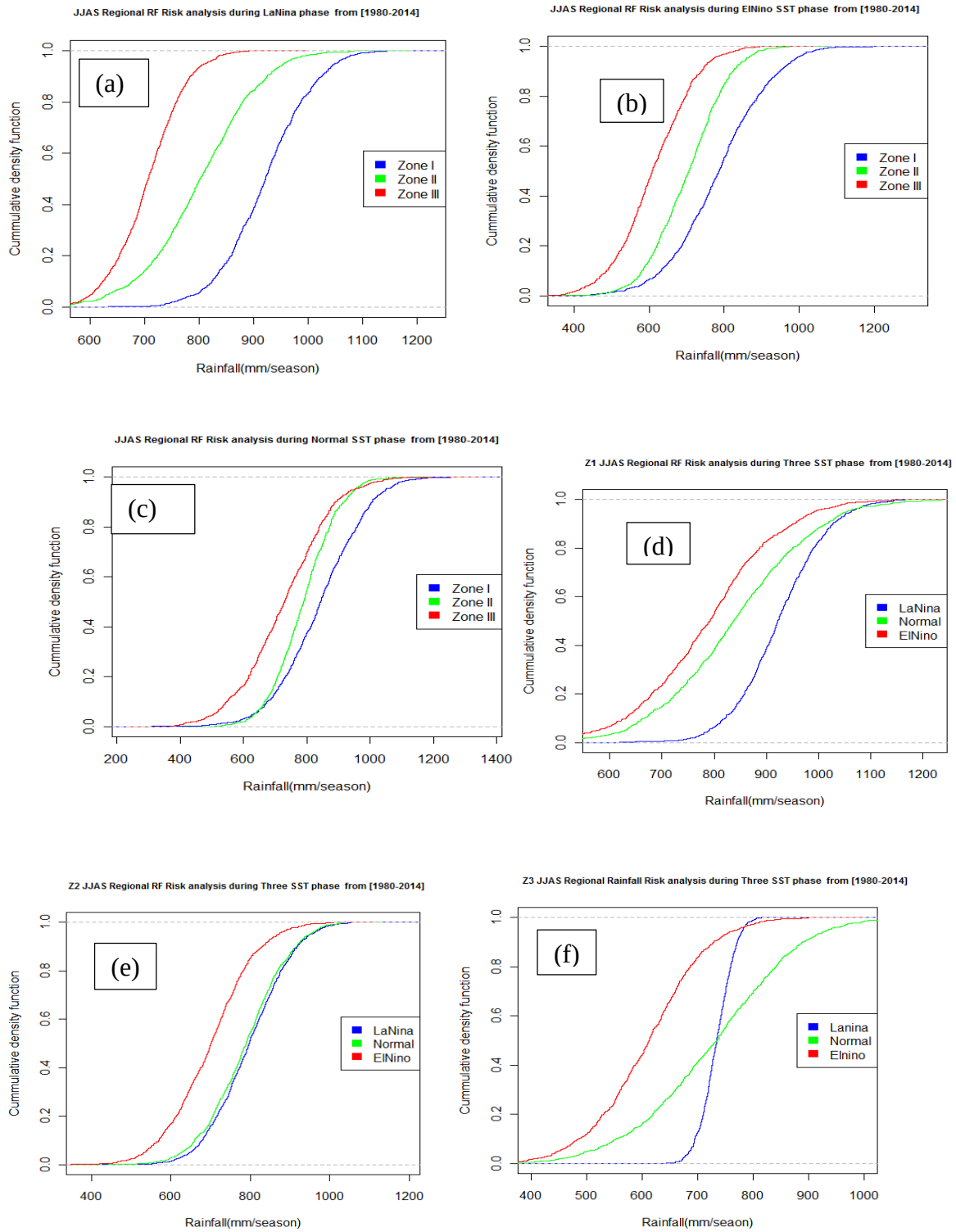


Figure 25: CDF of seasonal Rainfall at each ENSO phase for the three Zones

4.12. Seasonal Climate Predictions for Cropping Decision Support Strategies

In order to promote sustainable development of crop production to maximize yield, it is very necessary to maximize the use of current available agro-meteorological knowledge, farming technology and up to date local climatic information and predictions on timely manner. To reduce climate related risks systematic use of climate information and climate knowledge in strategic planning is advisable. Climate information only has value when there is a clearly defined adaptive response and a benefit once the content of the information is considered in the decision making process. Information at seasonal timescales can be useful in crop strategic planning and risk assessments, though scientific understanding of seasonal climate variability.

