ENHANCING RESPONSE FARMING FOR IMPROVED STRATEGIC AND TACTICAL AGRONOMIC ADAPTATION TO SEASONAL RAINFALL VARIABILITY UNDER THE SEMI-ARID CONDITIONS OF ETHIOPIA

BY

HABTAMU ADMASSU AYANA

A THESIS SUBMITTED IN FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY OF SOKOINE UNIVERSITY OF AGRICULTURE. MOROGORO, TANZANIA.

2013

ABSTRACT

Rainfall variability in the drylands of Ethiopia greatly impacts on agricultural planning, performance, food security, livelihoods of the people and the national economy. Therefore, rainfall prediction models that can facilitate strategic agronomic planning and tactical management of in-season risks are necessary. A study based on thirty two years of climatic data for Melkassa and Adami-Tulu research centres was conducted with objective of improving strategic and tactical response farming (RF). Applying a multi-factor onset definition approach that accounts climate, soil and crop types, and farmers' perceptions of onset and the principles of RF, April was found to be the most risk-wise acceptable time of season onset for planting of a 150-day maize crop. However, simulation modelling accepting April onset revealed 63% and 41% crop failure at Melkassa and Adami Tulu respectively. Thus, predictive capacity was found crucial because April onset enabled flexible combination production of maize varieties maturing in 150, 120 and 90 days. Regression analyses revealed the first effective rainfall date (FRD) to be the best predictor of the date of onset (R^2 = 89% for Melkassa and 95% for Adami-Tulu), and a good indicator of the duration of next season (Melkassa: R^2 = 71%, Adami-Tulu: R^2 = 68%). The R^2 for both are statistically significant at 1% probability ($P \leq 0.001$). The new agronomically useful strategic predictor (FRD) advanced prediction of both rainfall parameters by a lead time of two to three months, markedly improving Stewart's RF. The date of onset was also found to be a useful predictor of season duration (Melkassa: R^2 = 86%, $P \leq 0.001$; Adami-Tulu: R^2 = 71%, $P \leq 0.001$). Using the amount of off-season and cumulative early season rainfall, seventeen prediction models that can facilitate in-season tactical RF were developed. An increased in maize grain yield by 70% was achieved from enhanced RF (ERF) forecasts guided maize production strategy that were tested at 55 sites during 2010-11 seasons. The overall findings suggest that strategic agronomic planning of farm operations and tactical management of in-season risks should be guided by ERF forecasts. Research on the feasibility of ERF approach is recommended for similar dryland agro-ecologies in other areas.

DECLARATION

I, HABTAMU ADMASSU AYANA, do hereby declare to the Senate of Sokoine University of Agriculture that this thesis is the result of my own original work and has neither been submitted nor being concurrently submitted for a degree award in any other institution.

	30/10/2013
Habtamu Admassu Ayana	Date
(PhD Candidate)	

This declaration is confirmed by:

	30th October 2013
Prof. Filbert B. Rwehumbiza	Date
(Supervisor)	
Mahoo	30/10/2013
Prof. Henry F. Mahoo	Date
(Supervisor)	
Siza	30/10/2013
Prof. Siza D. Tumbo	Date
(Supervisor)	

COPYRIGHT

ACKNOWLEDGEMENTS

I wish to express my sincere thanks to the Ethiopian Institute of Agricultural Research (EIAR) for permitting me to benefit from the scholarship opportunity, Climate Change Adaptation in Africa (CCAA); an initiative of Canada's International Development Research Centre (IDRC) and the United Kingdom's Department for International Development (DFID) and the Association for Strengthening Agricultural Research in Eastern and Central Africa (ASARECA) for their financial support. I am very grateful to Dr. Solomon Aseffa; Director General of EIAR, Dr. Tolessa Debele; Director of the Directorate of Soil and Water Research Process, and Dr. Adugna Wakjira; Deputy Director General of the EIAR for their administrative support.

I wish to extend an indebted thanks to Prof. Filbert B. R. Rwehumbiza, Prof. Henry F. Mahoo, and Prof. Siza D. Tumbo for their excellent professional guidance, and support during the entire period of the study. This work would never have come to fruition without their genuine support.

I extend special thanks to Prof. Nuhu Hatibu for creating the scholarship opportunity. My special thanks also go to the late Dr. J. Ian Stewart; the father of response farming and the founder and president of the WHARF Foundation (World Hunger Alleviation through Response Farming) for providing the computer software used for the study. Prof. Boniface P. Mbilinyi and Dr. K. P. C. Rao are also very much acknowledged for their professional support.

I am also grateful to the staff of SUA Soil Science Department and Soil-Water Management Program for their support. I would also like to extend my special thanks to Winfred Mbungu, Placid Jumanne and Dr. Ludovic Kashaga who always provided support whenever requested. I am also grateful to the staff of MARC for their encouragement during the study period. My special thanks go to Dr. Getachew Ayana, Mesfin Hundessa and Fitih Ademe for their moral support.

I would like to express my sincere thanks to my parents who created in me a vision of being an educated person and did their best to get me educated. I am especially grateful to Mr. Wondimu, Dr. Melaku, Mrs. Assegedech, Mrs. Birhane, and Mr. Getachew, Mrs. Sinknesh, Mrs. Genet, Mr. Daniel and Mr. Desalegn, Mrs. Shibire and Mrs. Beletech for their encouragement and prayers for my well-being and success.

My deepest appreciation is to my wife, Tihitina Desta, for taking care of the family during my absence; to my beloved daughters: Amerti, Yeron for their patience, best wishes, and prayers, and above all Natati for withstanding my unfortunate absence when she needed me most.

I also thank all those who supported me in one way or another but are not mentioned here. Above all, I Praise the Almighty God: for keeping me well and safe and, for giving me the courage that led to successful accomplishment of this study.

DEDICATION

This thesis is dedicated to my parents: My late Grand Father, my Grandmother, my Father and Mother, uncles Mr. Wendimu, Dr. Melaku, aunts: Mrs. Birhane, Mrs. Asegedech, and Mr. Getachew who laid down the foundation for my educational life; and to my beloved wife: Tihitinna Desta, and to my beloved, kind and warm-hearted daughters: Amerti, Yeron and Natati.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

ABBREVIATIONS

ANOVA	Analysis of variance
ASARECA	Association for Strengthening Agricultural Research in Eastern and Central Africa
ATARC	Adami Tulu Agricultural Research Centre (Adami Tulu)
AWC	Available water capacity
C.V.	Coefficient of variation
CCAA	Climate Change Adaptation in Africa
CIA	Central Intelligence Agency of the United States of America
CRV	Central Rift Valley
DF	Degrees of freedom
DFID	United Kingdom's Department for International Development
DSSAT	Decision Support System for Agro-technology Transfer
DW	Durbin-Watson statistic
Eact	Actual evaporative loss of pre-onset Rainfall, mm
ENSO	El Niño–Southern Oscillation
Epan	Pan evaporation
ERF	Enhanced response farming
ETo	Reference grass evapo-transpiration
FAO	Food and Agricultural Organization of the United Nations
FC	Field capacity

FRD	First effective rainfall date
GDP	Gross domestic product
IDRC	International Development Research Centre
IPCC	Intergovernmental Panel on Climate Change
Kp	A standard "pan factor" or pan coefficient
MARC	Melkassa Agricultural Research Centre (Melkassa)
MATDPM-I	Melkassa and Adami Tulu Duration Prediction Model-I
MATDPM-II	Melkassa and Adami Tulu Duration Prediction Model-II
MATOPM-I	Melkassa and Adami Tulu Onset Prediction Model-I
MATP-ORFPM-I	Melkassa and Adami Tulu Post-Onset Rainfall Prediction Model-I
MATP-ORFPM-II	Melkassa and Adami Tulu Post-Onset Rainfall Prediction Model-II
MDGs	Millennium Development Goals
MOA	Ministry of Agriculture and Rural Development
MOFED	Ministry of Finance and Economic Development
PET	Potential evaporation
PORF	Pre-season (pre-onset) rainfall
PWP	Permanent wilting point
r	Correlation coefficient
R^2	Coefficient of determination (variation)
RF	Response farming
RH	Relative humidity

SAT	Semi-Arid Tropics
SE or RMSE	Standard error of regression or root mean squared error
SOI	Southern Oscillation Index
SSA	Sub-Saharan Africa
SST	Sea Surface Temperature
TAR	Third Assessment Report
TSW	Total crop seasonal water supply
USDA	United States Department of Agriculture
USDS	United States Department of State
VIF	Variance inflation factor
WAR	Water adequacy ratio
WHARF	Foundation for World Hunger Alleviation Through Response Farming
WMO	World Meteorological Organization

CHAPTER ONE

1.0 INTRODUCTION

1.1. Background

Ethiopia's economy is based on agriculture which accounts for 46% of Gross Domestic product (GDP) and 85% of total employment. However, the sector is heavily dependent on rainfall. As a result, it suffers from frequent droughts and unsustainable agricultural production practices (CIA, 2012). The drylands of Ethiopia, which cover over 66% of arable land (MOA, 1998), accounts for only 10% of the total crop production (Reddy and Kidane, 1994). According to Grey and Saddoff (2007), rainfall variability seriously undermines growth and perpetuates poverty in Ethiopia. In addition, population growth (USDS, 2007) is seen as a major challenge to the overall economic welfare and people's livelihoods. Climate change is also expected to increase extremes of drought and floods (Admassu *et al.*, 2012). The problems of rainfed agricultural production are exacerbated by poverty and inadequate institutional set-ups (IPCC, 2001; Fischer, 2005). Thus, interventions that have a potential to support dryland farmers to better prepare, better respond and better manage climatic uncertainties and shocks are crucial (Sadras *et al.*, 2003; Steiner, 2004). Such interventions will lead to yield stabilization, enhancement, food security and well-being of the livelihoods of dryland farmers and economic growth.

1.2. Problem Statement

Inter- and intra-annual rainfall variability in the semi-arid areas of Ethiopia greatly impact on the performance of agriculture. A cross these areas, the greatest challenge to rain-fed farming are to deal with extreme variability in rainfall, both within and between seasons. Typically, rainfall during a crop season varies from about a third to twice the long-term mean (Admassu, 2004). Particularly, the uncertainty with respect to the direction and extent that variability will assume in any given season forms the greatest source of risk to crop production (McCown *et al.*, 1991). The high risk of rainfall and resultant poor crop yields are among the major disincentive to adoption of yield improving inputs (McCown *et al.*, 1991; Stewart, 1991b; Fujisaka *et al.*, 1996; ICRA, 1999).

In recent years, farmers are facing serious decision challenges due to their traditional knowledge based forecast of season potential being ineffective (Admassu *et al.*, 2011a, b, c). The consequences of enhanced seasonal rainfall variability together with farmers' reliance on unsustainable farming practices (Admassu *et al.*, 2011a, b, c) have been acute shortage of food and pasture and depletion of assets, mass migration, and loss of life (Grey and Sadoff, 2007). The situation is expected to worsen due to the on-going climate change (Admassu *et al.*, 2012).

In order to address seasonal rainfall variability risks in dryland farming systems, agro-climatic approaches and dynamic cropping strategies that utilize climate forecasts are critical (Stewart, 1988a; Sivakumar, 1988; McCown *et al.*, 1991; Simane and Struick, 1993; Kanemasu *et al.*, 2000; Sadras *et al.*, 2003; Steiner *et al.*, 2004). Steiner *et al.* (2004) emphasized that if the upcoming season's climate was predictable, farmers could tailor practices to match anticipated climate, reducing risks during adverse seasons, while investing more to benefit from favourable seasons. Nevertheless, Steiner *et al.* (2004) and Vogel and O'Brien (2006) indicated that seasonal forecasts produced by national and regional meteorological institutions as problematic owing to lack of adequate information on their reliability and usefulness, spatial inexplicitness, difficulty of interpretation and uncertainty of the value and impact of forecast information in multi-variable decision system.

There exist a number of approaches (FAO, 1978; Sivakumar, 1988; Stewart, 1995) in order to define the date of onset of rainy seasons. Almost all approaches consider a very stringent onset criterion and thus tended to nearly avoid the risks that are commonly experienced in the wider semi-arid areas of the world (Kanemasssu *et al.*, 1990). For the semi-arid areas of Ethiopia, Simane and Struick (1993) adopted one of such approaches and recommended production of early maturing and thus low yielding varieties. Such definitions of the date of onset result in short season duration with low seasonal water supply. Consequently, yields may suffer significantly due to either a late onset or early cessation of the growing season (Kanemasssu *et al.*, 1990).

In Ethiopia, agro-climatic research efforts over the past decades were limited to understanding of the general influence of atmospheric conditions on rainfall amount, anomalies, trends, probabilities of dry spells, and assessments of predictability of drought (Abate, 1994; Tadesse, 2000; Mamo, 2004; Admassu, 2004; Tesfaye, 2004; Adugna, 2005; Araya *et al.*, 2010; Mideksa, 2011). However, efforts particularly to develop predictive capacity for the date of onset and other seasonal rainfall characteristics that facilitate strategic planning of agronomic operations and tactical management of in-season rainfall related risks that are applicable at local farm scale are typically lacking. As a result, the use of climate information from the past research in agricultural decision making by resource poor farmers has not been realized. This circumstance will mean that the predominantly rainfed crop production in the semi-arid areas will continue to suffer from great inter-seasonal rainfall variability making smallholder farmers to be highly vulnerable to food insecurity (Fraisse *et al.*, 2006).

1.3. Justification

The major concerns of dryland farmers are to know in advance, when the rainfall will become fairly continuous and become sufficient to ensure enough moisture in the soil to enable planting (the onset of rainfall season). They are also concerned with the information on whether or not this level will be maintained or even increased as the season advances (Walter, 1967; Stewart, 1988a). Ethiopian government has been desirous of enhancing the productivity of smallholder agriculture in order to put an end to the chronic food insecurity, mass starvation and loss of lives, and to alleviate poverty and achieve the Millennium Development Goals (MDGs) by 2015 (MOFED, 2010). Accordingly, Ethiopia developed its Growth and Transformation Plan (GTP) in 2010 (MOFED, 2010) that emphasized the need to improve agricultural productivity of smallholder farmers and pastoralists through scaling-up of best-bet technologies, irrigation development and improved extension services (MOFED, 2010). To address the above concerns, use of climate information with appropriate agronomic packages becomes important priority.

Since early 1960s, field studies to reduce risks and uncertainties through the use of detailed climatic information have given rise to a methodology termed response farming i.e. RF (Stewart, 1988a; McCown *et al.*, 1991). RF couples a seasonal rainfall forecast with appropriate agronomic response tactics guided by the predictions (Stewart and Hash, 1982; Stewart, 1988a). In response farming, Stewart, (1988a) used the date of onset as a strategic predictor of season length. The tactical management of in-season risks in RF has been based on the relationship between cumulative early season rainfall and eventual total season water (Stewart and Kashasha, 1984).

Considerable potential of RF in reducing risk and in increasing crop yield and improving food security under semi arid conditions has been reported by Stewart and Faught (1984), Sivakumar (1988), Stewart (1989a, b, c), Wafula (1989), McCown *et al.* (1991), Wafula *et al.* (1992) and Admassu *et al.* (2010). Such strategies that match cropping decisions according to season potential are therefore essential for yield stability and enhancement (Stewart, 1988a; Sadras *et al.*, 2003). Response farming was also used for developing guide lines for early warning of drought (Stewart and Hash, 1982; Stewart 1988a; Stewart, 1991c).

Despite the potential of RF, the assessment of the next season's potential and the planning of farm operations and selection of variable inputs such as fertilizer has been founded on and revealed at the date of onset of the season. This denies the farmer sufficient lead time to prepare well in advance. Thus, research is absolutely necessary to develop predictive capability for date of onset in order to advance knowledge of highly probable time of season onset. Research is required to markedly advance the time of prediction so as to effectively reduce cropping risks. It is also important first to realistically define the date of onset of cropping seasons for a specific locale. This is believed to enable dryland farmers to better prepare, better respond, and better manage the uncertainties presented by highly variable rainfall. This will improve strategic agronomic planning of farm operations at local scale and will overcome the weaknesses of RF. The development of predictive capability for determinant seasonal rainfall characteristics is also a major concern for tactical management of in-season risks through facilitating rapid changes in on-farm tactics at local scales. Such predictive capacity could reduce risk and lead to use of yield-improving technologies (Stewart, 1988a; Stewart, 1989c; McCown *et al.*, 1991; Stewart, 1991a; Wafula *et al.*, 1992).

Given the problem dryland farmers are facing due to extreme rainfall variability, rainfall prediction capacity for localized strategic planning of farm operations and tactical management of risks assumes key importance for vulnerable communities to better prepare, better respond, and better manage the uncertainties presented by highly variable rainfall. Such practical actions to reduce crop failure and to improve the capacity to adapt are of major concern for the Ethiopian government and resource poor dryland farmers since the gradual and sudden changes associated with climate are projected to increase vulnerability of dryland farmers. Thus, this study was conducted with objective to improve response farming methodology through developing prediction models for the date of onset and seasonal rainfall characteristics. The ultimate aim was to facilitate strategic agronomic planning of farm operations and tactical management of in-season risks and increase maize production and contribute to the Ethiopian government efforts for alleviation food insecurity challenges that are frequently experienced in the semi-arid areas of Ethiopia.

1.4. Study Objectives

1.4.1. Overall objective

The overall objective of the study was to develop prediction models for the date of onset and determinant seasonal rainfall parameters that will improve strategic and tactical RF for food security under variable seasonal rainfall conditions of the semi-arid agricultural systems of the Central Rift Valley of Ethiopia (CRV).

1.4.2. Specific objectives

The specific objectives of the study were:

1. To establish a multi-factor based, agronomically risk-wise acceptable date of onset, and its predictors,
2. To develop prediction models for date of onset that will facilitate strategic agronomic planning of maize production operations,
3. To develop prediction models for seasonal rainfall characteristics that will improve tactical agronomic management of in-season risks and improve response farming of maize, and
4. To evaluate on-farm performance of the developed prediction models in guiding strategic and tactical response farming and in improving maize yield.