The cropping systems of the Upper Awash Basin are characterized by the opportunity to produce a wide range of cereal, pulse and oilseed crop according to the soil properties, topographic features, amount and distribution of seasonal rainfall. In the study area rain-fed agricultural crop production is closely related to weather and climate state.

The importance and visibility of seasonal climate information products can be applied for decision-making for climate-related risk management strategies. According to the result of seasonal climate prediction by statistical multiple linear regression and analogue year selection approaches evaluation, the use and potential benefits of the seasonal climate information to create confidence among the farmers and policy makers in order to identify opportunities for stakeholders and development of customized solutions. As an application tool, seasonal climate prediction has been found to be preferred forms of communicating with stakeholders on the likelihood climatic anomalies of the following season.

In Ethiopia, seasonal climate predictions are provided three times during the year so far at national and branch level of NMA, matching the agricultural decision calendar. The seasonal outlook released for *kiremt* season, prior to mean onset date of the season emphasizes on, which ENSO phase is going to prevail as well as, features of regional ocean system and position of ITCZ. Understanding the most dominant regional and global feature enhances local knowledge to determine onset, cessation and dry spell probability of the season and used for selection of crop types. Similarly seasonal climate outlooks released for *belg* season mainly used to determine planting dates of long cycle dry spell resistant crop, forest fire risk

management, land preparation and potential soil moisture levels. In contrast, seasonal climate Outlooks released during *bega* season provide a priori information that used to know the time and intensity of climatic extremes likely to prevail during the crop harvesting, probability of frost occurrence and possible measures to lessening climate-related risks during crop harvesting season. Therefore, getting a priori information on seasonal climate patterns can reduce risk while enhancing and better on-farm water management through rain water harvesting or making channels in farm field to reduce water logging risks during wet season. Over all, it can improve crop yield and productivity, which creates an opportunity to upgrade current farming practices in the regions where climate extremes are chronically harsh enough to adversely affecting well-being of local communities.

In fact, when and what to plant is determined by integrated farmers skill and scientific weather/climate indicators and interpreting within the space and environment and use of modern meteorological climate forecasts. Therefore farmers are using sowing of long cycle crops such as sorghum and maize depend on onset of *belg* rainy season, while sowing of pulses crops depend on the cessation of *kiremt* rainy season. Such kinds of relevant and local-based information should relay to all farmers by decision-makers to develop a powerful tools to that enable the local community to manage climate resources and the associated risks. Farming/fallowing system and variety/crop type selection should be determined according to predicted seasonal rainfall amount and distribution for the agricultural season. However, so far farmers saw any type of crops as they accustomed during the normal climate without considering the current seasonal rainfall prediction issued for the UAB. Predictions with long-term seasonal rainfall and short term forecasting have important role in increasing benefits of improving crop yield, reducing risk of losses of properties and life due to extreme seasonal climate events. Indeed non-ENSO event is preferable than the others two phases in creating conducive conditions for better crop yield performance.

In order to realize the potential value of seasonal climate prediction for agriculture application; the links between producers of climate information and various end-users should be enhanced. This can be made through appropriate mechanisms that include capacity building through trainings for intermediaries and end-users, and strengthening institutional partnerships Meteorological administration. Making quantitative and intelligent use of probability forecasts

requires an effective chain of communication between information providers and users as well as involving the relevant sectorial scientists and decision-makers with collaborating partners. Quantifying and intelligent use, in the very early process, particularly critical to ensuring relevance, trust and ownership of climate-related decision systems for crop risk management and best decision-making strategy is crucial. Warnings to be disseminated based on best available technical and scientific information and the agro-meteorological advices that are important for crop production planning with respect to seasonal climate prediction value and the soil characteristics of the farm level.

The National Meteorological Agency of Ethiopia should also establish partnership with user community to enhance dissemination of seasonal climate information into user in perceivable language in all climate-sensitive sectors and to acquire relevant feedback from the climate information they provide. Moreover, establishing focus groups from different user-communities at NMA branch offices are recommendable in order to assess the impact of particular dissemination strategies. During seasonal climate outlook forums, it is important to involve some of end users from model farmers, intense media coverage, training agricultural extension workers and above all effort must be invested in demonstrating use and increasing utilization of climate information. When the forecast given by NMA is tending to below normal, it means that rainfall will less and dry spell expectation is more. The development works on individual farms should therefore target by including in-situ water harvesting, selecting less water requirements crops such as wheat, barley and other pulse crop for the given season.

If early cessation of rainy season is predicted, then early sowing of each crop from normal sowing period should be advised. For instance, in Zone three, where more sand soil component is existed, early sowing of crops is therefore highly advised. Fallowing the soil between crops in order to build-up soil moisture storage in the generally high water-holding soils (Zone one and two homogenous rainfall regimes) is management strategy to offset the risk of low in-season rainfall and improved crop residue and weed management are very important strategy.

Under La Niña episode, better *kiremt* rainfall distribution is mostly prevail as expected throughout the study area. In most parts of UAB, which have more clay soil component and exposed to serious problems of water logging due to La Niña episode. On the other hands there is a scope in exploring in-situ rainwater harvesting technologies in order to prolong the period of soil's water availability in rain-fed smallholder cropping systems. Farmers' should do better soil water management practice (such as in-situ rain water harvesting) like contour bunds, ridging to improve soil water availability of the soil water yields in site where dry spell frequency is more.

5. SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1. Summary and Conclusions

This study was carried out at Upper Awash Basin of central highlands of Ethiopia, which has high potential for varieties of crop production. Basically, the study examined characterizing seasonal climate and predicting for better decision supportive strategies for crop production and planning. To determine local climatic patterns and establish better climate forecast method, the principal component analysis has been applied, from which the UAB climate was classified into three homogenous rainfall zones. The onset of the growing season is commonly in the month of April with highly variable and dry spell risk, while cessation is in the month of September with less variance have been found. The number of rainy days of long year observation has no statistically significant change in *kiremt* season. The local surface temperature analysis has shown that, there is statistically significant change of increasing annual trends of temperature in the study area.

According to the result output established between zonal rainfall index and global sea surface temperature correlations, which are mostly manifested as ENSO phenomena and IOD phase. It has been found that, SST anomalies of the Nino regions and IOD phase have relatively strong correlated with all zonal rainfall indices during *belg* season, while Nino regions, cross equatorial flow and the associated monsoon systems are the mostly identified as rain bearing system during *kiremt* season. IOD phase has more significant signal to *belg* rainy season rather than *Kiremt* season. Hence, seasonal climate pattern in UAB is affected by the El Niño-Southern Oscillation (ENSO) phases and there is a close relationship between the increase and decrease of rainfall depending upon the warm or cold phases of the phenomenon. Therefore the variability of rainfall patterns during the major and small rainy seasons as well as annual totals rainfall at UAB were strongly linked to ENSO phases. The rainfall patterns during the major seasons shown that, there is different risk level during different ENSO phases at UAB. For instance, the results revealed that rainfall amounts of major rainy season became very high in La Niña but low in El Niño years. Conversely, during small rainy season, comparatively high rainfall amounts were observed when El Niño was apparently established. There is

enough rainfall amounts prevail during non-ENSO years over most parts of the Upper Awash Basin.

According to the tools of crop risk management resulted on crop yield risk analysis, the stochastic dominance described the weight of risk on crop yield in comparing alternative cropping systems on the risks producers of different ENSO phase. Teff, maize, wheat and sorghum cereal crops risk analysis showed that, crop yield has good performance and less risk during non-ENSO years than El Niño and La Niña phases.

Therefore, this study revealed that there are a lot of techniques to reduce the challenges on the effective use of seasonal climate information for various cropping practices. This has been manifested as a lack of knowledge in climate information; lack of specific local climate information and lack of knowledge about climate variability impacts and the associated decision responses. Users can get a clear indication of forecast reliability and accuracy developed in skillful model prediction and the timely provision. Hence, decision makers can take comparisons based on alternate ENSO forecasts for further insight to crop risk planning and management strategy. Therefore using seasonal climate prediction that focus on managing seasonal climate variability is an important means of preparing for the near future of climate change.

5.2. Recommendations

The progress of relevant observing systems, including many of the ocean and land components of the Global Climate Observing System (GCOS), is crucial for improving seasonal prediction. Thus, statistical multiple linear regression models (SMLR) and forecast systems across a range of time scales are also good practice in addition to pre-seasonal ocean SST and surface wind flow which are valuable information in order to identify the analogue years from past years history. However, due to presence of climate change and variability, climatological (long term) observations alone are no longer sufficient for seasonal rainfall prediction for crop production planning in the future. Therefore, due to the presence of climate change and variability, seasonal predictions based on GCOS, SMLR and pre-seasonal ocean SST and analogue year approaches alone are not sufficient. Hence, different sophisticated computer models like super computer and dynamic atmospheric circulation models need to be considered while predicting seasonal rainfall.

A better seasonal climate prediction service for decision-making must be delivered by the National Meteorological Agency not only at national level but also at stations level for local users. Such information are farming practices that allow timely preparation of the land and planting of long and short cycle dry spell resistant crops and effective use of rainfall received during the April to May season are more essential. In the *belg* season due to existence of dry spell risk and onset variance as well as its unevenly and erratic distribution over time makes difficult to decide annual regular crop planting period starting from April. Therefore, *Kiremt* rainy season is more advisable strategic plan for regular rain-fed crop production planning in the Upper Awash Basin.