It is the higher overall risk due to lack of predictive capability that impact on strategic decisions and tactical management of risks in areas of variable and uncertain rainfall. The study results described in this thesis addressed the above objectives. Key achievements were a multi-factor based approach for establishing agronomically risk-wise acceptable date of onset, models useful for prediction of the date of onset and other seasonal rainfall parameters that led to enhancement to Stewart's RF. The enhanced RF forecasts guided maize production strategy was also proven to be useful in increasing maize yield. Answers to the objective of this study combined with adoption of climate smart options such as rainfall risk insurance schemes and prudent management of natural resources can contribute to sustainable agronomic adaptation to seasonal rainfall variability. This can in turn stabilize and enhance maize production and lead to achievement of food security under semi-arid conditions.

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1. Agro-ecological Features and Agriculture in the Semi-Arid Tropics

Estimates show there are over 700 million people living in the semi-arid tropics (SAT) which form 13% of the world's land. The SAT fall under Troll's climate classes 3 and 4a (Troll, 1965) (Table 1). Class 3 is for wet-dry tropical climates with 4.5 to 7 humid months (Dry savanna), and Class (4a) is for tropical dry climates with 2 to 4.5 humid months (Thorn savanna) (Kanemasu *et al.*, 1990).

Table 1: Troll's climate classes

Climate class	Length of rainy season	Associated vegetation
1	Tropical rainy climates with 9.5 to 12 humid months	Tropical rainforest
2	Tropical rainy climates with 7 to 9.5 humid months	Humid savanna
3	Wet-dry tropical climates with 4.5 to 7 humid months	Dry savanna
4a	Tropical dry climates with 2 to 4.5 humid months	Thorn savanna
5	Tropical semi-desert climates with less than 2 humid months	Semi-desert

Source: Kanemasu *et al.* (1990)

The SAT spread over nearly 20 million square kilometres and cover parts of 50 nations on five continents. Climatically, the SAT is occasionally wet, but is characterized by limited, erratic rains and uniformly high temperature throughout the year. The rainy season generally ranges between 60 and 150 days or longer. The dry season lasts for several months during the year (Sivakumar, 1990; Kanemasu *et al.*, 1990). With high evaporative demand of approximately 1.5 - 10 times the average annual rainfall and low soil water holding capacity, water followed by low soil fertility is considered a major environmental constraint to rainfed cropping systems (Barron, 2004).

Kanemasu *et al.* (1990) noted that for some locations, the hottest months experience average open-pan evaporation of about 10 mm day^{-1}. On some days it could be as high as 15 mm. High rates of evaporation coupled with low and variable rainfall in the SAT often lead to periods of water deficit. Such water deficits have serious implications for stability of crop production in this ecological zone. For semi-arid areas in Ethiopia, it is only during the rainy period of the year when rainfall exceeds PE that the soil moisture reserves are fully recharged (Admassu, 2004). Such period extends from 2 to 4.5 months in the dry SAT (Kanemasu *et al.*, 1990). The reliability of the rainfall at the beginning of the season is generally low (Simane and Struick, 1993). Surface soil temperatures range between 40 to 50°C. The variability of rainfall at the end of the season is also high, affecting crop yield and their quality (Kanemasu *et al.*, 1990). Thus, the area is characterized by harsh conditions of limited and erratic rainfall and soils low in nutrients especially nitrogen and phosphorus (Lehmann *et al.*, 1998). Rainfall occurs as short duration, high intensity storms. Complete crop failure due to drought and reduced crop yields due to frequent intra-seasonal dry spells make rainfed crop production risky.

Subsistence agricultural production dominates the SAT. Only 15% of the people produce 11% of their food. Current yields are low and production is unstable because of aberrant weather. As a result of rising populations, food deficits in the SAT are increasing. The climate of the SAT is a primary constraint to agricultural development (Kanemasu *et al.*, 1990). Thus, harnessing the soils, climatic and other natural resources in an agro-ecologically balanced sense is a major pre-requisite for sustained and increased agricultural production (Kanemasu *et al.*, 1990).

2.2. The Impacts of Rainfall Variability and Climate Change on Agriculture

Rainfall exhibits notable spatial and temporal variability (Taddesse, 2000; Hulme *et al.*, 2001). Such variability was reported to be large over most of Africa and, for some regions, multi-decadal variability is also substantial (Nicholson *et al.*, 2000; Chappell and Agnew, 2004).

It has long been recognized that the climate system is highly complex consisting of atmosphere, hydrosphere, cryosphere, land surface and biosphere, and the interactions between them (IPCC, 2001). Climate (classical period is 30 years as defined by World Meteorological Organization (WMO) includes temperature, precipitation, and wind.

It is well documented that the climate of Africa is controlled by complex maritime and terrestrial interactions that produce a variety of climates across a range of regions (Christensen *et al.*, 2007). Thus, climate exerts a significant control on the agricultural and water-resources sectors, at regional, local and household scales. Climate projections show that there would be phenomenal impacts on the planet earth and IPCC (2007) warned that global warming could lead to large-scale floods and water shortages. Africa is the most vulnerable region to climate change (Fields, 2005). The Third Assessment Report (TAR) shows greater warming trend since the 1960s. Although these trends seem to be consistent over the continent, the changes are not always uniform. For instance, decadal warming rates of 0.29°C in the African tropical forests (Malhi and Wright, 2004) and 0.1 to 0.3°C in South Africa (Kruger and Shongwe, 2004) have been observed.

The TAR of the IPCC identified a range of impacts associated with climate change. Many countries in Africa already face semi-arid conditions that will make agriculture a challenging enterprise. These are due to its effect on reduction of the length of growing season that will force large regions of marginal agriculture out of production. Climate change is expected to increase extremes of drought and floods which are exacerbated by poverty, poor institutional and policy support and frequent natural disasters (Fischer, 2005). In the sub-Saharan Africa (SSA) region, climate change is believed to heighten recurrent food insecurity and famine. These are due to extended droughts and floods (Vogel and O'Brien, 2006). Thus, climate change is predicted to impact many developmental sectors in SSA. Agricultural production and food security (including access to food) in many African countries are likely to be severely compromised by climate change (Fischer, 2005).

According to the CSIRO global climate model from the IPCC AR4, annual precipitation will decrease in most highland areas of Ethiopia by 2050, whereas. MIROC shows a dramatic increase in precipitation over much of Ethiopia. The

MIROC and CSIRO models have similar results for changes in average daily maximum temperatures during the warmest month in 2050, while some areas would experience a temperature increase of 1.5 to 2°C, temperatures in most of the country would only increase by 1 to 1.5°C. Such increase in temperature will increase rates of evapo-transpiration, possibly leading to a deficit in the water balance and posing a major challenge to rainfed agriculture (Admassu *et al.*, 2012).

CSIRO model projections for rainfall and temperature was used for assessing the impacts of climate change on rainfed maize in Ethiopia using Decision Support System for Agro-technology Transfer (DSSAT) crop modelling software. The simulation results suggested a gain in maize yields of more than 25% in the eastern highlands of the edge of Great Rift Valley and in the north-central highlands. The model also projected patches of new area gained along the eastern parts of Amhara and Tigray. CSIRO model also projected an equal amount of existing maize land would be marginalized, or completely become unsuitable for maize. Moreover, it projected marked decrease in maize yield over the south-western and eastern parts of central Ethiopia (Admassu *et al.*, 2012).

A recent assessment indicates that much of Ethiopia today is facing serious food insecurity (Admassu *et al.*, 2012). About 60% of the population consumes fewer calories than their daily physiological requirement. Any worsening of food insecurity under changing climate will thus heighten the vulnerability of the people. Thus, climate change in conjunction with population growth presents a major challenge to the overall economic welfare and people's livelihoods (USDS, 2007).

2.3. Farmers' Decision Challenges and Coping Mechanisms

Farmers in the semi-arid areas are faced with a number of strategic and tactical decision challenges. Thus, they must make a number of irreversible decisions as each new season approaches (Fujisaka *et al.*, 1996; ICRA, 1999; Admassu *et al.*, 2011a, b, c). Strategic decisions include those that shape the cropping system for the entire season, where as tactical decisions are those that are made in response to the rainfall pattern that follows onset. Both strategic and tactical decisions and actions relate to crop establishment operations, and influence effective water supply, crop water utilization or crop water use efficiency (yield per unit of water). Stewart (1991b) summarized such operations as follows:

i. Land and seed bed preparation, i.e. imparting slopes to plant rows and modifying infiltration characteristics of the soil, thus influencing the balance between water retention versus runoff,

ii. Selection of crops to be planted, i.e. determining amounts and sequences of water requirements, capabilities for soil water extraction during dry periods, and yield responses to water excesses or deficits,

iii. Selection of cultivars, i.e. influencing the above factors and determining the length of the growing season from germination to physiological maturity (cultivar maturity, or maturity),

iv. Selection of seed rates and spacing between rows, i.e. influencing crop water requirements and patterns of soil and water extraction,

v. Selecting of initial fertilizer types and rates of application, i.e. determining potential water use efficiency, with attendant risks on both extremes of the range of rainfall amounts, and

vi. Approximately 30 days after crop germination, final commitments on plant population and fertilizer application, i.e. conforming crop water requirements and/or potential water use efficiency to observed early season rainfall.

Owing to a very high spatial and temporal variability, and erratic distribution of the rains during the rainy season, local farmers face problems to decide when to start sowing preparations. Dry spells following onset constitute major farmer's decision challenges. The above seasonal challenges imply that, farmers must set up contingency plans to be able to respond to variable climatic conditions long before the onset of a new cropping season (Stewart, 1988a). For dryland farmers, expected season duration, rainfall amount, intensity, frequency, and variability are major factors to shape the cropping system (Stewart, 1988a). Their planting date, seeding rate, fertility, and crop protection measures must be planned for the optimal yield for that anticipated single rainfall pattern (Stewart, 1988a).

These seasonal rainfall related decision challenges, the general poverty of agro-ecosystems, and farmer's socio-economic circumstances circumscribe dryland developmental potentials (Kanemasu *et al.*, 1990). Accordingly, it is crucial that farmers are informed about expected dates of onset of next crop seasons and water supply conditions long before the onset of current season to enable them make better strategic decisions. As well, it is crucial that farmers are informed following the actual date of onset so that they can make tactical decisions as seasonal rainfall develops.

It is well documented that dryland farmers have developed strategies for coping with rainfall variability. Exchange of information on rainfall, time-dependent measures such as dry seeding, re-sowing, and the use of differently maturing crop varieties, field apportionment, reducing the land area to sow, and measures for sustaining soil fertility are cited responses (Graef and Haigis, 2001). Similarly, Ethiopian dry land farmers relate rainfall onset dates to season length. They perceive good to normal seasons begin relatively early, while normal to dry seasons tend to start later. Thus, due to their observation of the correlations between season length and the date of onset, they are aware of risks that arise from a single management plan. Noting this, they traditionally alter some of their management decisions from season to season to conform to projected rainfall (Fujisaka *et al.*, 1996; ICRA, 1999). They allocate longer duration crops with higher water requirements to land/fields which receive runoff (Admassu, 2004). If the date of onset is perceived early, they plant long maturing maize as early as possible. In case of failure of early rains, farmers grow early maturing crops and cultivars in late seasons.

Farmers use different indicators for judging season potential. Such traditional decision criteria include the observation of the behaviour of some insects or birds or flowering of certain trees. According to (Boko *et al.*, 2007), such adaptations may not be sufficient for future changes of climate. In recent years, such decision systems based on traditional perceptions were also reportedly ineffective due to enhanced variability (Admassu *et al.*, 2011a, b, c). Thus, the demand for a scientific decision aid has increased among local farmers.

Under the described circumstance, it becomes important to inform the farmer, with a significant degree of confidence, about the expected rainfall before the growing season in order to help him prepare in advance and make sound strategic planning decisions. Similarly, it is important that, following sowing, farmers are updated to make tactical decisions.

2.4. Conventional Agro-meteorological Approaches-based Maize Production Recommendations

In typical semi-arid Central Rift Valley (CRV) of Ethiopia, average maize yields of improved varieties with maturity in the range of 90 to 120 days under farmers' conditions is typically low: 1.6 t ha^{-1}. Moisture-stress has long been recognized as a major maize production constraint that causes frequent severe droughts. As a result, dry land farmers who depend on maize as their main staple often suffer from massive, often acute food shortages (Admassu *et al.*, 2011a, b, c).

In order to address the impacts of rainfall variability on crop production, agro-climatic approaches were recommended in developing crop production technologies for dry land farmers (Admassu, 2004, 2007). Studies by Simane and Struick (1993) established the pattern of rainfall in the drier areas as bi-modal. The early/short season starts in February and ends in April/May. The long rains begin in late June and ends by early October. Thus, recommendations were developed for farmer adoption for the season that begins in late June. The recommendations include late planting calendars, late sown short cycle crops, and corresponding rates of fertilizer and seeds rates, and soil moisture conservation practices (Berhane *et al.*, 1993;

Reddy and Kidane, 1994; Lemma *et al.*, 1995; Admassu *et al.*, 1996; Teshale *et al.*, 1996; ICRA, 1999). Their superior on-farm performances have been proven (Deressa and Seboka, 1996).

Farmers who differ in their definition of rainfall, and recognize differences in expectations of water in early and late seasons, tend to ignore the recommendations. This is because if they relegate themselves to this corner, they believe that the chance for bumper harvest in more favourable early starting seasons are merely forgone (Fujisaka *et al.*, 1996). These farmers' native observations of the correlations and management decisions systems have been scientifically proven to be sound (Stewart, 1988a; Sivakumar, 1988). Unfortunately the view of considering all seasons as uniform still persists. The result is a single fixed cropping prescription for farmers' use in any given season (Fujisaka *et al.*, 1996; ICRA, 1999).

The role of climate information has long been recognized to effectively manage seasonal variation in water supply conditions (Simane and Struick, 1993). According to Stewart (1991b), uncertainty with respect to rainfall expectation is lessened when information is available concerning the possible variability and frequencies of historical occurrences. Since the advent of computers, the rate of generation rainfall probability analyses has greatly increased. This has produced initial and conditional rainfall probabilities for 10-day period in addition to monthly and annual values for many regions (Sivakumar *et al.*, 1979; Hargreaves and Zemani, 1986; Sivakumar and Gnoumou, 1987).

Stewart (1991b) questioned the adequacy of such information in guiding the farmer in crop establishment decision making process. Stewart (1991b) emphases that these conventional probabilities leave the farmer confined to a single set of decisions, and therefore, the same actions each season. This is so because the information from probability analyses informs the farmer that any prior rainfall amount, high or low, could recur this season. Thus, the farmer has only one decision to make without any information regarding at what level of risk, represented by a rainfall probability, the he will prefer to operate. According to him, probability information should be translated in to an expected seasonal rainfall amount so that all crop establishment decisions are then predicted on that expectation (Stewart, 1991b).

According to Stewart (1995), the basis for seasonal rainfall prediction lies in the fact that monsoon rains do not begin on the same date each year. In nearly all parts of the tropics and sub-tropics, the date when rains first become sufficient to germinate and sustain a crop varies between seasons over a period of 60 days. Stewart (1995) emphasized that risk in crop production differs both in kind and intensity in different crop growth stages. Early season risk of seedling death does not relate to mid-season pollination risk, nor do the decisions and actions one might take to reduce risk. However, the date of occurrence of a given growth stage may differ from year to year by weeks, or even months. Thus growth stage related risk factors - and most risk factors are - are not addressable using probabilities for fixed calendar periods (Stewart, 1995). Thus, probabilities referenced to past onset/germination dates rather than strict calendar periods become more meaningful as compared to conventional approaches (Stewart, 1995).

To make rainfall probabilities more relevant to design and improvement of cropping systems, they must be based on time periods which relate directly to the crop growing season - or portions thereof such as growth stages of particular interest - rather than to fixed calendar periods. Each season's point of reference should be the first date after sowing when soil water build-up from the early rains becomes adequate for germination. The signal for sowing may be either a fixed calendar date, or attainment of some arbitrarily selected build-up of stored soil water which (Stewart, 1995) termed *onset*.

Crop season based rainfall probabilities makes it possible to rearrange rainfall seasons by germination dates, from earliest to latest, and study concomitant changes in rainfall probabilities. If, in the study locality, cropping season rainfall probabilities shift very noticeably across the spectrum of possible germination dates, it is concluded that delayed germination conditions warrant one or more modifications in the management decision package. This suggests flexibility in the cropping system aimed at maximizing efficiency of use of the available water resource, both in terms of yields and economic returns, while reducing risk to the practical minimum (Stewart, 1995). Ati *et al.* (2002) concluded that in the future, improved climate prediction skill may replace the classical probabilistic approaches presently suffering from increasing rainfall variability.

2.5. The Role of Climate Information for Agronomic Adaptation

Weather and climate risks are one of the biggest production challenges impacting on agricultural systems performance and management (Stewart, 1991a). Thus, strategic and tactical adaptation becomes a necessity to respond to current and changing climate (Smit *et al.*, 2000; Burton, 2004). According to Ioan *et al.* (2007), adaptive capacity is increasingly recognized as essential for maintaining the resilience of social-ecological systems and for coping with environmental change.

In the SAT of Ethiopia, recent studies show that extreme climatic events such as severe droughts, floods, or changes in temperature will impede sustainable agricultural development (Admassu *et al.*, 2012). Hence, adaptation to rainfall variability should form an integral part of agricultural development. This calls for technology generation, innovation and adoption to satisfactorily counteract the effects of the ongoing changes in climate conditions.

To effectively minimize agro-meteorological risks and uncertainties, up-to-date climate knowledge and agronomic decision packages responsive to the forecasts are imperative pre-requisites for sustainable planned adaptation (Admassu *et al.*, 2011a, b, c). Thus, improvements in predictive capacities and response mechanisms to current weather are required (Stewart, 1988a). Climate information is crucial in order to properly plan and implement agricultural operations (Stewart, 1988a; McCown *et al.*, 1991). A climate prediction or climate forecast provides information on the most likely description or estimate of the actual evolution of the future climate at different time scales (IPCC, 2001). Hansen (2002) stated that for such forecasts to be useful, they must address field level problems by matching decision options with farmer's goals. According to Nicholls (2000), they must enable the farmer to take full advantage of seasonal rainfall by influencing management decisions that have potential to change the outcome (Stone and Meinke, 2005). However, information on the field benefits of forecasts is scanty.

Improved understanding of ocean-atmosphere interactions and advances in modelling climate systems is said to offer usable forecast several months in advance (McCown *et al.*, 1991). El Niño and La Niña events are essential components of the ocean-atmosphere interactions which assume important position in seasonal rainfall prediction. Understanding of the influence of 'El Niño–Southern Oscillation' (ENSO) phases on climate variability and computation of the associated risks in crop production at a particular location and season is a growing aspect of climate forecasting techniques (Goddard *et al.*, 2001). Seasonal climate predictors based on Southern Oscillation Index (SOI) are seen as important in climate risk reduction in certain regions in the SAT (McCown *et al.*, 1991).

Easterling (1987) claimed the ability to forecast rainfall variability based on ocean-atmosphere interaction as one of the premier advances in atmospheric sciences during the twenty century. Currently, rainfall variability is predicted using SST and pressure anomalies. Tactical responses based on SOI phases have been found to improve risk management and profitability (Hammer *et al.*, 1996; Meinke *et al.*, 1996; Phillps *et al.*, 1998).

Successful prediction of seasonal temperature and rainfall at a lead-time of up to a year is now possible. However, accurate prediction of the state of weather beyond six days still remains a challenge and almost impossible beyond 10 to 14 days. Such premier advances in atmospheric sciences (Easterling, 1987) being under improvement, their use by low resource farmers is only in the beginning in some of the SAT of Africa (Hansen, 2002). Such forecasts should give information about the expected amount and distribution of rainfall for a specific locale to enable farm level decision-making. The information need to be more spatially specific so as to be useful to agriculture (Stone and Meinke, 2005).

According to Patt (2001), applying the forecasts at the level of the individual farmer offers both the greatest challenges and the greatest rewards. This user group has little experience making use of external scientific and technical knowledge, and faces a diverse set of decisions that vary geographically and from year to year. But if these farmers can use the forecasts to make better decisions, not only their vulnerability to El Niño but also their dependence on national and international aid will be less. But the evidence is scarce and mixed as to whether farmers actually have used the forecasts (Glantz, 2001).

Based on a review of the 2000 food crisis in Ethiopia, Broad and Agrawala (2000) reported that seasonal climate forecasts to be of no use to farmers. They concluded the state of the science of seasonal forecasting to be sobering and underscore the need to foster more realistic expectations among both policy-makers and scientists about the uses and limits of climate forecasts in alleviating complex social problems. Patt (2000) presents several constraints to application of seasonal forecasts. With respect to scale constraint, the forecasts cover a wide geographical area, such as en entire continent, region, or country with no clear information of the forecasts at local scale. Thus, the predictions tend to greatly deviate from climatology across a diverse landscape where the distributions of seasonal rainfall differs significantly generating confusion. This is very true in mountainous parts of Ethiopia where rainfall patterns are very heterogeneous over a small physical area (Mamo, 2004). According to Patt (2000), a more accurately downscaled forecast should predict the probabilities of different amounts of actual rainfall for each location, examining the historical record for each. Moreover, the probabilistic nature of forecasts and farmers lack of awareness about measurements of rainfall in terms of millimetres makes downscale forecasts no sense to local farmer.

Patt (2000) also raises the credibility constraint which is founded on failure of past years' forecasts to be accurate, and from the failure of the forecast communicator to have built a reputation of trust. Glantz *et al.* (1997) and Nicholls (1999) have suggested that citizens are incapable of understanding a probabilistic forecast, and hence it may be better to disseminate one that is deterministic, telling exactly what will happen. Patt (2000) also discussed the legitimacy constraint which arises when users question the political agenda of the communicators. For instance, Broad (1999) shows how, in Peru, large corporations benefited from the forecast, while individual farmers and fishermen suffered when market conditions changed. In Zimbabwe, lending agencies restricted credit to farmers when the 1997 forecast predicted drought (Patt, 2000).

In Ethiopia, the National Meteorological Agency has been issuing operational seasonal climate forecasts (Mamo, 2004). However, the application of the forecasts in farm level decision-making still remains to be seen. The major limitation is that the forecasts are not site-specific. Thus, they fail to respond to unique problems that arise due to diverse micro-climates. Farmers, lacking practically tested and well demonstrated, down-scaled prediction information, tend to limit adoption of yield improving production technologies that are required to stabilize and enhance crop yields and improve their livelihoods. The single choice they have is to continue with their tradition of hit-or-miss system of prediction (Admassu *et al.*, 2011a, b, c).

2.6. Role of Response Farming for Agronomic Risk Management

Richard *et al.* (1999) stated that planned adaptation requires strategic actions, based on awareness that climate is changing and that action is needed to better respond to the changes. Planned adaptation is thus aimed at changing present management practices via continuous and iterative cycle. If farmers had prior knowledge of what the rainfall conditions are going to be during the forthcoming season, they could consider a number of adjustments in the management practices to adopt. For example, farmers may opt for higher plant population, use recommended dose of fertilizers, and adopt intercropping options during wet years because of lower risk. In the drier seasons, they may use low plant population and avoid application of costly fertilizer (Stewart, 1988a).

Since mid-1960's , field studies to reduce risks and uncertainties through the use of detailed climatic information which both accounts for flexibility in crop production in risky climates have brought a methodology termed response farming (RF) (Stewart, 1988a; McCown *et al.*, 1991). Stewart (1988a) defined RF as a flexible system of farming in which crop water utilization and crop yield are modified each season in response to pre-season and early season predictions of seasonal rainfall amount, duration, intensity index and other parameters as appropriate. The concept is based on the relationship between the time the rainfall begins (date of onset) and the rainfall amount and duration thereafter.

According to Mamo (2004), RF methodology for rainfall prediction precedes all the earlier described ocean-atmosphere interactions based predictions. The development of the scheme was founded by Stewart (1988a) based on research on crop water balance modelling and estimation of crop water requirements for use in estimating actual evapo-transpiration (ETa). It was also based on production functions developed for estimating crop yields from estimates of ET, and water-nitrogen-plant population interrelationships.

Response farming strategy constitutes an approach for coping with seasonal rainfall variation with three major components:

(a) Agriculturally relevant rainfall analyses followed by both pre-season and early season predictions of expected rainfall behaviour;

(b) Flexibility in farming systems permitting modifications of decisions and practices to maximize production per unit rainfall received; and

(c) Incorporation of farmer's priorities or focuses on the type of feasible enterprise to operate.

The strategy is devised to minimize the impacts of variable rainfall with two principal facets:

(a) Reduction of effective variability as it relates to the rainfall season at hand. This is accomplished through improved rainfall prediction or physically using water harvesting and / or supplemental irrigation; and

(b) Sowing time decisions aimed initially at the upper half of the reduced range of rainfall possibilities, but which may, at the appropriate growth stage, be shifted downward, by thinning plant stand and withholding further fertilization, should the actual early-season rainfall be less than normal.

Field application of RF involves a series of iterative analyses of historical rainfall record, specifically oriented to crop production requirements. The processes involve risk assessment and risk management to evolve rainfall prediction criteria and appropriate decision packages for responding to different predictions (Stewart, 1991b).

Stewart (1988a) illustrates the usefulness of the date of onset as a predictor of effective rainfall, and developed detailed RF recommendations for production of maize at Katumani, Kenya. Stewart and Hash (1982) strengthened these recommendations with an economic valuation of the advice. Stewart and Kashasha (1984) demonstrated the wider applicability of the approach in Eastern Kenya. They reported, out of four seasons of farm verification trials, three seasons were correctly predicted. RF increased average yields of mono-cropped maize from 1170 to 2775 kg ha^{-1} and bean yields from 375 to 775 kg ha^{-1}. In the good season (1982 short rains), inter-cropping was found advantageous, with Land Equivalency Ratio of RF plots averaging 1.32 (Stewart and Faught, 1984). Sivakumar (1988, 1990) developed detailed relay inter-cropping of cowpea and sorghum for Sahelian zones of West Africa using onset-duration relationship. Similarly, the feasibility of RF has been demonstrated for Ethiopia (Admassu, 2004, 2007; Admassu *et al.*, 2010). Konate and Traore (1987) also attested the feasibility of RF for Western Africa.

Response farming analyses of daily weather record have been used to generate information for development of criteria for early warning of impending drought aimed at providing seasonal guidance for decision-making by national and regional planners, farm advisors, and farmers as well as the basis for early warning analysis and programs (Stewart, 1991c). The concepts underlying scientific RF have long been in use by farmers in India, Jordan and West Africa to reduce potential variability associated with any given date of onset, and, when onset actually occurs, to remove considerable measures of uncertainty of the coming season (Stewart, 1988a). This practicality makes it more appealing. As a result, RF has slowly been emerging as an important branch of the science of operational agro-meteorology (McCown *et al.*, 1991).

McCown *et al.* (1991) concludes RF as an attractive approach with sound biological bases for strategic risk management. Nevertheless, despite its potential, RF has not benefited from continuing research. In light of the enhanced variability, it is argued that advancing RF particularly the prediction of date of onset is much required than waiting for the date of onset to occur. The same is true concerning the need for advancing prediction of in-season rainfall and prediction of thinning time and mid-season rainfall amounts.

The above assessments imply RF couples a seasonal rainfall forecast with appropriate agronomic response tactics that are guided by the predictions. Stewart (1988a) suggested that the present level of predictability can be markedly improved, and time of prediction possibly advanced, to before the date of onset (Stewart and Hash, 1982).

2.7. Methods of Defining and Predicting the Onset of Rainfall

The onset of the rainy season is of major interest for farmers. Thus, there have been extensive studies that have been conducted since early eighties in an effort to predict the onset of rains. Extensive studies over the past six decades in an effort to identify criteria for defining and determining the onset of rains. A variety of methods have been used to identify and calculate the onset of the rainy season. Most of the approaches adopted were dependent on the available data and the purpose of the study.

Chmielewski and Rötzer (2002) used phenology to assess variability in the start of season. Walter (1967), Kowal and Knabe (1972), Benoit (1977), Stern *et al.* (1981) and Olaniran (1983) used rainfall-evapo-transpiration relationships to determine the date of onset. Whereas, Sivakumar (1988), Omotosho *et al.* (2000), Sarria-Dodd and Jolliffe (2001), and Ati *et al.* (2002) used accumulated rainfall totals. Others used upper-atmospheric winds (Omotosho, 1990, 1992) and sea surface temperature (SST) models (Lamb and Peppler, 1992; Eltahir and Gong, 1996; Janicot *et al.*, 1998). Usman (1999) used temperature to determine the onset of the rains.

Troup (1961), Ramage (1971), Murakami and Sumi (1982), and Holland (1986) proposed wind-based definitions. Troup (1961) and Nicholls *et al.* (1982) used the levels or amount of accumulated soil water. Davidson *et al.* (1983, 1984) used summer monsoon to define monsoon onset as the first flare-up of tropical convection over northern Australia. Hendon and Liebmann (1990) used the low-level wind-based definition of Holland (1986) modified to include rainfall. Joseph *et al.* (1991) applied wind-based definition of Holland (1986) for study of the inter-annual variability of monsoon onset and how it is influenced by the Indian summer monsoon, El Ni˜n o and SST.

Tadros *et al.* (2005) defined onset criteria as a pentad at which the amount of rain required to successfully germinate and grow maize during the first month after planting; the first "dekad" (10 days) with a total rainfall of 25 mm, and this must be followed by two dekads with a total of at least 20 mm of rain occurred. Kousky (1988) determined the climatological onset date using satellite-based outgoing long wave radiation measurements. Studies by Rao and Erdogan (1989), and Lenters and Cook (1995) show that atmospheric heat source over most of the Bolivian Altiplano that is dominated by the contribution of latent heat to be the reason for the episodic and convective nature of rainfall over the Altiplano associated with uplifting of moist air from the lowlands to the east of the Andes. Simane and Struick (1993) adopted Hargreaves (1975) concept of dependable rainfall and defined 75% probability as reasonable risk value of moisture availability to crops in semi-arid environment in Ethiopia.

Marengo *et al.* (2001) defined onset (end) as the pentad in which rainfall exceeds (falls below) a given threshold, provided that average rainfall was well below (above) the threshold for several pentads preceding onset (end), and well above (below) the threshold for several pentads after onset (end). Ati *et al.* (2002) defined the onset of the rains and the start of the growing season as receipt of sufficient rain for survival of seedlings after sowing without shortening the growing season beyond the necessary length for the crop varieties selected owing to the increasing problem associated with false starts.

Several models have been proposed for determining the date of onset of the rainy season (Ati, 1995). Ati *et al.* (2002) list five methods for calculating the date of onset of the rains. These are a traditional technique called Ramadan method (Ati *et al.*, 2002), Walter's (1967) and Sivakumar's (1988) methods which use accumulated rainfall totals and Kowal's and Knabe (1972), and Benoit's (1977) methods which use rainfall-evapo-transpiration relationships. The merits and demerits of these methods are amply discussed by Ati *et al.* (2002).

Ati *et al.* (2002) developed a hybrid methods to define the date of onset as the dekad when rainfall exceeding 25 mm is received and with subsequent dekads of rainfall exceeds 0.5PET (potential evapo-transpiration) with no dry spell exceeding three days within the next seven days. If such a dry spell exists, the onset date would be the date of the first rains after the dry spell. The hybrid method eliminated false starts, particularly when annual onset dates are considered instead of average onset days.

The Food and Agriculture Organization of the United Nations (FAO) (1978) defined the onset of rainfall as the time of year when precipitation equals or exceeds 0.5ET0. PET (Potential Evapo-transpiration) is a measure of evaporative power of the atmosphere. A normal growing period is characterised by a dry period, a moist period and a wet (or humid period). The beginning of the growing period occurs when precipitation equals half PET and marks the start to the normal rainy season. A value of 0.5PET is considered as germinating crops do not evapo-transpire at the full rate of PET and false starts to the rainy season are eliminated. The beginning marks the transition from the dry period to the intermediate period when $0.5PET<R<PET$. A wet (humid) period is the period during which precipitation exceeds PET. The beginning and ending dates are the two points where the precipitation and PET curves cross. The end of the growing period occurs at the point where the precipitation curve crosses the one half PET curves.

The determination of the beginning of the growing period is based on the start of the rainy season. The first rains fall on soil which is generally dry at the surface and which has a large soil moisture deficit in the soil profile. In the absence of soil moisture reserves, seedbed preparation, seed germination and the initial growth of crops are therefore entirely dependent on the amount and frequency distribution of these early rains. According to Dastane (1974), the effectiveness of early rains increases considerably once precipitation is equal to, or exceeds half ET.

Berger (1989) qualifies the FAO (1978) criteria further by considering a 15-day period during which if the cumulative rainfall within five consecutive days is more than 20 mm, and the next 10 days also receive more than 20 mm, then the first day of the period marks the onset of rainfall. Similarly, rainfall cessation was defined as the time when precipitation falls below 0.5ET0. However, within the defined rainy season, intra-seasonal dry spells occur, and if crop-growing period extends beyond the rainy season, off-season dry spells occur that may affect the crop at maturity stage. These dry spells affect crop production depending on their timing and magnitude with respect to crop growth stages and sensitivity to water stress. Stephen *et al.* (2005) established onset windows for the long and short rains of Kenya by combining the FAO (1978) and Berger (1989) criteria as 5 - 18 March and 7 - 18 October respectively.

Stewart (1991b) defined the date of onset for RF as the first acceptable (risk-wise) point in time at which, assuming zero runoff, the new rains have wetted the soil sufficiently to germinate a newly seeded crop, plus a further amount of water which, when combined with assured rainfall to follow (at the selected level of risk), will fulfil the water requirements of the seedling crop until the initiation of rapid vegetative growth.

Stewart (1991a, 1995) has programmed a method for rainfall analyses oriented to identify and solidify onset criterion and dates. The program incorporates bare soil water balance algorithm requiring mean monthly PET (Hargreaves and Zamani, 1986) and soil water holding capacities. For Niamey, Niger, Stewart (1991b) defined onset as 40 mm of rainfall stored in the surface soil - a somewhat stringent requirement due to the high evaporation rates and temperatures. A year with an early onset is expected to have longer dry spells in the beginning of the rainy season, which might affect the crop negatively.

Stewart's (1991b) onset definition uses a critical date before which onset is not allowed unless a more demanding criterion is met (Kanemasu *et al.*, 1990). Thus, for each day before the critical date, an extra two millimetres of stored rainfall is required. On the other hand, for the Niamey, Niger, Sivakumar (1988) defined the onset of rainfall as the date after 1 May in which rainfall had accumulated over three consecutive days of at least 20 mm, and when no dry spell occurred (>7 days of no rain) over the next 30 days. The ending of the rainfall is taken as the date after 1 September in which no rainfall occurs for 20 consecutive days.

One important difference between the onset definitions of Stewart (1991b) and Sivakumar (1988) is that, in Stewart's (1991b) case, the predictor is the date of onset and in Sivakumar's (1988) case the onset date plus one month. In the latter definition, a possible onset is prevented from being a false one, up to one month afterwards. It is false if there is a long dry spell within this first month. The major weakness in this method is the near avoidance of a longer dry period that is commonly experienced in the SAT. This greatly reduces season length. In general, yields may suffer significantly with either a late onset or early cessation of the growing season, as well as with a high frequency of damaging dry spells within the season, making the rainfall distribution unreliable. This situation calls for at least the ability to predict effectively the actual start of the season (Ati *et al.*, 2002).

Stern *et al.* (1981) considered onset to be the first date of the year, on which the following three constraints are valid simultaneously: (1) A total of at least 25 mm of rainfall are observed within a five-day period; (2) The starting day and at least two other days in this five-day period are wet (at least 0.1 mm rainfall recorded); (3) No dry period of seven or more consecutive days occurring in the following 30 days.

Laux *et al.* (2008) utilized two fuzzy logic based definitions of the onset. The method uses daily precipitation data and accounts for important plant physiological aspects. Such definition adopts the accumulated rainfall approaches with site-scaled threshold values which were established by Stern *et al.* (1981) and modified later on by Sarria-Dodd and Jolliffe (2001), because it tended to give onset dates which were too late to be reasonable.