A stochastic dominance analysis using cumulative density function (CDF) of crop yield based on different ENSO phase has identified the treatments that would be preferred by individuals within a range of preferences. The outcome of CDF of yield has a preferred on normal ENSO phase than La Niña and El Niño. Therefore, users in the study area can take comparisons based on alternate ENSO forecasts for further perception to crop risk planning and management strategies. Hence, using CDF of crop yield analysis is recommended as tools for crop yield risk management.

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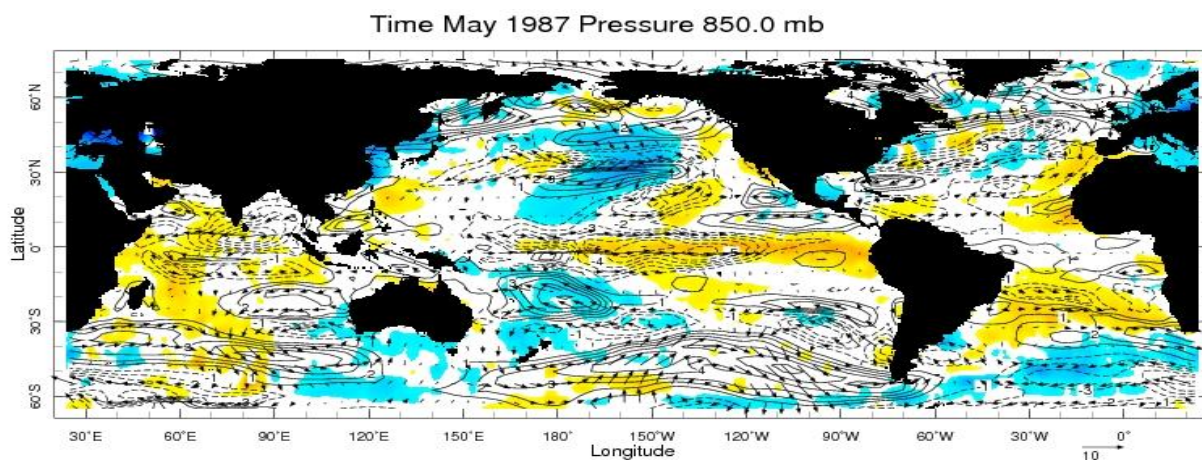
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7. APPENDICES