Sarria-Dodd and Jolliffe (2001) describe two different methodologies operating on different predictive time frames to predict the onset of the current rainy season on regional scale. The first approach employs linear discriminant analyses using simple rainfall indices and the second one employ Linear Regression Analysis using onset dates of regions with earlier onset to predict onset of neighbouring areas. Laux *et al.* (2008) and Sarria-Dodd and Jolliffe (2001) definitions are derived from the work of Stern *et al.* (1981).

The above assessments of literature reveals revealed a number of approaches that are followed in order to define the date of onset of rainy seasons (FAO, 1978; Sivakumar, 1988; Simane and Struick, 1993; Tadro *et al.*, 2005). These approaches consider only one criterion and are very stringent in nature. The approaches also tended to nearly avoid the risks that are commonly experienced in the wider semi-arid areas of the world (Kanemasssu *et al.*, 1990). Thus, they leave farmers with very short season duration with lower seasonal water. This relegates farmers to produce low yielding varieties in any given season. Thus, a multi-criteria-based definition of onset is realistic and vital since it will offer the chance for farmers to grow alternative varieties according to time of season onset.

The review revealed a gap in knowledge concerning valid predictors for the dates of onset that can be used to predict onset for specific locale. This calls for the need to develop predictive capacity for the date of onset in order to allow farmers to make sound strategic planning of farm operations.

2.8. Progress in Predicting Seasonal Rainfall

Stewart (1988a; b) presents ample evidence of predictability of main-season rainfall characteristics using the date of onset for Asia, Africa, Near East and North America. Other researchers (Sivakumar, 1988; Kanemasu *et al.*, 1990; Punyawardena, 2002) also provide similar accounts. More recently, Admassu (2004) also reported the date of onset to be good predictor of season duration. Stewart (1988a) and Admassu (2004) reported high degree of association between cumulative early season rainfall and eventual total season water especially for later onset. Such information has very significant practical implications in the semi-arid regions where the problem of within season variability is great. It enables farmers to minimize the effects of drought by making the most efficient use of the scarce rainfall in a poor (dry) season, and to capitalize on good seasons (Stewart, 1988a; McCown *et al.*, 1991; Punyawardena, 2002). However, studies in Sirilanka by Punyawardena (2002) found no clear evidence of the potential of the date onset as predictor of expected seasonal rainfall and season duration.

Across 20 locations in 11 countries in Africa, Asia, Near East, and North America, Stewart (1988a) has demonstrated the influence of the date of onset on essential crop season rainfall characteristics (season duration, amount and intensity). For all the locations, the date of onset was the most accurate predictor of season duration, and that the predictions are intermediate for seasonal rainfall and least accurate for intensity. The relationships between these factors and the date of onset were all practically valid to guide farmers in their crop management decisions.

The search for ways to predict seasonal rainfall more closely and/or earlier in time has been the goal of the WHARF foundation since early 1980's. Accordingly, for Hydrabad in India, winter/spring rains were found to be good predictors of the character of monsoon to come. On the other hand, for Kusum in Nepal, extremely light or heavy off-season rainfall were found to be predictors of the date of onset, amount of monsoon rainfall and season duration (Stewart, 1988a, b). Stewart (1988b) concluded that rainfall prior to onset coupled with actual date of onset may better indicate both time of onset and strength of the monsoon. He further indicated that intermediate off-season rainfall also predicts rainfall amounts, but only weakly predicts whether onset is early or late. In such cases, he reported that, predictability can be improved at the time onset actually occurs. However, for the Sahelian zone, Stewart (1991a) concluded that pre-season rainfall as a predictor in addition to date of onset does not significantly improve the predictions, as compared to onset date as the only predictor.

2.9. Farmers' Traditional Signals of the Onset of Rainfall Seasons

In the CRV of Ethiopia, dryland farmers use different indicators to forecast onset of planting season and drought expectations in the up-coming season (Admassu *et al.*, 2011a, b, c). They first ensure that rains have truly arrived using both rainfall amount and sustained change in wind flow from west to east that bring them rain. These two conditions must be simultaneously true, or else it's a false start of rains. Next, they check if rains have established. They insert the tip of ox-drawn *maresha* down into the soil to 25 cm depth, and check soil water condition, and declare onset if the tip is moist at that depth. They initiate planting if a ball of moist soil thrown up falls on the ground without dispersing. Nevertheless, in recent years, these farmers' predictions were reportedly in-efficient (Admassu *et al.*, 2011a, b, c).

2.10. Synthesis

Seasonal migration of the equatorial trough or the inter-tropical convergence zone (ITCZ) has been reported as the cause of spatial and temporal variations in rainfall in the SAT (Mamo, 2004). The atmospheric demand for water in the SAT is high particularly before or at the beginning of the rainy season. For semi-arid areas in Ethiopia, it is only during the rainy period of the year when the rainfall exceeds potential evapo-transpiration and the soil moisture reserves are fully recharged. Such a period when mean monthly rainfall exceeds potential evapo-transpiration is not more than 60 days (Admassu, 2004). High rates of evaporation coupled with low and variable rainfall in the SAT often lead to periods of water deficit and have serious implications for stability of crop production in this ecological zone (Kanemasu *et al.*, 1990). The length of the crop growing season in the SAT is limited by soil water holding capacities and other characteristics of the rainy period. The variability of rainfall at the end of the season is also high, affecting crop yields and their quality.

Crop production in Ethiopian dry lands is heavily dependent on rainfall, and thus it is a risky enterprise. Periodic drought occurs frequently, and this has been the cause of low crop yields and loss of human lives and of livestock. In particular, the start of the rains is not instantaneous. It is usually preceded by a succession of isolated showers of uncertain intensity with intermittent dry periods of varying duration. There may be false starts when the supposed onset is followed by prolonged dry spells whose duration may last for one, two or more weeks. This dries out the top soil and prevents the germination or emergence of plants or kills emerging seedlings. The calamities arise from intermittent initial rains at the start and periodic dry spells, and late onset and early cessation. In general, yields are low and crop failure is observed with either a late onset or early cessation of the growing season, as well as with a high frequency of damaging dry spells within the season.

Enhanced climate variability has rendered farmer's forecasting indicators ineffective. This has resulted in low productivity of traditional agriculture, and thus the threat of serious food shortages is looming. What is more frustrating today is climate change that will change the length and the quality of the growing season. Climate change projections show that climatic extremes will increase in frequency, and will form a fundamental challenge to agriculture. This situation calls for the ability to effectively predict the actual start of the season.

There have been many methods for estimating the average date of onset of the rains that may be taken as the start of the growing season. Most of the criteria applied appear to be so much dependent on the available data and the purpose of the study. The major feature of the definitions has been the commonality and differences in time scale of the data used and the geographical location of the study. Apparently, the most predominant criteria are rainfall amounts, soil water holding capacities, pre- and post-onset dry-spell expectations and the historical occurrences in rainfall and evaporative rates, and the types of crops and cultivars chosen to be grown in particular area. Most methods currently in use are varied and appear to be limited by stringent criteria. Some of the methods result in too short duration which significantly delay onset or cause early cessation of the growing season. Other methods cause high frequency of damaging dry spells within the season, making the rainfall distribution unreliable. This situation calls for at least the ability to predict effectively the actual start of the season.

There has been lack of efforts to establish a multi-criteria based risk-wise acceptable agronomic rainfall criteria, corresponding dates of onset, and predictors for the date of onset and seasonal rainfall parameters which would have led to alternatives that enables farmers to consider growing of different crop varieties according in seasons that vary in their dates of onset. There have been few successful efforts in developing predictors for onset using an already detected onset in another part of the region to predict onset for a neighbour. However, the value of such a regional scale predictions in reducing risk and increasing profitability at local scale is not yet ascertained. What is evident is lack of efforts devoted to identify predictors and develop functions to predict the dates of onset as it directly applies to impending season for a specific locale.

It is important to emphasize that the increase in food production in the future must be supported by more flexible, and multi-stage planned agronomic decision systems. Fortunately, today, climate change adaptation based on advanced knowledge of climate is receiving more attention (Rao *et al.*, 2011). The recognition of the value of climate forecast has brought important developments in minimizing cropping risks in the semi-arid areas. The most notable among this has been RF (Stewart, 1988a). Response farming technology offers use of better agronomic adaptation options to overcome climatic risks.

Traditional RF practices and field developments in RF appear promising to improve on farmers' adaptive responses. However, in RF planning starts at onset of the season denying sufficient lead time for farmers to prepare and respond. This appears to be a major factor limiting the adoption of the technology. Although, like any scientific method, RF methodology needs to benefit from continuing research, there is serious lack of research to improve RF. Thus, research is required to improve strategic and tactical RF through developing predictors for onset to facilitate the process of strategic planned adaptation. These should be grounded on sound understanding of the general agro-climate in defining risk-wise acceptable dates for which predictive capacity is required. This is believed to bridge the gaps of usually wide and coarse forecasts issued by meteorological agencies. Moreover, it would not be sufficient to predict onset date.

Predictive capability is also required for determinant main season rain behaviour parameters that can facilitate tactical management of in-season risks through making rapid changes in on-farm tactics. Such ability to predict the date of onset and determinant main season rainfall parameters can lead to use of yield-improving. Moreover, the potential of RF predictors in improving strategic and tactical decisions and in reducing failure and increasing yield should be confirmed at field scale. It will be in this way that farmers can be assisted in making sound strategic and tactical decisions. This study was sought to bridge the crucial gap that exists - lack of locally valid spatially explicit predictors that can facilitate the process of proper strategic planning of agronomic operations and tactical management of in-season risks. The ultimate aim is to improve strategic and tactical response farming of maize so as to ensure food security under the semi-arid areas of Ethiopia.

CHAPTER THREE

3.0 MATERIALS AND METHODS

3.1. The Central Rift Valley of Ethiopia and the Study Sites

3.1.1. Climate and soils of the Central Rift Valley

The study was carried out in the semi-arid areas of the CRV of Ethiopia. The CRV is tectonically formed depression bounded by two major and parallel escarpments that split the Ethiopian highlands and lowlands. The floor of CRV is dotted with mountains and many alkaline lakes (Reddy and Kidane, 1994).

The broad characteristics of the climate, with its recurring wet and dry seasons, are determined largely by the annual movements across the country of equatorial low pressure zones. The dry north-easterly winds and the moist winds of south-westerly origin typify the dry and wet season climate patterns of the CRV respectively (Mamo, 2004). The CRV of Ethiopia is characterized by erratic and undependable seasonal rainfall that is exceeded by potential evapo-transpiration (Simane and Struick, 1993). In the CRV, the maximum temperatures are uniformly high throughout the year. The relative humidity is also high during the growing season and lower during rainless periods. Sunshine hours except during the growing period are long. Strong winds and high evapo-transpiration triggered by high temperatures that exceed 25°C during the rainy season exacerbate soil moisture stress. Thus, drought is the most pressing problem causing frequent crop failure (ICRA, 1999).

The soils of CRV are of sandy loam texture with pH ranging from slightly acidic to very alkaline. Nearly all the soils of the area are degraded (Reddy and Kidane, 1994). Adverse physical properties such as weak structure, high bulk density, surface sealing and hardpan formation are the indications of the land degradation in the CRV region. Low organic matter, essential and trace nutrients, low water retention and infiltration capacity are the main characteristics of the soils. In some places, toxic heavy metals are also reported (Itana, In press). In the semi-arid CRV of Ethiopia, erratic rainfall, high temperatures, strong winds with poor water holding capacity of soils causes severe moisture deficit to crops (Reddy and Kidane, 1994).

3.1.2. Research sites

3.1.2.1. Location of weather stations in the study sites

Two study sites located within the CRV viz. Melkassa Agricultural Research Centre (MARC or Melkassa) and Adami Tulu Agricultural Research Centre (ATARC or Adami Tulu) representative of wider semi-arid areas were selected. The CRV region, and the study sites and location of weather stations are shown in Fig. 1: and Table 2 shows the exact geographical locations of weather stations, the time period and number of years of data studied.

Table 2: Locations of meteorological stations, the study sites and data used for the study

Location	Latitude	Longitude	Altitude (m a.s.l)	Period	No of years of data studied
MARC	08°.14'	039°.34'	1578	1977 - 2008	32
ATARC	07°.65'	038°.85'	1698	1977 - 2008	32

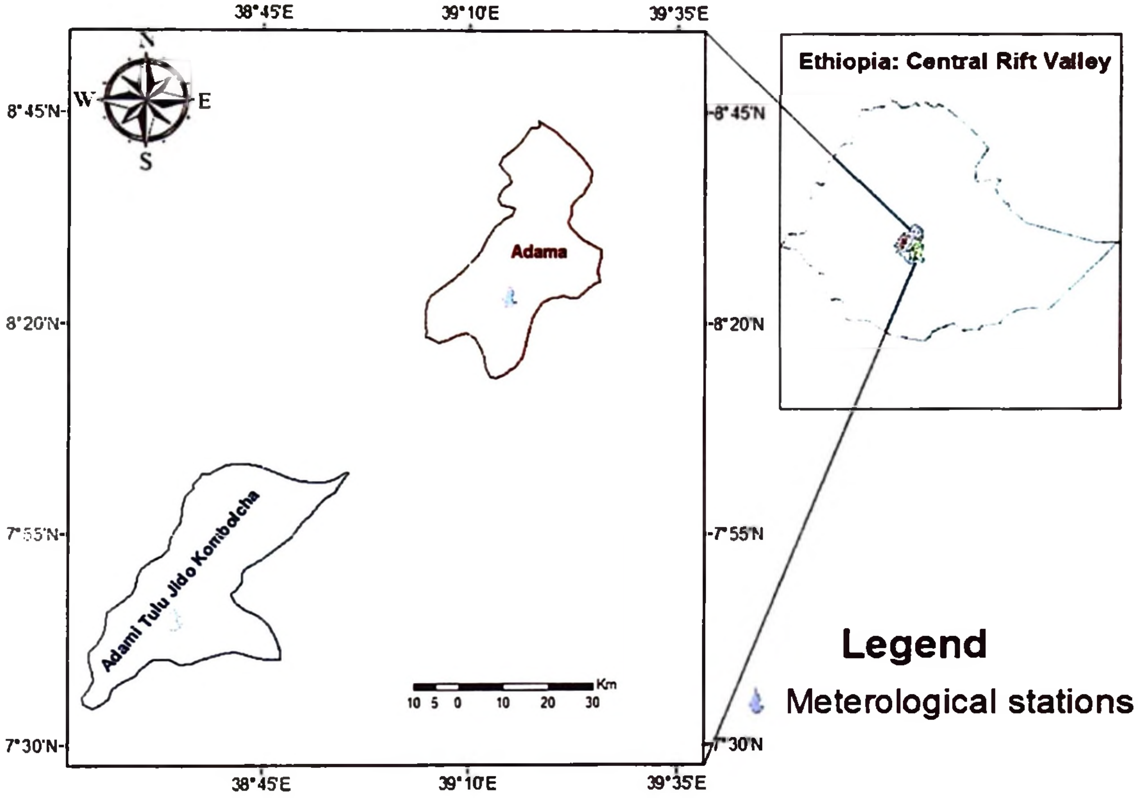

Figure 1: Map of Central Rift Valley region of Ethiopia showing the two study sites and location of meteorological stations

(**Source**: Gizachew, Unpublished)

3.1.2.2. The climate of the study sites

Tables 3 and 4 respectively list statistics of mean and annual total rainfall recorded at MARC and ATARC during 1977 - 2008. Both Tables show persistence of rainfall at the two study sites throughout the year, and exhibit of tremendous variability. It is this variability that underlies major crop production risks in these areas.

Tables 5 and 6 show uniformly higher maximum temperatures and evaporative rates especially during January through May which can cause higher evaporative losses of rainfall received during this period. Evaporative rates are generally lower than mean monthly rainfall during late June to August. Winds at both locales particularly at ATARC are strong (Allen *et al.*, 1998).

Table 3: Monthly and annual rainfall statistics of Melkassa (mm)

Statistic	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
Mean	15	23	61	55	56	62	188	198	94	33	9	10	803
Maximum	59	110	152	162	204	128	335	326	201	146	95	58	1 129
Minimum	0	0	0	0	1	3	72	90	41	0	0	0	501
C.V. (%)	115	114	69	60	95	60	33	26	44	132	247	175	17

(**Source**: Own computation based on MARC database)

Table 4: Monthly and annual rainfall statistics of Adami Tulu (mm)

Statistic	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
Mean	14	32	48	83	80	77	137	141	81	35	18	5	751
Max	82	152	185	211	225	224	347.8	300	199.4	177	291	42	1 271
Min	0.0	0.0	0.0	2.2	0.0	14	30	57	7.0	0.0	0.0	0.0	386
C.V. (%)	155	127	87	66	75	62	50	41	61	128	346	216	28

(**Source**: Own computation based on MARC database)
Note: Max = maximum; Min= minimum

Table 5: Statistics of other climatic parameters for Melkassa

	Temperature (°C)			RH	Wind speed (2 m)	Sunshine duration	ETo (mm
Statistic	**Min**	**Max**	**Average**	**(%)**	**(m sec^{-1})**	**(h)**	**day^{-1})**
Mean	13.8	28.6	21.3	54	2.8	8.3	3.6
C.V. (%)	14.8	5.2	6.38	14.2	13.7	10.5	7.2
Minimum	10.7	26.2	19.5	46.0	2.0	6.8	3.2
Maximum	16.3	30.8	23.5	69.0	3.0	9.4	4.0

(**Source**: Own computation based on MARC database)
Note: Min= minimum; Max = maximum; RH = relative humidity

rainfall received during this period. Evaporative rates are generally lower than mean monthly rainfall during late June to August. Winds at both locales particularly at ATARC are strong (Allen *et al.*, 1998).

Table 3: Monthly and annual rainfall statistics of Melkassa (mm)

Statistic	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
Mean	15	23	61	55	56	62	188	198	94	33	9	10	803
Maximum	59	110	152	162	204	128	335	326	201	146	95	58	1 129
Minimum	0	0	0	0	1	3	72	90	41	0	0	0	501
C.V. (%)	115	114	69	60	95	60	33	26	44	132	247	175	17

(**Source**: Own computation based on MARC database)

Table 4: Monthly and annual rainfall statistics of Adami Tulu (mm)

Statistic	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
Mean	14	32	48	83	80	77	137	141	81	35	18	5	751
Max	82	152	185	211	225	224	347.8	300	199.4	177	291	42	1 271
Min	0.0	0.0	0.0	2.2	0.0	14	30	57	7.0	0.0	0.0	0.0	386
C.V. (%)	155	127	87	66	75	62	50	41	61	128	346	216	28

(**Source**: Own computation based on MARC database)
Note: Max = maximum; Min= minimum

Table 5: Statistics of other climatic parameters for Melkassa

	Temperature (°C)			RH (%)	Wind speed (2 m) (m sec^{-1})	Sunshine duration (h)	ETo (mm day^{-1})
Statistic	Min	Max	Average				
Mean	13.8	28.6	21.3	54	2.8	8.3	3.6
C.V. (%)	14.8	5.2	6.38	14.2	13.7	10.5	7.2
Minimum	10.7	26.2	19.5	46.0	2.0	6.8	3.2
Maximum	16.3	30.8	23.5	69.0	3.0	9.4	4.0

(**Source**: Own computation based on MARC database)
Note: Min= minimum; Max = maximum; RH = relative humidity

Table 6: Statistics of other climatic parameters for Adami Tulu

	Temperature (°C)						
Statistic	**Min**	**Max**	**Average**	**RF (%)**	**Wind speed (2 m) (m sec^{-1})**	**Sunshine duration (h)**	**ETo (mm day^{-1})**
Mean	12.9	27.5	12.9	58.4	7.3	8.0	3.6
C.V. (%)	13.2	5.7	13.8	12.2	17.9	14.7	6.9
Min	10.2	24.5	14.9	51.0	5.0	5.6	3.2
Max	14.9	29.8	10.2	71.0	10.0	9.5	4.0

(**Source**: Own computation based on MARC database)
Note: Min= minimum; Max = maximum; RH = relative humidity

3.1.2.3. Soils of the study sites

Characteristics of soil presented in Appendix 1 and 2 are based on samples collected at 0 - 15, 15 - 30, 30 - 45, and 45 - 60 cm depths from three randomly selected maize fields that were located in the study sites. Appendix 1 and Appendix 2 show particle size fractions quantified by Bouyoucos hydrometer method (Gee and Bauder, 1986) and textural class determined using the USDA textural triangle (USDA, 1975), soil water content at Permanent Wilting Point (PWP) and Field Capacity (FC) determined using Pressure plate apparatus and 50 ml burette, and Available Water Capacity (AWC). Both Appendices show that the soils in the study sites are generally poor both in organic matter content and water holding capacity. These characteristics contribute to periodic water stresses in the study sites.

3.1.2.4. Maize production in the study sites

In the vicinity of MARC and ATARC, maize is a staple food crop, but frequently suffers from moisture stress in different growth stages (Ransom *et al.*, 1997; Admassu *et al.*, 2011a, b, c). Thus, at both localities, maize productivity is generally very low; averaging 0.8 t ha^{-1} for short-term maize, 1.0 t ha^{-1} for medium, and 1.6 t ha^{-1} for long term cultivars due to erratic rainfall. Admassu *et al.* (2011a, b, c) describe three maturity groups of maize grown in the study sites. The longer-term cultivars are favoured by farmers because, in years with early onset with better rainfall, they produce higher yields than those that are sown late and mature sooner (Fujisaka *et al.*, 1996; ICRA, 1999).

The above presented climatic and soil characteristics of the study sites typify high risk agricultural systems of the SAT (Kenemassu *et al.*, 1990). This makes agricultural venture a very risky enterprise. The general sensitivity of the agro-ecosystems of the study sites and the low resource base of the farmers (Admassu *et al.*, 2011a, b, c) make the sites representative of the majority of dryland situations in the country.

3.2. The Research Plan

The methodological procedures that were followed in order to achieve the study objectives are summarized in Fig. 2. To begin the search for risk-wise acceptable date of onset, a multi-factor based definition that accounted for climate, soil types, farmers definition of rainfall and RF practices, crop varieties and Stewart's definition of onset for RF was adopted. First, effective rainfall analyses (Dastane, 1974) was conducted on mean monthly rainfall using CROPWAT ver. 8.0 (Smith, 1992). Based on effective rainfall-evapo-transpiration (ETo) relationship study (FAO, 1978), effective rainfall start and end dates were pinpointed. Probabilities of dry spells and expected rainfall amount were computed to assess risks associated with the identified effective rainfall start dates for starting of crops (Stern *et al.*, 2002). Based on the assessments of the risks, potential onset dates were identified for further evaluation. The evaluation of the identified dates was carried out using WHARF program (Stewart, 1995). Onset dates for which predictive capacity were required were determined based on the evaluation impacts of seasonal rainfall amount, dry spell of different lengths and season duration on three maize varieties. Then, predictors for the date of onset and seasonal rainfall parameters were identified based on exhibit of their variability and time of their occurrences of pre-onset rainfall parameters. The predictors were then used to develop prediction models for the date of onset and seasonal rainfall parameters. Off-season rainfall was used to develop prediction models for post-onset rainfall amount. Moreover, cumulative early season rainfall amount were used to develop prediction models for thinning time and for mid- to late-season rainfall amount. Finally, the performances of the developed predictors were evaluated at 55 on-farm sites during 2010-11 cropping seasons.

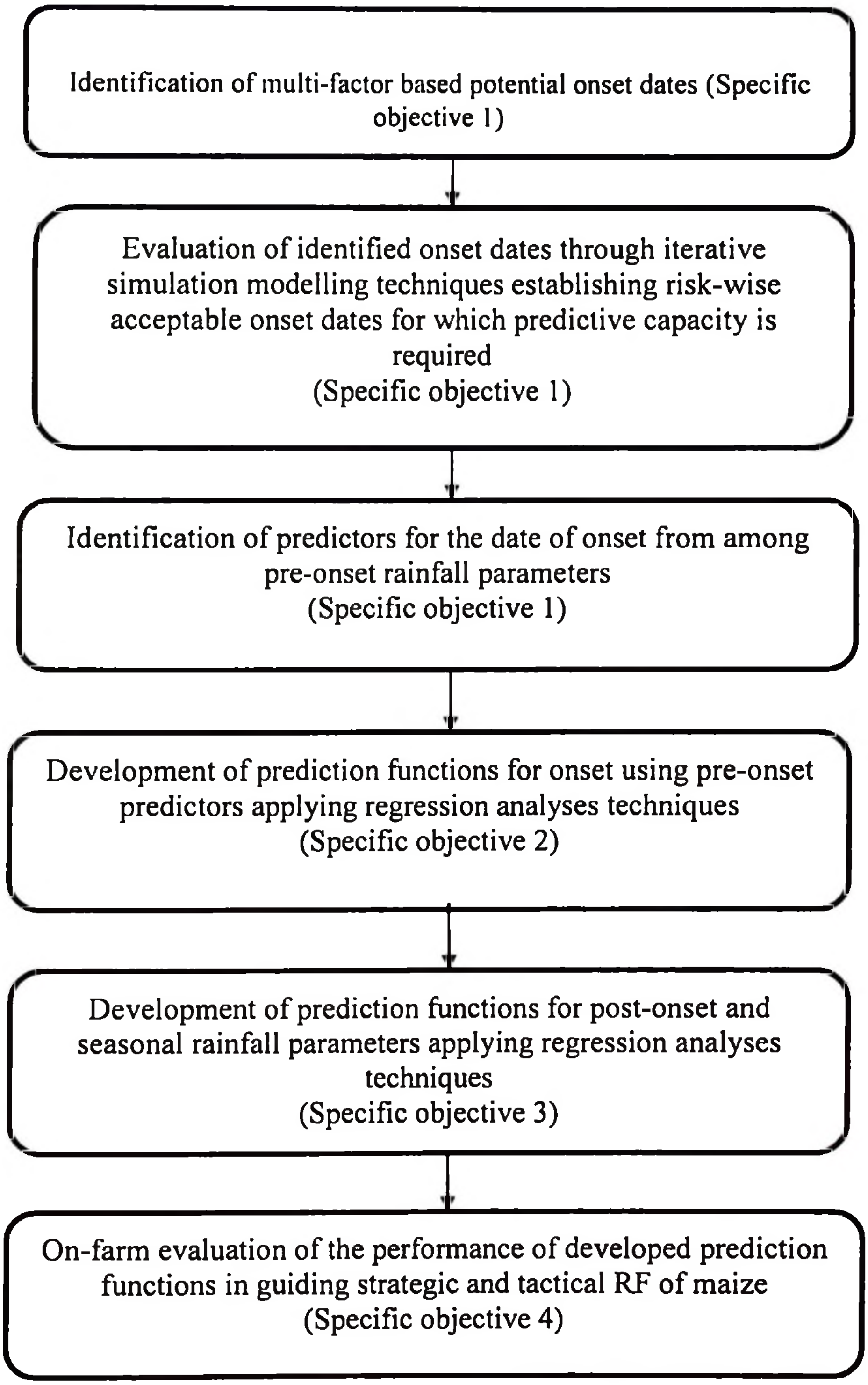

Figure 2: The stages in implementation of the research

3.3. Establishing the Dates of Onset, Rainfall Criteria and Predictors for Date of Onset and Seasonal Rainfall Characteristics

This section was concerned with specific objective one which was aimed at establishing a multi-factor based agronomically risk-wise acceptable dates of onset and corresponding rainfall criteria, and the identification of predictors for the established date of onset and seasonal rainfall parameters. It was pursued in a series of steps: identification of effective rainfall start dates, onset dates and corresponding rainfall criteria through effective rainfall-evapo-transpiration relationship studies, analyses of probabilities of dry spell and expected rainfall, evaluation of identified onset dates and rainfall criteria for onset through assessing the impacts of onset dates and onset criteria on maize production in general and in-depth evaluation of their impacts on different maize varieties applying simulation modelling techniques. Finally, based on statistical analyses of pre-onset rainfall behaviour parameters, predictors for the date of onset and seasonal rainfall were identified. The details of each step are presented in the following sections.

3.3.1. Identifying effective rainfall start and end dates, and the dates of onset of cropping seasons, and rainfall criteria for onset

3.3.1.1. Assessing effective rainfall-evapo-transpiration relationship

To begin the search for potential rainfall onset dates and rainfall criteria for which predictive capacity was required, mean monthly rainfall amount was used to determine effective rainfall (Dastane, 1974) for each of the months applying fixed percentage method as programmed in CROPWAT (Smith, 1992).

For agricultural production purpose, effective rainfall refers to that portion of rainfall that can effectively be used by plants because part of the rainfall available to the crops is lost through runoff and deep percolation. Rainfall is highly effective when little or no run-off takes place. Small rainfall amount are not very effective as these are quickly lost to evaporation (Dastane, 1974). In this study, the months which received effective rainfall exceeding 15 mm were taken as a start dates of effective rainfall that provide soil water build up for onset under the climatic and soil conditions of the two study sites.

In order to pinpoint the potential dates of onset following receipt of effective rainfall on those dates, CROPWAT was used to compute ETo (reference crop evapotranspiration or evaporating demand of the atmosphere) for each of the 12 months using mean minimum and maximum temperature, relative humidity, wind speed and duration of sunshine. The 0.5ETo and 0.33ETo values were computed from the calculated mean monthly ETo values using EXCEL.

The 0.5ETo threshold has been applied by the FAO (1978) in defining the date of onset. The half ETo threshold level was thus included in this study to determine its feasibility in defining the most risk-wise acceptable dates of onset and the degree of flexibility for risk management it provides. Thus, at this threshold level, the maximum cropping season length and the amount of total seasonal effective rainfall possible for production of different maize varieties were evaluated in order to determine the most risk-wise acceptable dates of onset. The 0.33ETo level was included in the study taking the risks that are commonly experienced in the semi-arid areas into account. It was also included in the study because crop water needs during early growth stage are low (Frère and Popov, 1979). Another important rationale for the choice of this threshold value was the desire for early starting of crops in order to benefit from potentially longer season duration and high water total effective rainfall that can be attained. Obviously, this lends itself to risks but provides maximum flexibility for strategic and tactical management of risks. The threshold level also matches with the concept underlying the development of RF methodology which seeks to provide maximum season length and corresponding flexibility for combination production of different crop varieties. Consequently, at 0.33ETo levels, it was assumed that long season crops could be started early (accepting an earlier risk-wise date of onset). A switch to medium maturing maize was assumed possible during median onset seasons when earliest sown crops fail or the sowing of early maturing maize during the time when effective rainfall exceeds the 0.5ETo and the full ETo levels. This finds agreement with basic tenets of traditional farmer's definition of rainfall and dates of onset and risk attitudes and their RF practices (Fujisaka *et al.*, 1996; ICRA, 1999). Thus, the consideration of 0.33ETo level lent itself to possible risks that are prevalent in the drier areas.

For both study sites, graphs that related mean monthly rainfall total, mean monthly effective rainfall to the mean monthly total ETo, 0.5ETo and 0.33ETo were developed. The graph was visually inspected to determine earliest risk-wise acceptable dates of onset to be considered for further study of their impacts for safe starting of crops. Daily rainfall was then summarized into monthly dekadal total rainfall using EXCEL. The values were then taken as rainfall criteria corresponding to the identified dates of onset.

3.3.1.2. Analyses of dry spell and expected rainfall

In order to assess risks associated with starting of crops during the identified onset dates, occurrences of dry spell of various lengths and expected rainfall amount were determined using *Instat+* software (Stern *et al.*, 2002) that applies a first-order Markov chain model. Probabilities of dry spell were determined taking a dry day as a day receiving less than 2 mm rainfall. This threshold value is recommended since moisture available below half of the daily potential evapo-transpiration of crops is considered inadequate for important physiological processes (Dastane, 1974).

3.3.2. Evaluation of the identified onset dates and rainfall criteria for onset

3.3.2.1. Assessing the general impacts of the date of onset on maize production

Simulation analyses were conducted on the 32 years (1977 to 2008 inclusive) of daily rainfall data for each of the locations using the WHARF agro-climatic analytical and simulation modelling program (Stewart, 1995).

The evaluation of the impacts of the date of onset on maize production was carried out accepting onset as early as April to as late as early July using the analytical input factors presented in Table 7. Then, the impacts of the designated onset dates and criterion on production of three maize varieties were assessed. Using the WHARF program analytical inputs in Table 7, two steps were followed in the analyses for evaluation of the identified onset dates and criteria. The first was concerned with general characterization of historical rainfall behaviour as limited by dates of onset and rainfall criteria. The second evaluation of the identified dates was carried out in order to determine the impacts of the dates and rainfall onset criterion on three maize varieties applying simulation modelling techniques using the WHARF program.

Sequencing of simulation modelling to assess the impacts of identified dates

In order to determine the rate of success of each in each of the study varieties in each of the past season based on the adequacy of TSW and season duration, the simulation modelling was carried out assuming post-onset planting of maize varieties maturing within 150, 120 and 90 days. The risks to the three maize varieties from too short season duration was assessed assuming minimum desired season length to mature the different maize varieties.

According to Stewart (1995), the growing period continues beyond the rainfall season since crops often mature on moisture reserves stored in the soil profile. Thus, soil moisture holding capacity is determines the length of crop growing period (Stewart, 1995). This provides the basis for assumption of minimum desired season duration for different crop varieties that the rainfall can be allowed to cease before they mature. Accordingly, minimum season duration of 125 days was assumed sufficient for 150 days maize variety, 100 days for 120 days maize and 70 days for 90 days maize. Moreover, the risks from too little TSW supply were assessed by comparing seasonal crop water requirements as determined using CROPWAT against TSW. Then, probabilities for production of the three maize varieties were determined for different onset dates (April, May, June and July). The dates of onset and corresponding rainfall criterion providing the greatest chance of success and maximum flexibility for production of the three maize varieties were determined as the most risk-wise acceptable dates of onset for each study site.

Description of WHARF agro-climatic analytical and simulation modelling program

The WHARF program was chosen because it meets the stated objectives of the research. The program integrates modules for characterization of daily rainfall and simulation study of post-onset and dry-planting scenarios. The WHARF program is easy to use and demands less data as compared to other simulation models. The program incorporates distinct algorithms that enable evaluation of rainfall risks in different crop production scenarios and crop growth sequences (Stewart, 1995). The program begins with a bare soil water balance sequence, which determines the effective start of each season of record.

The first algorithm of WHARF program designated as F1 enables assessments of the general behaviour of historical water supplies on crop production. Thus, the program does not account for losses to soil surface runoff and/or deep percolation. The WHARF program determines dates when onset and/or germination conditions are met, and estimates actual stored soil water on those dates. Users define the soil water conditions that constitute onset for cropping, and rainfall intensities (daily averages) marking the effective end of the rainfall season. This provides the basic water/time information required for initial judging of suitable crop types and cultivars. It also provides initial information on seasonal rainfall behaviour that could pose risks, such as early season weakness in rainfall, early cessation of rainfall, or very dry or overly wet periods in the crop production period.

The second WHARF program algorithm designated as F3 emulates the water situation when sowing is done as deemed feasible after attainment of specified onset conditions. WHARF F3 requires setting up of the first acceptable date of soil water accumulation, first acceptable onset, first normal onset, the last acceptable onset, soil-water conditions that constitute onset for cropping, germination criterion, rainfall intensities, effective end of rainfall season, the last search date for final rainfall, final rainfall criterion and a minimum season-end intensity index. The time period required for sowing is also specified as a given number of dry days defined in terms of tolerable maximum rainfall that will allow planting to proceed. The program assumes germination to follow on the first day that seedbed water conditions are adequate.

The second part of the analysis enables assessments of water supply impacts that influence crop production in different growth stages. The program outputs total seasonal rainfall, and divides the total seasonal water into 14 periods. The length of each period is dependent on the length of each growth stage of the cultivar being studied. Thus, the user can specify the number of days per period. This allows evaluation of water supply impacts facing each of the test cultivars in each growth stage.