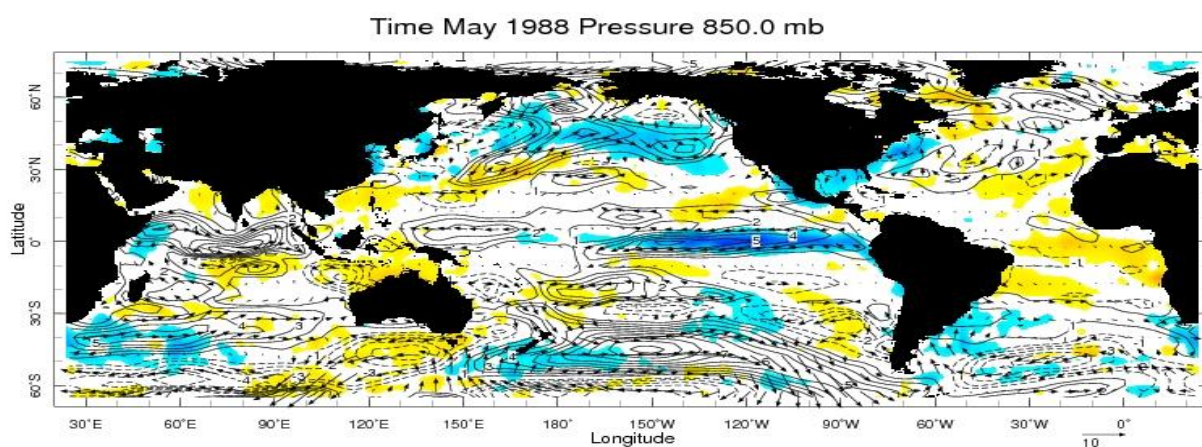


Appendix figure 1: Field crop and farm land photo of some selected area of UAB

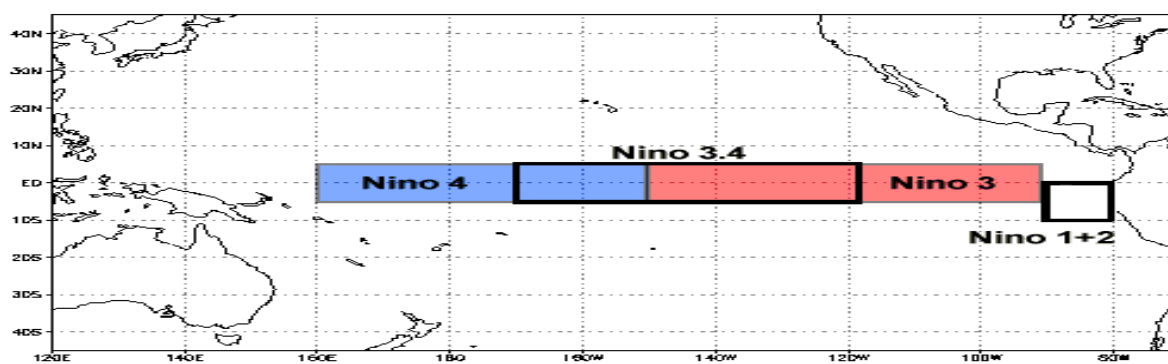
^a Perennial weed at alemtena, ^b Soil sampling from dima, ^c Contour farming system at kalacho, ^d Wheat crop at kalacho, ^e Teff crop at tullu bolo, ^f Enset plant at rache, ^g Goya crop at ginch, ^h chickpea at kalacho and ⁱ Soil sampling from leman



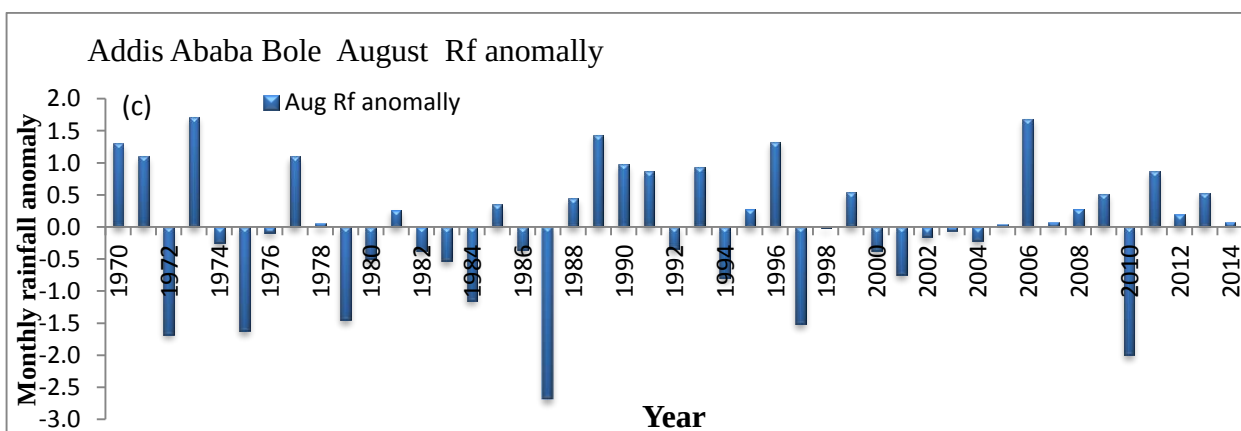
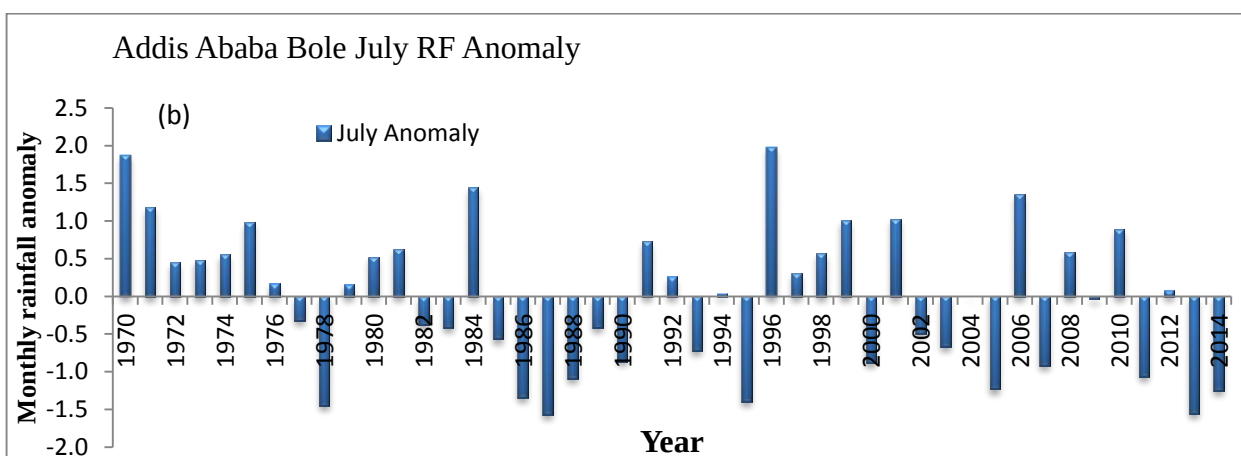
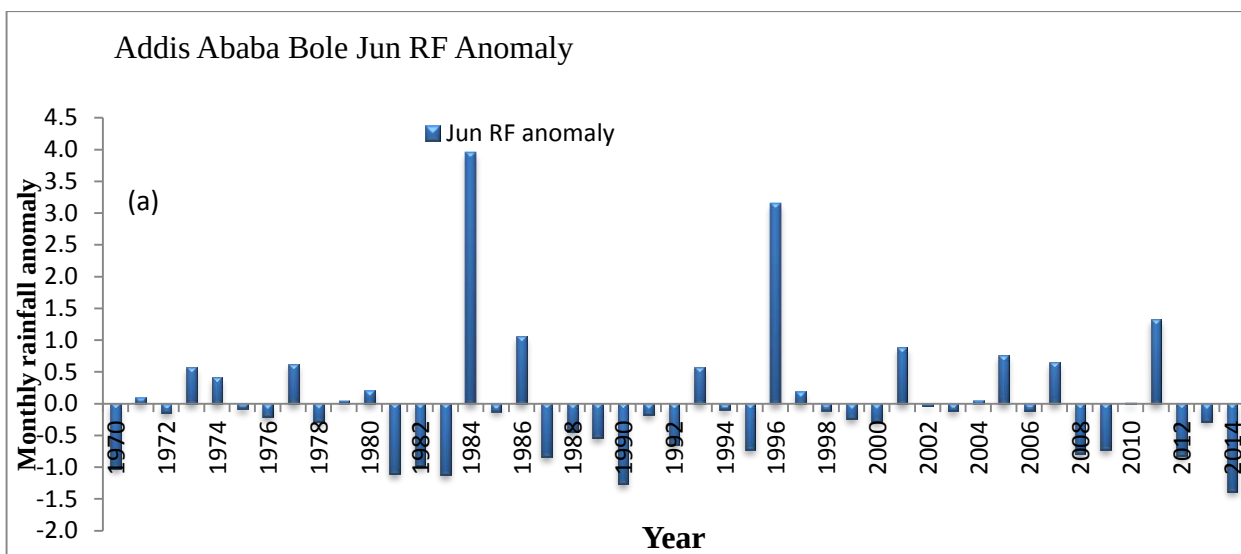
Appendix figure 2: Pre- *Kiremt* seasonal indicators of SSTa and wind vector of May 1987