WHARF program analytical inputs

The first acceptable date soil water accumulation is the earliest date that rainfall (if any) is to be considered in the soil water balance, leading up to attainment of onset as defined for cropping purposes. First acceptable onset date is the earliest date of onset that is accepted regardless of soil water status. First normal onset date is the earliest date onset may be accepted with the user specified onset criterion. Earlier acceptable onset requires additional soil water build-up, automatically calculated in the soil water balance algorithm of the WHARF program. The last acceptable onset date is the final date that onset is acceptable for growing the planned crop and/or cultivar, after which changes must be made in crop/cultivar choices. The last search date for final rainfall is normally selected based on study of season end rainfall when the crop matures at the study localities. Onset criterion is designated as the amount of rainfall that is required in the seedbed, sufficient to germinate crop seed and sustain seedlings through commonly experienced early dry spell (35 - 40 days after sowing) (Stewart, 1995).

Final rainfall criterion is specified as the amount of rainfall during the final rainfall days, sufficient in quantity, and intensity to count as effective crop seasonal water. Minimum end of season rainfall intensity is the average intensity over the final in-season rainfall days to be counted as effective. The WHARF program determines the last rainfall day of a specified amount or more, on or before the last search date, and then search back until prior rainfall totalled the specified final rainfall criterion. For this study, the last search date for final rainfall date was determined based on effective-rainfall-ETo relationship study.

WHARF program requires daily rainfall and daily average evaporative rates (PET) on monthly basis. Thirty two years of daily rainfall data (1977 - 2008) was obtained from MARC data base for each of the study weather stations. The data was entered into data storage module of the WHARF program called WHARFDAT. Thirty-two years (1977 – 2008) of MARC and 20 years of ATARC (1985 - 2005) daily pan evaporation (Epan) data (from Class A type pan well screened with a 25 mm square mesh and sited in 20 m by 20 m well grassed area which dries out in October, and in some years in November) were also obtained from MARC climate database. Corresponding PET values were computed by adjusting recorded Epan using a standard pan factor or pan coefficient (Kp) of 0.7 (Kaihla, 1983). The resulting PET data were summarized into daily averages for each month using EXCEL and were used as an input to the WHARF program. Soil water holding capacity at field capacity at 30 cm soil depth was determined from soil data presented in Appendix 1 and Appendix 2. The data were entered into the WHARFDAT.

WHARF program analytical inputs

The WHARF program analytical input factors presented in Table 7 were derived based on ETo-effective rainfall relations and dry spell probability analyses described under Section 3.3.1.2.

Table 7: WHARF simulation program analytical inputs

Description of analytical inputs	MARC	ATARC
The first acceptable date of soil water accumulation	1 January	1 February
The first acceptable onset	1 April	1 April
The first normal onset	10 April	10 April
The last acceptable onset	10 July	10 July
The last search date for final rainfall	30 September	30 September
Onset criterion (mm)	20.9	21.4
Final rainfall criterion (mm)	92.5	72.6
Minimum season-end intensity index (mm day^{-1})	3.1	2.4
Water holding capacity at field capacity (mm)	99.0	80.0
Soil texture	Clay loam	Fine sandy loam

WHARF program analytical outputs

For each of the past seasons of the data analyzed, WHARF program outputs seasons during each of the studied years that met the designated onset dates and criteria. These include dates of onset and actual water amount stored in the 15 cm and 30 cm soil layers, pre-onset rainfall parameters (the first effective rainfall date, the amount of pre-onset rainfall and actual evaporative losses of pre-onset rainfall). In this analysis, the first effective rainfall date was taken as the initial date when rainfall exceeding 15 mm was received. This amount was accepted as having contribution for soil water build up on and after the designated onset date. Pre-onset rainfall amount is the total amount of pre-season rainfall received from the first effective rainfall date to the designated date of onset. Actual evaporation (Eact) is the amount of pre-onset rainfall lost to evaporation.

The WHARF program also determines seasonal rainfall parameters. These include the duration of rainfall season which is the total number of days (having rainfall regardless of amount) in the rainfall period from date of onset to final rainfall date. When referring to specific cultivar maturity, it is defined as the number of days having rainfall, regardless of amount, in the period beginning the day following germination and ending on (including) the final rainfall date. While rainfall record is evaluated for overall crop production potential, the season (each year separately) is the period of time, which begins on the date of onset and ends on the final rainfall date. However, when the analysis is for production of a specified crop, the season begins either on the date of onset or the crop germination date and ends on the final rainfall date or crop maturation date. The rainfall season duration is the key factor in deciding on maturities of cultivars to be grown in the study sites rainfall regimes (Stewart, 1995). The final rainfall date is defined as the last date in the crop season on which that day's rainfall amount is sufficient to sustain average season wetness in the preceding dry (or nearly dry) days. It denotes the last rainfall that effectively augments the crop water supply.

In-season rainfall is the actual amount of rainfall received from the date of onset until the final rainfall date (excluding that stored at onset). The amount of total seasonal water (TSW) (the sum of total water stored at onset and in-season rainfall) is the gross cropping season water supply which crops might utilize. Intensity index denotes average season wetness calculated by dividing TSW by duration.

The number of rainfall days in the crop season is defined as the total number of days having rainfall, regardless of amount, in the period beginning the day following the date of onset, (or crop seed germination date when referenced to a particular crop cultivar), and ending on (including) the final rainfall date. Other WHARF program outputs are the number of season heavy rainfall days exceeding 100 mm, number of season heavy rainfall days with 75 - 100 mm, 50 - 74 mm, and 25 - 49 mm, total number of season dry days, number of season dry days exceeding 31 days, number of consecutive season dry periods of 20 - 29 days, 10 - 19 days, and 0 - 9 days.

3.3.2.2. In-depth evaluation of the impacts of the date of onset on the success rate of different maize varieties

In-depth evaluation of the risks from too short season duration, too little seasonal total water supplies and dry spells of various lengths in different crop growth stages of the different maize maturity types was conducted using the WHARF program algorithm designated by F3. The algorithm simulates post-onset planting scenario and enables assessments of water supply impacts that influence crop production in different growth stages. The program outputs years with the date of onset chronologically sorted by the date of germination with corresponding stored soil water at onset and dates of germination, rainfall in different periods with total seasonal rainfall. The program allows division of the total seasonal water into a maximum of 14 periods as desired. The length of each period (each growth stage of the variety studied), and the number of days per period are specified according to the number of days of each growth stage of the studied varieties. This allows evaluation of water supply impacts facing each of the study varieties during each growth stage.

CROPWAT was used to calculate seasonal ETc (crop evapo-transpiration or crop water supply needs) and for each of crop growth stage. Crop coefficients values for the whole season and for each of the different growth stages of each maize variety were obtained from world standard FAO published figures (Doorenbos and Pruitt, 1977). The actual water use by the crop (ETa) for each of the past seasons was calculated by multiplying the total gross seasonal water supply by 0.6 (assuming that the crop would utilize 60% of gross available water). Water Adequacy Ratio (WAR) was determined as a ratio of the calculated ETa to ETc. The WAR enables assessments of the degree of satisfaction of crop seasonal water needs (Stewart and Hash, 1982). For maize, WAR between 0.75 - 1.00 is considered adequate water to realize maximum yield, and WAR between 0.50 - 0.74 implies moderate (fair) amount of water available that enables average (normal) yield level, whereas WAR in between 0.00 - 0.49 implies insufficient water available to the crop, thus the crop suffers water deficit and poor yield or possible crop failure is assumed. Accordingly, WAR was used to determine the degree of success of the study varieties with respect to their satisfaction of seasonal water needs.

First, season duration in each of the past seasons as determined by the WHARF program were compared to the minimum desirable season duration of each of the three varieties studied. Based on minimum desired season duration, the degree of success for producing each of the study variety was determined. Based on the degree of risks from water deficits experienced by the designated variety in the various growth stages, and season duration in each past season, percentage probabilities of success for producing the different maize varieties at each of the study sites were determined. Finally, based on the probabilities, agronomically risk-wise acceptable onset dates and corresponding rainfall criterion for the three varieties were established. These dates were then taken as dates for which predictive capacity was required.

3.3.3. Identifying predictors for the date of onset and seasonal rainfall characteristics

For the identified dates of onset, predictors were sought from among the different pre-season rainfall parameters through study of their descriptive statistics. Thus, those that exhibited greatest inter-seasonal variability much more than the date of onset were selected for further study to determine their potential for use as predictors for the date of onset and other seasonal rainfall behaviour parameters.

3.4. Developing Prediction Models for the Date of Onset of Next Season

This section was concerned with specific objective two of the study that was aimed at developing prediction functions for the date of onset in order to improve strategic response farming.

Statistical analyses

MINITAB ver. 14 statistical packages (MINITAB Incorporated, 2009) was used for regression analyses. The date of onset was regressed on the various pre-onset rainfall parameters described under section 3.3.2.1 using linear regression techniques. Detailed description of MINITAB and output parameters is presented in Appendix 3. MINITAB assumes the dependent variable y as a linear function of an independent variable x plus an error ε introduced to account for all other factors using the 'least squares methodology' which minimizes the sum of squares of the error term in the equation. Non-linear regression analyses were thus conducted for modelling curvatures in the relationship between a response variable and a predictor variable when non-linearity was implied by MINITAB. Accordingly, polynomial regression analyses of order two and three were applied using MINITAB which calculates regression analyses by extending the simple linear regression model to include X^2 and X^3 as predictors.

The statistical software enables assessments of model predictive ability via testing the goodness-of-fit between the predicted and the observed values of the predictand using the developed model enabling conclusion regarding the use of the model in operational forecasting. Accordingly, MINITAB applies a one-year-out cross validation technique to determine prediction models capability in reproducing the observed series (Wilks, 1995).

The statistical software also outputs prediction interval and confidence interval of the prediction. Prediction interval represents a range that a single new observation is likely to fall given specified settings of the predictors. Confidence interval of the prediction represents a range that the mean response is likely to fall given specified settings of the predictors.

Analysis of goodness-of-fit between observed and model generated data for polynomial functions were performed using curve fitting toolbox programmed in MATLAB ver. R2013a (The MathWorks Incorporated, 2013). By default, the program outputs the goodness-of-fit statistics that enable model evaluation and selection. These include the adjusted R^2 value, the standard error (SE) of the regression model or the root mean squared error (RMSE) statistics and the 95% prediction bounds. A final conclusion about model capabilities was thus based on graphical examination of the fit, and these goodness-of-fit measures.

Determination of prediction error is crucial especially for practical use of the model. For each of the developed models, prediction error was calculated by dividing the mean value of the predictand by the SE of estimated regression equation and multiplying by 100 to obtain the mean absolute percentage error.

3.5. Developing Prediction Models for Seasonal Rainfall Characteristics

This section dealt with specific objective three of the study that was aimed at developing prediction models for seasonal rainfall in order to improve tactical response farming. The steps included developing of prediction models for season duration, total seasonal water supply, post-onset rainfall and thinning time and mid- and late-season rainfall.

3.5.1. Developing prediction models for season duration and total seasonal rainfall

Prediction models for season rainfall parameters were developed by regressing season duration and total seasonal water supplies on the date of onset applying the statistical tools and procedures described under section 3.4 and Appendix 3.

3.5.2. Developing prediction models for post-onset rainfall using the amount of dekadal off-season rainfall

Together with the ability for predicting the date of onset and season duration, it was also found important to develop prediction models that can be used to determine the expected post-onset rainfall amount for the purpose of strategic and tactical response farming ahead of the actual onset dates. Accordingly, daily off-season rainfall data was summarized in to dekadal total using EXCEL for different dekads of October through March. Then, MINITAB was used for regression analyses in order to develop prediction models for post-onset rainfall using off-season rainfall amount.

3.5.3. Developing prediction models for thinning time and mid- to late-season rainfall using the amount of cumulative in-season rainfall

Prior knowledge of expected thinning time and post-thinning rainfall are critical to facilitate in-season and mid- to late-season tactical management of risks. Thus, in order to facilitate decisions on plant stand and use of additional fertilizer at the time of thinning (40 to 50 days after sowing) and to enable mitigation of dry spell risks that might arise during mid- and late-season, cumulative rainfall (as determined by WHARF program analyses) was exported to MINITAB for regression analyses. Accordingly, for MARC, 20 days cumulative rainfall was used for developing prediction models for 30, 40 and 50 days rainfall, and 30 days rainfall was used for developing prediction models for 50 days rainfall amount, and 40 days rainfall was used for developing prediction models for 60, 90, 100, and 110 days rainfall amount. Similarly, for ATARC, 20 days rainfall was also used for developing prediction models for 30, 40, 50, 60 and 90 days rainfall. On the other hand, 40 days rainfall was used for developing prediction models for 70, 80, 90, 100 and 110 days rainfall amount.

3.6. Evaluation of On-farm Performance of the Developed Prediction Models

This section addresses specific objective four of the study that was aimed at evaluation of on-farm performance of the developed predictors in guiding strategic and tactical response farming and in improving maize yield under semi-arid conditions. The evaluation of the performance of the strategies were carried out in the vicinities of MARC (Marmarssa and Dibibissa), and ATARC during 2010-11 cropping seasons.

3.6.1. Description of evaluated strategies

Three sets of strategies viz. strategies that farmers are currently adopting in maize production, and farmer's production strategy that was improved with the developed models forecasts, and maize RF strategy that were guided by RF forecasts using the developed prediction models were evaluated at 55 sites during the two seasons.

3.6.1.1. Strategy I: Farmers' traditional maize production strategy

These are strategy set by farmers for maize production based on their own perceptions of seasonal rainfall prospects. When onset is perceived early, farmers expect longer duration with higher water supplies. Hence, they plant long duration maize cultivars in April and medium maturing maize cultivars in May. If onset is perceived late, they expect shorter duration and lower water supply. Hence, they sow early maturing maize cultivars during late June to early July. In each case, they follow a range of soil, crop and fertility management practices (ICRA, 1999). Each farmer ploughed their plots four times by a local ox-drawn implement called *maresha* (traditional oxen mounted iron used to perform tillage). *Limat,* a popular local maize cultivar grown in the study areas maturing within 120 to130 days (ICRA, 1999), was sown by broadcasting at a rate of 60 kg seed ha^{-1}. All farmers did not use fertilizer at sowing. S*hilshalo* (a traditional cultivation practice of broadcasted maize fields performed by oxen mounted *maresha* aimed at thinning of plant stand, kill weeds and loosening of the soil surface to enhance infiltration) were performed 45 days after sowing.

3.6.1.2. Strategy II: Farmers' maize production strategy guided by enhanced response farming rainfall forecasts

This strategy is farmers' traditional maize production strategy that was guided by enhanced RF forecasts. Farmers at each study sites were provided with RF forecasts both for onset and season duration before the actual start of the seasons. Ploughing was performed by *mareshsa*. Cultivar selection, planting timing, seed rates, planting methods as well as fertilizer type and amount were left for farmers to decide. Accordingly, most farmers chose to sow *Melkassa II* (an improved drought tolerant white seeded maize variety that matures within 130 days). It was sown by broadcasting using 100 kg DAP ha^{-1} fertilizer and 50 kg urea ha^{-1}. Weeding was performed by *shilshalo*. None of the farmers used herbicides.

3.6.1.3. Strategy III: Enhanced response farming forecasts guided maize production strategy

Enhanced RF strategy utilizes new strategic agronomic predictors for the date of onset and season duration. Thus, it starts with prediction of the date of onset and season duration in order to prepare in advance and take advantages of early seasons. To conform to actual rainfall conditions, the strategy incorporates adjusting of initial and final plant population, and fertilizer levels. Fertilizer application is split between basal application at planting and side-dressing at the time of thinning. In early seasons when higher yields are the goal, nitrogen is applied at sowing and phosphorus is applied at planting for good early root development. When onset is late, and a poorer season is anticipated, nitrogen is either withheld or around half dose is considered. In very late seasons, the strategy is to completely avoid use of fertilizer. Application of either half the recommended rate or none is to be considered at later date during thinning based on actual monitoring of season type.

First stage enhanced strategic response farming - predicting the date of onset and season duration

Portable rain gauges were installed at each study site in order to record the first effective rainfall date of the up-coming season and the actual amount of rainfall received on those dates. The first rainfall date (as of January for MARC and February for ATARC) which received rainfall exceeding 15 mm was recorded. These were taken as having significant contribution for build-up of soil-water for onset in April. Prediction models relating the dates of onset to its respective first effective rainfall date and the date of onset, and season duration were used to estimate the expected date of onset and season duration. Once the earliest, mean and latest date of onset and mean, shortest and longest season duration were predicted, initial decision concerning the type of maize variety to be sown was made. Moreover, the time of start of tillage and its frequency, and the type of soil and water management practices to be considered for sowing of the selected variety, and seed rate, and type and amount of initial fertilizer to be applied were tentatively fixed.

First stage enhanced tactical response farming – revising expectations of season duration

The actual dates of onset were detected through regular monitoring of rainfall using portable rain gauges. Using the observed dates of onset, the regression models developed for determination of season duration based on the date of onset as a predictor was used to revise the initial forecasts of season duration based on the observed first effective rainfall date. This enabled estimation of season duration more closely and facilitated decision on cultivar maturity that fits into projected season length.

First stage enhanced tactical response farming – estimating total seasonal water at onset

The regression models developed for prediction of TSW supply using the date of onset as a predictor were used to estimate TSW.

First stage tactical decisions

Accordingly, based on the actual dates of onset, expected season duration and TSW, decision on soil and water management practices, maize maturity to be sown, seed rate, initial fertiliser type and amount and sowing time were decided. On RF plots, the prediction guided management practices for RF of maize developed by Admassu (2004) for the semi-arid CRV areas were adopted (Table 8).

Table 8: Response farming recommendations for maize production in the Central Rift Valley of Ethiopia

Recommendations at planting time			**Season category and recommended actions**		
Onset date and planting instructions	**Initial DAP (kg ha^{-1})**	**Population (plants ha^{-1})**	**Predicted season category**	**Final population (plants ha^{-1})**	**Side-dress urea (kg ha^{-1})**
Early onset: 1 April - 14 June; If onset in April, plant 150 day maize and 120 day maize in May	100	53 333	A	53 333	50
			B	44 444	35
			C	38 095	None
Late onset: 15 June - 16 July; plant 90 day maize	100	66 666	A	66 666	50
			B	53 333	35
			C	44 444	None

Source: Admassu (2004)

Land was prepared by *mareshsa*. The land was tilled four times. In early seasons, for medium maturity maize (*Melkassa-II*), the spacing was 0.25 m between plants and 0.75 m between rows with a total of 53 333 plants ha^{-1}. For early maturing variety (*Melkassa-IV*), the spacing was 0.20 m between plants and 0.75 m between rows with a total population of 66 666 plants ha^{-1}. At sowing, furrows were opened using oxen-mounted tie-ridging implement, and sowing was done in the furrows of the tied ridges. Fertilizer was applied at the rate of 100 kg DAP ha^{-1} at the time of sowing and 50 kg urea ha^{-1} at thinning.

Second stage tactical response farming

Since decisions made prior to and at onset are embedded with uncertainty, a means of revising earlier made decisions is necessary. RF relies on cumulative amount of early crop season rainfall (from onset to top-dressing and thinning time) to reach a conclusion as to whether the original plant stand should be maintained or not and whether additional fertilizer should be applied or not. The rainfall criteria developed by Admassu (2004) for CRV locations presented in Table 9 was used for tactical adjustment of the input variables (fertilizer and plant stand).

Table 9: Thinning time rainfall criteria for adjusting plant stand and fertilizer application

Season type	Early: 1 April - 14 June			Late: 25 June - 16 July		
Rainfall totals	>167 mm	92 - 166 mm	< 91 mm	> 401 mm	291 - 400 mm	< 290 mm
Actual season type	A = Good	B = Fair	C = Poor	A = Good	B = Fair	C = Poor
Plant population after thinning*	66 666	53 333	44 444	53 333	44 444	38 095
DAP**		100			100	
Urea to side dress***	50	35	None	50	35	None

Source: Admassu (2004)
Note: * = population: plants ha^{-1}; ** = DAP to be applied at planting (kg ha^{-1}); *** = urea to side-dress (kg ha^{-1}) at planting; plant

Actual rainfall was monitored from the date of onset. Based on comparison of cumulative 40 days rainfall against the criteria listed in Table 9, decision was made on plant stand and use of additional fertilizer (urea).

3.6.2. On-farm data collection and analyses

On-farm evaluation of the performance of RF predictors in guiding agronomic planning and farm decision making were conducted at four sites in the vicinity of ATARC in 2010 cropping season, and at 51 sites at Dibibissa and Marmarssa during 2010-11 cropping seasons. All the three strategies were tested on plot size of 10 m wide by 30 m long. Randomized complete block deign was used considering individual farmer field as replication. Maize grain yield data from the various strategies tested were collected. Comparisons of performance of the three strategies at each site in each of the seasons and across sites were conducted on maize grain yield by subjecting the data to ANOVA using MSTATC ver. 3.2 (Michigan State University, 1993). Significance of maize grain yield differences between farmers' strategy and the other two strategies was determined by computing the mean differences and comparing it against the computed values of Least Significant Difference (LSD) at 1% level of significance. The yield increase over farmer's strategy was computed as percentage.

CHAPTER FOUR

4.0 RESULTS AND DISCUSSION

4.1. Agronomically Risk-Wise Acceptable Dates of Onset of Growing Seasons

Under this section, results of the study conducted in order to address specific objective one (which was aimed at establishing agronomically risk-wise acceptable date of onset and corresponding rainfall criteria and identification of predictors for the identified dates) are presented and discussed.

4.1.1. Effective rainfall signalling the onset of maize growing seasons

4.1.1.1. Effective rainfall-evapo-transpiration relations

Effective rainfall-evapo-transpiration relationship studies were carried out in order to identify the start and rainfall end dates. Figure 3 for MARC and Fig. 4: for ATARC compares mean monthly total rainfall and mean monthly effective rainfall against three levels of ETo. Figure 3 show that MARC receives rainfall exceeding 15 mm in January. However, effective rainfall exceeded ETo during July and August. This produces a 62 days season with total effective seasonal rainfall of 302 mm, whereas effective rainfall exceeded the 0.5ETo level from July to September producing a 92 days maize season with total effective water supply of 376 mm. On the other hand, effective rainfall exceeded the 0.33ETo levels during March through September. This produces the longest season of 214 days with total effective seasonal rainfall of 566 mm. The 62 and 92 days maize seasons at MARC are short and only enable production of shorter maturing crops during late season, while the

214 days maize season offers longer duration with higher seasonal rainfall.

During early onset seasons, farmers can prepare land from January until March and start sowing longer season maize during April. If earliest sown maize fails, farmers can re-plow and re-sow medium maturing maize in May. During late seasons, farmers can sow shorter duration maize cultivars. Thus, taking into account the risks and uncertainties that are commonly experienced in the semi-arid areas around the world (Kanemasu *et al.*, 1990), accepting onset as early as late March or during April when effective rainfall exceeds 0.33ETo levels is worth considering. This also matches well with RF precepts and the perceptions of farmers in the study areas (ICRA, 1999).

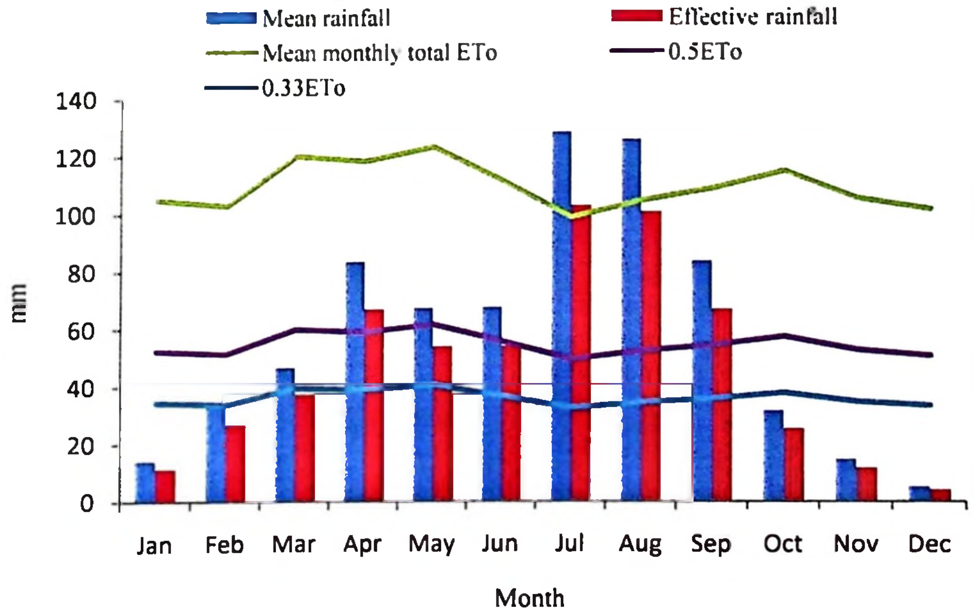

Figure 3: Mean monthly total and effective rainfall and three evaporative levels at Melkassa during 1977 – 2008

The results depicted in Fig. 3: are summarized in Table 10. The Table shows the mean dekadal total rainfall thresholds for April, May and July to be accepted for onset (risk-wise).

Table 10: Dates of onset and corresponding rainfall criteria for Melkassa

Evaporative level (mm)	Effective season		Season duration (days)	Effective rainfall (mm)	Maize variety (days)	Onset criterion (mm)
	date of onset	end date				
ETo	July	August	62	302	70 - 90	15
0.5ETo	July	September	92	376	70 - 120	15
0.33ETo	April	September	214	566	90 - 150	18 - 21

Effective rainfall exceeding 15 mm at ATARC is received in February (Fig. 4). However, effective rainfall exceeds full ETo levels only during July. This produces short season with 100 mm of total effective seasonal rainfall. On the other hand, effective rainfall exceeds 0.5ETo level during June to September producing a 122 days season with 325 mm total effective seasonal rainfall. Whereas, effective rainfall exceeds the 0.33ETo levels during April to September; this produces a 183 day season with total effective seasonal rainfall of 446 mm. Like for MARC, the later corresponds with farmers cropping season in the vicinity of ATARC. Farmers use February and March rainfall to prepare maize fields to start sowing of longer duration maize in April. If earliest sown maize fails, they sow medium maturing maize in May and shorter maturing maize during late June. Table 11 summarizes the results presented in Fig. 4: and lists mean dekadal total rainfall to be accepted as onset criteria for the various months.

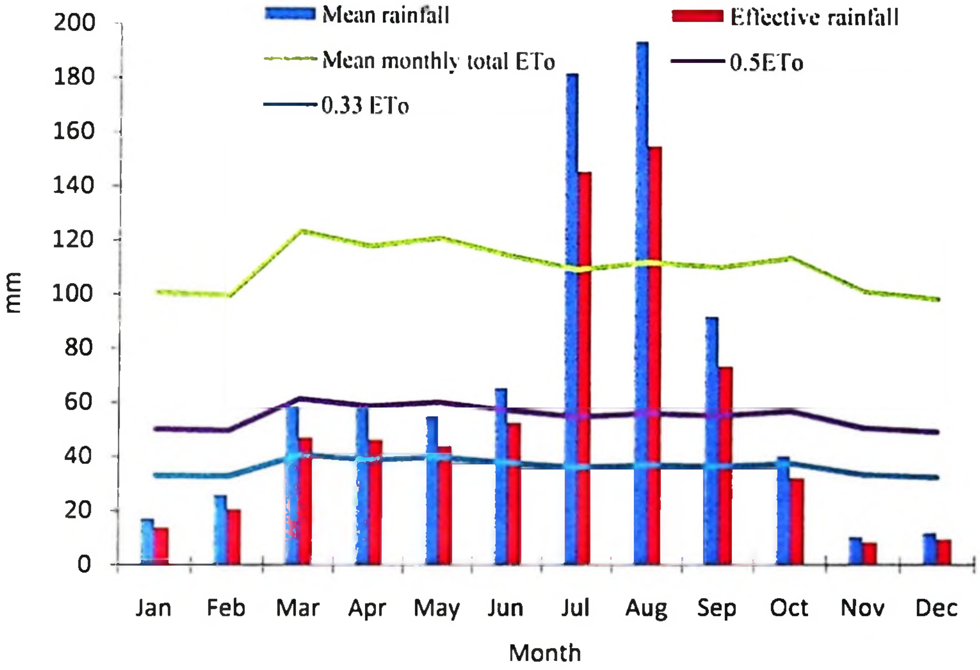

Figure 4: Mean monthly total and effective rainfall and three evaporative levels at Adami Tulu during 1977 - 2008

Table 11: Dates of onset and corresponding rainfall criteria for Adami Tulu

Evaporative level (mm)	Effective season		Season duration (days)	Effective rainfall (mm)	Maize variety (days)	Onset criterion (mm)
	date of onset	end date				
100%	August	August	31	100	-	15
0.5ETo	June and July	September	122	325	90 - 120	15
0.33ETo	April	September	183	446	90 - 150	21

4.1.1.2. Probabilities of dry spell and expected rainfall

At Melkassa, Fig. 5: shows that, rainfall during March to May period has high probability of dry spell exceeding five days (P = 98%). The probability of dry spell exceeding 10 days ranges from 73% to 90% during the same period. Dry spell are less commonly experienced from late-June until early-September. Thus, rainfall during this period appears relatively reliable. The probability of dry spell exceeding 15 days from March until April is also considerable (53 - 57%). The probability of dry spell exceeding 10 days and 15 days during the first two weeks of June are respectively 48% and 13%, whereas it drops to 23% and 4% in the remaining last two weeks. This indicates high risk of seedling failure if planting is done during early June.

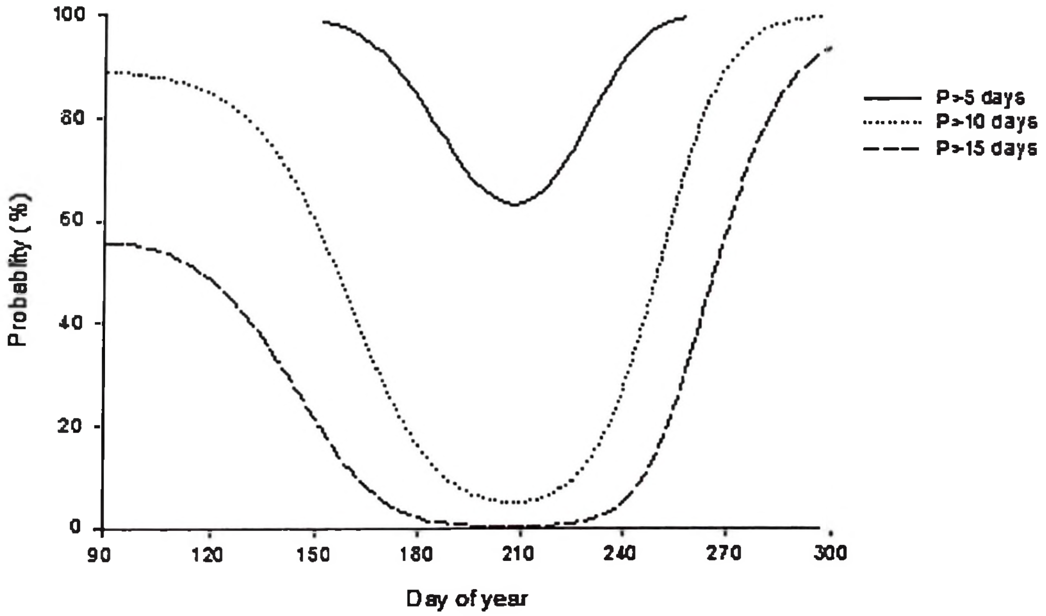

Figure 5: Probability of dry spell at Melkassa

Table 12 shows that expected rainfall amount at MARC during any of the 12 months and annual totals exceeding the climatological means and totals.

Table 12: Probabilities of pre- and post-onset rainfall at Melkassa

	Probability levels (%)			Mean rainfall (mm)
Month	75	80	90	
January	38.4	43.5	58.9	15
February	47.3	55.0	78.7	23
March	80.4	91.5	125.1	61
April	76.3	85.3	112.4	55
May	73.2	86.3	127.6	56
June	97.4	109.7	146.7	62
July	223.5	235.7	270.0	188
August	217.2	227.3	255.2	198
September	106.5	112.1	127.9	94
October	60.3	72.4	111.4	33
November	25.1	30.5	48.0	9
December	22.2	25.5	36.0	10
Annual total (mm)	882.8	907.4	974.2	803

Figure 6 shows that, at ATARC, the probability of dry spells exceeding five days ranged from 89 - 100% and the probability of dry spells exceeding seven days ranged from 59 - 100%. The probability of dry spell exceeding 10 days follows the same trend with that of MARC except that of August at ATARC with considerable dry spell (36%). The probability of dry spell exceeding 15 days is high during March and decreases gradually in May and June, and is minimal in July. Though there is high risk of dry spell in April and May both for 10 and 15 days, considerable rainfall that forms a first peak (Fig. 4) is received by mid-April. This offers farmers the chance for starting planting of longer season maize in April. Like for MARC, Table 13 shows expected rainfall amounts at ATARC during any of the 12 months and annual totals exceeding the climatological means.

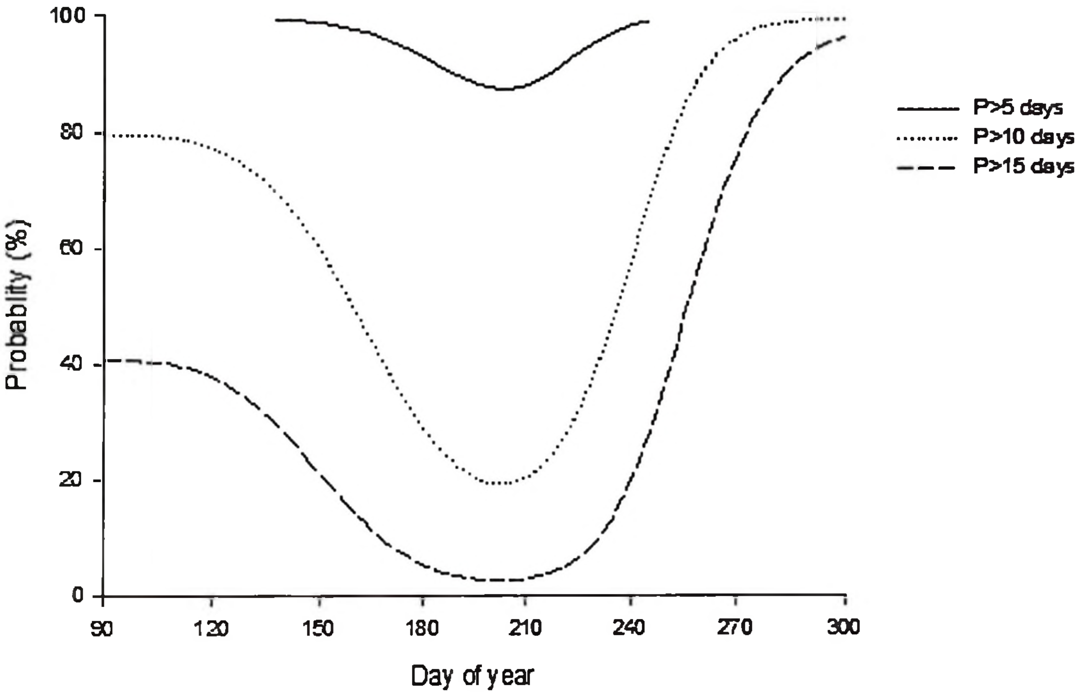

Figure 6: Probability of dry spell at Adami Tulu

Table 13: Probabilities of pre- and post-onset rainfall at Adami Tulu

	Probability levels (%)			Mean rainfall
Month	75	80	90	(mm)
January	43.7	50.1	69.8	14
February	81.6	97.0	145.8	32
March	91.1	104.3	144.5	48
April	127.7	140.9	179.8	83
May	116.0	133.0	185.1	80
June	100.9	110.0	136.2	77
July	177.9	189.8	223.7	137
August	169.3	178.7	205.1	141
September	104.8	113.9	140.4	81
October	73.0	86.6	130.0	35
November	18.5	21.6	31.0	18
December	19.7	23.7	36.2	5
Annual total (mm)	925.3	967.7	1 085.4	751

The results presented above suggest the period from January through March at MARC and from February through March at ATARC to be considered as months that can contribute effective rainfall which enables early onset. Farmers in the study sites accept onset as early as April, and if the earliest season onset fails, they accept onset in May, and if this fails, they accept onset later (ICRA, 1999).