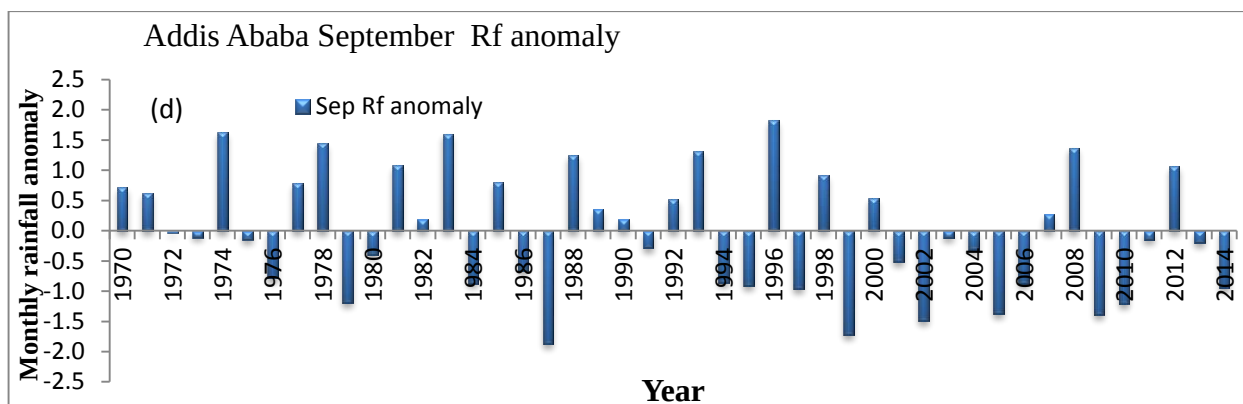


Appendix figure 3: Pre-*Kiremt* seasonal indicators of SSTa and wind vector of May 1988

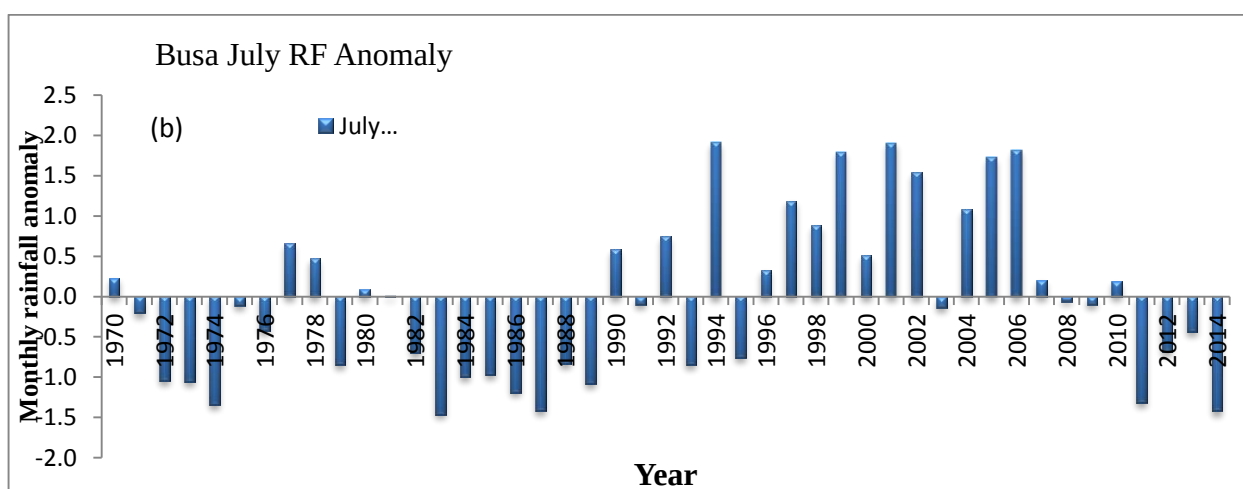
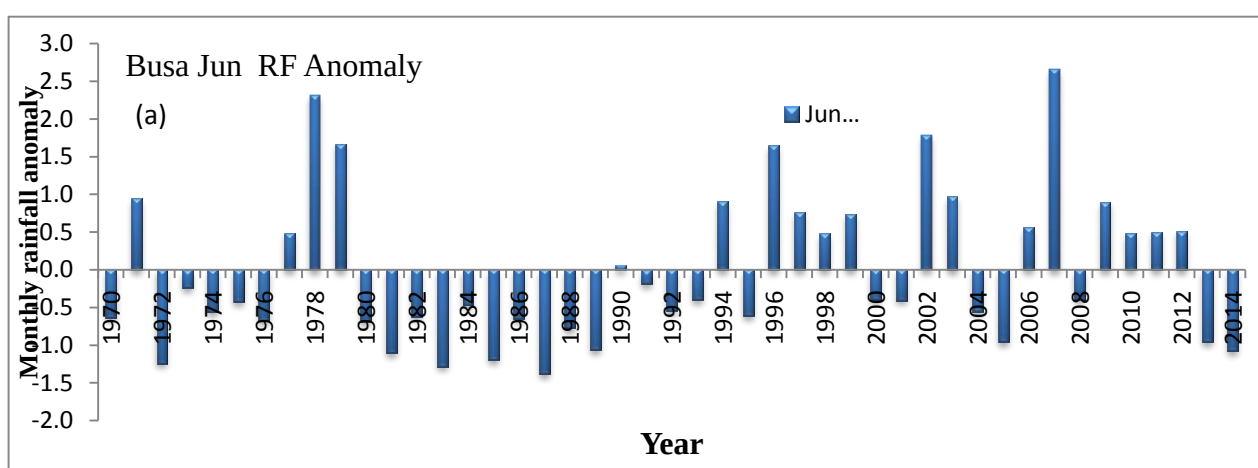


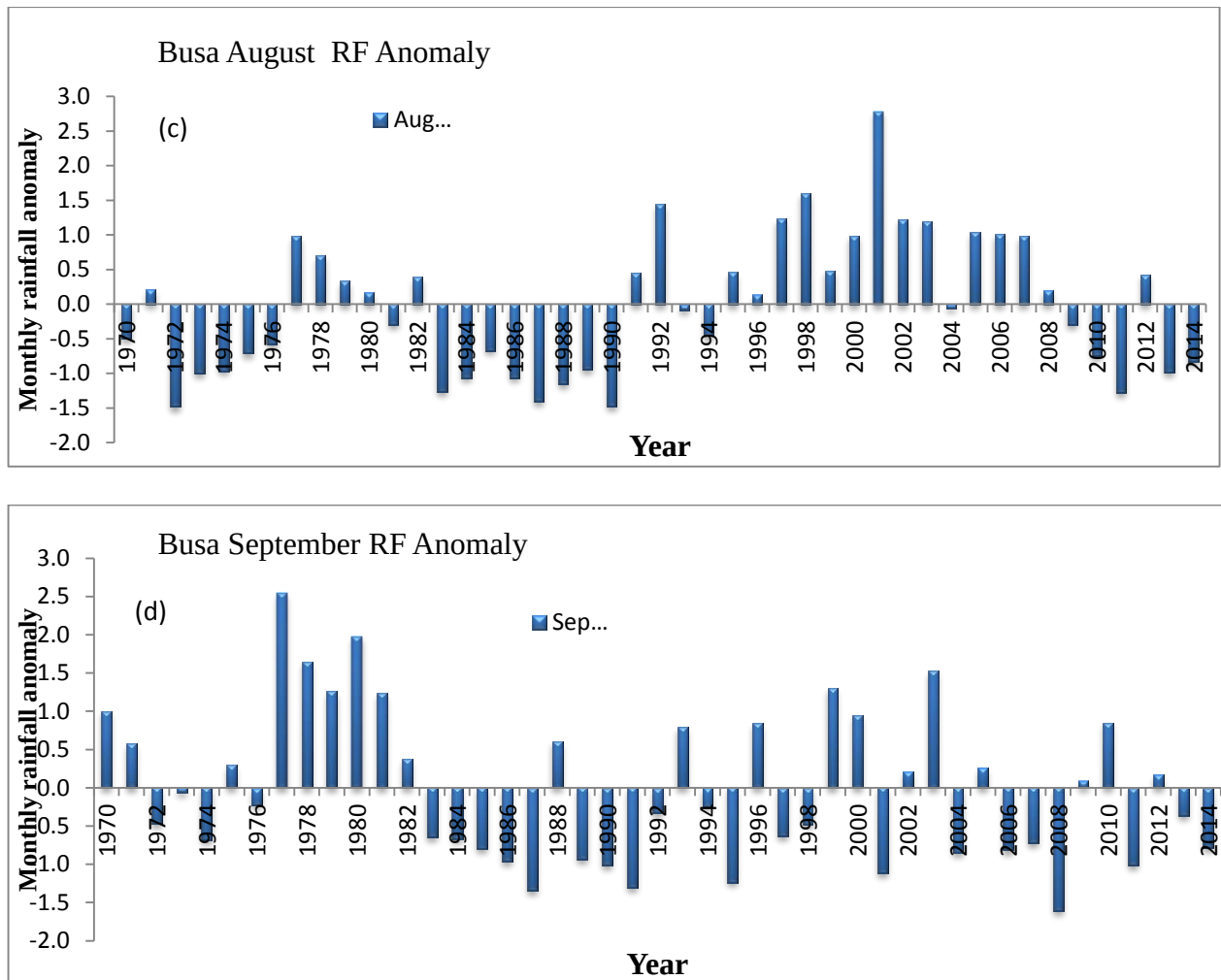
Appendix figure 4: Location of Niño regions





Appendix figure 5: Long year monthly rainfall Anomaly of Addis Bole from Jun to September





Appendix figure 6: Long year monthly rainfall Anomaly of Busa station from Jun to September

Appendix Table 1: Contingency table for statistical multiple linear regression model evaluation

Forecast	Observed			Total
	Below Normal(B)	Normal(N)	Above Normal(A)	
Below Normal (B)	a (hit)	b (false alarm)	c (miss)	m
Normal (N)	d (false alarm)	e (hit)	f (miss)	n
Above Normal (A)	g (false alarm)	h (miss)	i (hit)	o
Total	j	k	l	p

Appendix Table 2: Traditional crop planting and harvesting period

Types of Crops	Sowing Period	Harvesting period
Sorghum	20 th April to 10 th May	December to January
Maize	25 th April to 20 th May	November to December
Ben	15 th May to 5 th Jun	November to December
<i>Nueg</i>	20 th Jun to 30 th Jun	November to December
Wheat	25 st Jun to 12 th July	November to December
Teff	1 st July to 7 th August	November to December
Lentiles	2 nd Sept to 15 th Sept	December to January
<i>Goaya</i>	10 th Sept to 30 th Sept	December to January
Chick-peas	12 th Sept to 30 th Sept	December to January

Source: Information collected from Elders/Farmers in the study area