Research-based recommendation in the 1990s for crop production in the study sites are to use rainfall received during February and March for land preparation and the sowing of early maturing crops during late June until mid-July (Simane and Struick, 1993). The results presented above revealed that such recommendation would result in wastage of January through late June rainfall totalling 280 mm at MARC and February until late June rainfall totalling 298 mm at ATARC.

Effective rainfall-evapo-transpiration relationship study results presented above revealed that April onset to be the most risk-wise acceptable dates of onset at both locations. This would offer the farmers the chance for planting three maize varieties during April through early July. However, dry spell analyses revealed considerable risks that are associated with early onset due to low rainfall conditions during April. Nevertheless, at times, the areas receive considerable rainfall in April that can enable survival of April sown maize seedlings to grow until rainfall gain further strength by late June. The analyses revealed that accepting onset during the time when effective rainfall exceeds the evaporative levels at ATARC to be very risky. The need for stringent soil and water management practices as an integral part of the farming practice for safe starting of crops during April is explicit. Thus, it is advisable for farmers to perform the first tillage immediately after harvest of the preceding crop (Reddy and Kidane, 1994). This would encourage infiltration of occasional rainfall that is received during October through December period.

Moreover, early tillage would also enable farmers to store considerable amount of rainfall during January to March. This would enable attainment of onset in April.

The above findings differ with the approaches followed by Simane and Struick (1993) that established late-June as the reliable onset for the study sites. Moreover, it differs with FAO (1978) and Sivakumar (1988) criteria for definition of onset that are constrained by stringent assumptions. These approaches tend to nearly avoid the commonly experienced dry periods in the SAT (Kanemasssu *et al.*, 1990) and reduces the possibility of long season duration and high total seasonal water attainable by accepting April onset.

4.1.2. The onset of maize growing seasons

The results from WHARF program simulation analysis of daily rainfall data using the analytical assumptions stated in Table 7 revealed that at MARC, all the 32 seasons met the onset requirement of 20.9 mm. At ATARC, only 29 of the 32 seasons met the onset requirement of 21.4 mm. These were 1979-80 and 1988. Table 14 shows the occurrences in the date of onset of rainfall seasons at both MARC and ATARC. The overall probability for onset at MARC over 32 seasons would have been 100%, whereas that of ATARC would have been 91%. The Table shows that the inter-seasonal variation in the dates of onset was by two to over three months.

Table 14: Statistics of the date of onset at Melkassa and Adami Tulu

Statistic and relative earliness	Date of onset (Julian day)	
	MARC	ATARC
Mean	117	108
Earliest	91	91
Latest	185	159
Range (days)	94	68
C.V. (%)	24	18

The above results suggest accepting onset as early as April offers greater chance for starting crops early. Failure of the three seasons of the 32 seasons to meet the criterion stated for onset at ATARC suggests the need for developing predictive capacity for drought years. Overall, the higher inter-seasonal variability in the date of onset implies the need to develop predictive capacity for April onset. This can help farmers in pre-season strategic planning and in making sound management decisions.

4.1.3. Characteristics of seasonal rainfall as limited by onset dates and onset criteria

The results from statistical assessment of the ranges of occurrences in relevant seasonal rainfall parameters in each of the past 32 seasons at MARC and 29 seasons at ATARC from WHARF simulation analyses under the analytical assumptions stated in Table 7 are presented in Table 15. The Table shows the final rainfall date to be the most stable rainfall parameter at both locations. However, in-season rainfall, TSW, intensity index, duration of rainfall seasons, and the number of season rainfall days exhibit great inter-seasonal variation.

Minimum season duration of 125 days was assumed for 150 days maize variety, 100 days for 120 days maize and 70 days for 90 days maize. Table 18 shows that season duration at both locations would have been sufficient to produce maize varieties that mature within 90 to 150 days.

Gross seasonal water needs (ETc) under the climatic conditions of MARC for April planted a 150-day, May planted 120-day and June planted 90-day maize varieties are respectively 465, 384 and 270 mm. Similarly, for ATARC ETc for April planted 150-day, May planted 120-day and a June planted 90-day maize varieties are respectively 447, 338 and 261 mm. Thus, the available TSW (Table 15) would have easily met the demands of the three varieties in each of the 32 seasons at MARC and the 29 seasons at ATARC.

Table 15: Statistics of seasonal rainfall parameters at Melkassa and Adami Tulu during 1977 - 2008

	MARC					ATARC				
Variable	Mean	M	C.V (%)	Min	Max	Mean	M	C.V (%)	Min	Max
Final rain date (Julian)	252	254	5	232	272	253	253	5	230	271
Season duration (Days)	135	135	23	68	180	145	149	17	83	180
In-season rain (mm)	581	585	24	274	914	514	498	23	361	794
TSW (mm)	623	632	23	308	958	565	544	22	385	819
Intensity index (mm day^{-1})	4.8	5.2	24	2.3	6.8	3.9	3.8	20.1	2.6	5.5
Number of season rainfall days (number)	58	55	31	34	97	47.3	43	27.3	26	73

Note: M = Median; Min = minimum; Max = maximum

Table 16 shows ranges of occurrences in the number of heavy rainfall days and dry period's of different lengths at MARC and ATARC during 1977 - 2008 seasons. Both parameters exhibited extreme inter-seasonal variation except for the total number of season dry days and dry days of 10 days. This implies great challenges of predictability of these rainfall parameters.

Table 16: Heavy rainfall days and dry periods at Melkassa and Adami Tulu during 1977 - 2008

	MARC				ATARC			
Parameter	C.V. (%)	Mi	M	R	C.V. (%)	Mi	M	R
Heavy rain exceeding 100 (mm day^{-1})	566	0	1	1	539	0	1	1
Heavy rain of 75 - 100 (mm day^{-1})	316	0	1	1	539	0	1	1
Heavy rain 50 - 74 (mm day^{-1})	141	0	5	5	114	0	2	2
Heavy rain 25 - 49 (mm day^{-1})	41	2	11	9	57	1	14	13
Total number of season dry days	24	13	38	25	21	15	38	23
Number of season dry days exceeding 31 days	316	0	1	1	374	0	1	1
Number of season dry periods of 20 to 29 days	138	0	2	2	152	0	1	1
Number of season dry periods of 10 to 19 days	127	0	3	3	80	0	4	4
Number of season dry periods of 0 to 9 days	24	12	35	23	23	15	37	22

Note: Mi = minimum; M = maximum; R = range

The above results (Tables 16 and 17) show extreme variability in seasonal rainfall behaviour parameters except the final rainfall date. This calls for predictive capacity for successful cropping at the two study sites.

4.1.4. The general impacts of the date of onset on maize production

Results from assessments of the impacts of rainfall behaviour as limited by dates of onset and rainfall criteria on the rate of success from producing alternative maize varieties is presented in Tables 17 for MARC and Table 18 for ATARC. Both

Tables show probabilities for onset, and actual season duration and seasonal water supplies. The Tables list seasonal ETc and actual crop water use (ETa) for 150-, 120-, and 90-day maize varieties for both study sites. Finally, the rates of success are presented in both Tables. The results show greatest probability for April onset that allows the farmer to plant higher yielding 150-day maize in April, 120-day maize in May and 90-day maize in June in majority of the seasons.

Table 17: Probabilities of onset and the chance of success from production of three maize varieties at Melkassa

Date of onset	Prob. (%)	DUR (days)	TSW (mm)		ET (mm)	Maize maturity (days)	ETa (mm)	Prob. (%)		
			Range	Median				150	120	90
April	69	119 - 180	308 - 958	671	466	150	401	4F/18P	100	100
May	16	111 - 134	430 - 726	668	384	120	403	5P	100	100
June	13	68 - 104	460 - 755	523	270	90	304	All F	1F/3P	100
July	3	79	470	470	270	90	282	F	F	100

Note: Prob. = probability; DUR = duration; TSW = total seasonal water
Out of the 32 seasons, 22 seasons reached onset in April, five in May, four in June and 1 in July; P = successful production, F = complete failure

Table 18: Probabilities of onset and the chance of success from production of three maize varieties at Adami Tulu

Date of onset	P (%)	DUR (days)	TSW (mm)		ET (mm)	Maize maturity (days)	ETa (mm)	P (%)		
			Range	Median				150	120	90
April	72	134 - 181	390 - 819	575	447	150	345	1F/22P	100	100
May	13	99 - 131	385 - 716	420	338	120	252	3F/1P	100	100
Jun	6	83 - 110	449 - 540	495	261	90	297	All F	1P/1F	51

Note: Prob. = probability; DUR = duration; TSW = total seasonal water
Out of the 32 seasons, 23 seasons reached onset in April, four in May and two in June; P = successful production; F = complete failure

The overall results suggest that April onset would have had enabled production of the three maize varieties in 28 of out of the 32 seasons at MARC and in 28 out of the

29 seasons at ATARC. Although the probability for onset in April is greatest, risks are also greatest due longer dry spell as well as high evaporative rates and maximum temperatures. Farmers should therefore employ appropriate agronomic soil and water management practices in order to tackle the risks associated with April onset. Since April onset offers the opportunity to make flexible combination for the production of the three maize varieties, it was taken as the most risk-wise acceptable date of onset for which predictive capacity was required. The overall results confirm April onset as the most risk-wise acceptable dates of onset and differs from the approaches and recommendations by Simane and Struick (1993).

4.1.5. The impacts of the date of onset on production of three maize varieties

A quantitative assessment of the success rates from growing of three maize varieties by accepting the above established onset dates (April to late June and mid-July) applying simulation modelling techniques is discussed in this section.

4.1.5.1. The impacts of the date of onset on production of a 150-day maize variety at Melkassa

The simulation modelling here was concerned with the assessments of the rate of success by accepting April onset. Planting of a maize variety with 150 days growth period to physiological maturity on clay loam textured soils at MARC with water holding capacity of 99 mm per 30 cm soil depth was assumed. The first acceptable date of soil water accumulation was set to the first day of January, an onset criterion of 20.9 mm, with the first acceptable onset on the first day of April, the first normal onset on 10 April, and the last acceptable onset on 10 July. In each of the 32 seasons, planting of the crop was assumed seven dry days following the attainment of the designated onset criterion with no rainfall allowed on the planting day to avoid soil surface sealing that results in poor germination (Fuijsaka *et al.*, 1996). The germination criterion was set to 15 mm. The last search date was tied to crop physiological maturity and the final rainfall criterion was designated 92.5 mm with a minimum season-end intensity index of 3.1 mm day^{-1}.

The results from the analysis in Appendix 4 are chronologically sorted by the date of germination from earliest to the latest. Under the above analytical assumptions, all the 32 seasons would have met all of the requirements. Out of the 32 seasons, 21 seasons reached onset conditions during 1 - 29 April, five during 5 - 18 May, another five during 8 - 13 June, and only one season reached onset on July 18. Out of the 21 seasons reaching onset in April, 13 seasons germinated during 9 - 27 April, seven seasons during 3 to 25 May, and only one season germinated on 18 July.

Season duration during the 32 seasons ranged between 54 - 150 days (Appendix 4). Assuming 125 days as the minimum season duration desired for production of the 150-day maize, the crop would have been produced successfully in 12 of the 32 seasons. The rest of 20 seasons would have failed to produce the 150-day maize crop due to early cessation of rainfall although water supply was adequate.

Total seasonal water supply ranged between 277 and 886 mm (Appendix 4). Gross seasonal water needs of an April planted 150-day maize was 465 mm. Appendix 4 lists seasonal WAR which was 0.4 in one of the 32 seasons. This indicates clear failure of the 150-day maize crop. On the other hand, WAR ranged between 0.5 - 0.7 in 10 of the 32 seasons. This indicates that seasonal water requirements of a 150-day maize crop would have been fairly met and enabled low to normal maize yield, whereas, WAR ranged between 0.8 - 1.1 in 21 of the 32 seasons. This would have enabled harvest of good yield levels.

Results presented in Appendix 4 enables assessments of the degree of water adequacy and evaluation of historical water supply impacts in different crop growth stages. The growth stages for the 150-day maize seasons were divided in to four distinct time periods. The initial stage was 30 days, rapid vegetative growth period was 40 days, the flowering (tasselling / silking), pollination and blister kernel stage 30 days, and the fourth period (grain forming and grain filling, and maturation period) was 50 days. For analytical purpose, the WHARF program allows division of available water in to different growth sequences as desired. For the 150-day maize crop, the initial seedling growth period was set to 20 days, followed by 13 periods of 10 days each.

The water needs of the 150-day maize crop during seedling and rapid vegetative growth stages in seven of the 12 seasons were far less than the water demand of the crop (Appendix 4). However, each dekad was interspersed by little water supply which might have enabled survival of the crop. The onset and germination criteria used in this analysis assumed that the water stored at onset and germination would enable germination and seedling growth for 30 - 40 days until further rainfall is received. Thus, the rainless periods would have had little or no impact on crop growth as maize is not sensitive to water stress during early growth stage. Thus, the water available for the 150-day maize crop during the 35 - 40 days would have enabled survival of the crop under stress condition. In the rest of the growth stages, water stress would not have been experienced by the crop. Consequently, the 150-day maize crop would have been successfully produced during the 12 of the 32 seasons.

By accepting early onset, failure rate would have been high had a maize variety of 150 days been planted every season. However, farmers could have also planted 120- and 90-day maize varieties in the rest of the seasons which fail to produce the 150-day maize crop. The overall results call for the need to develop predictive capacity for April date of onset so that farmers can be informed about seasons during which production of longer season maize varieties should not be considered.

4.1.5.2. The impacts of the date of onset on production of a 120-day maize variety at Melkassa

The assessment here was concerned with simulation modelling that assumed production of a 120-day maize variety on clay loam textured soils at MARC with water holding capacity of 99 mm per 30 cm soil depth. Model inputs were the first day of January as the first acceptable date of soil water accumulation, an onset criterion of 20.7 mm, with the first acceptable onset was set to the first day of May, the first normal onset on 15 May, and the last acceptable onset on 14 June. In each of the 32 seasons, planting of the crop was assumed seven dry days following the attainment of the designated onset criterion with no rainfall allowed on the planting day. The germination criterion was 15 mm. The last search date was tied to crop physiological maturity and the final rainfall criterion was 92.5 mm with a minimum season-end intensity index of 3.1 mm day^{-1}.

The results from the analysis chronologically sorted by the date of germination from earliest to the latest are presented in Appendix 5. Under the above analytical assumptions, out of the 32 seasons, 1984, 1986, 1988-89, 1995, 1999 and 2002 seasons never got started. The rest 25 of the 32 seasons met the onset and germination requirements. Out of the 21 of the 25 seasons that reached onset during 1 - 18 May, 14 seasons germinated during 9 - 26 May and seven seasons germinated during 3 - 22 June. The rest four of the 25 seasons that reached onset during 8 - 14 June germinated during 17 - 30 June.

The durations the crop would have had in each of the past 25 seasons ranging from 62 to 120 days are listed in Appendix 5. Assuming 100 days as the minimum season duration desired for production of the 120-day maize crop, 15 of the 25 seasons would have easily produced the 120-day maize. In the rest of five seasons, duration ranged between 95 - 98 days. These would have had little impact on the crop. The rest five seasons would have duration of 62 - 89 days. The crop during these seasons would have suffered early cessation of rainfall and might have failed. In total, 20 of the 25 seasons would have produced the 120-day maize crop.

Total seasonal water supply ranged between 435 - 820 mm (Appendix 5). Gross seasonal water needs of a May planted 120-day maize crop was 384 mm. The WAR was 0.7 in two of the 25 seasons. This indicates that the seasonal water requirements of the 120-day maize crop would have been fairly met, and that it would have enabled harvest of normal maize yield levels. On the other hand, WAR ranged between 0.8 - 1.3 in 23 of the 29 seasons. This indicates that the 120-day maize crop seasonal water needs would have been fully met and enabled good maize yield.

Results presented in Appendix 5 enables the assessments of the degree of water adequacy and evaluation of the historical water supply impacts in different growth sequences. For the 120-day maize crop, the initial stage was set to 25 days, rapid vegetative growth period 30 days, the third stage 35 days, and the fourth 30 days. The initial seedling growth period in these analyses was set to 29 days, followed by 13 periods of seven days each.

The water needs in all of the 25 seasons were adequate (Appendix 5). However, 1992 season encountered a 30-day dry spell, and 1980 also encountered 30 day water stress during the first growth stage which would have been easily remedied with stored soil water at onset and germination. Thus, the water available for the 120-day maize crop would have enabled good yield in 24 of the 25 seasons. Nevertheless, taking season duration into account, only 20 seasons would have enabled successful production of the 120-day maize crop.

The above results suggest that the potential to produce the 120-day maize crop is higher than that of the 150-day maize crop. However, in both cases, for greater yield, appropriate management practices should be adopted in any given season.

Developing predictive capacity for the dates of onset is required to improve the overall success rate.

4.1.5.3. The impacts of the date of onset on production of a 90-day maize variety at Melkassa

The simulation modelling assumed production of a 90-day maize variety on clay loam textured soils at MARC with water holding capacity of 99 mm per 30 cm soil depth. Model inputs were the first acceptable date of soil water accumulation on 20 June, 15 mm as an onset criterion, with the first acceptable onset on 21 June, the first normal onset on 25 June, and the last acceptable onset on 15 July. In each of the 32 seasons, planting of the crop was assumed promptly following onset with two mm rainfall allowed on the planting day. The germination criterion was 15 mm. The last search date was tied to crop physiological maturity and the final rainfall criterion was 75.8 mm with a minimum season-end intensity index of 3.8 mm day^{-1}.

Appendix 6 lists the results from the analysis chronologically sorted by the date of germination from earliest to the latest. Out of the 32 seasons, 29 seasons met the criteria stated above. But, seasons 1981, 1988 and 2002 never got started and failed. Eighteen of the 29 seasons reached onset during 23 - 28 June of which 16 germinated during 25 June - 2 July, and the other two seasons germinated during 2 - 8 July. Eleven of the 29 seasons that reached onset during 1 - 15 July germinated during 3 - 17 July.

Season duration in each of the 29 seasons ranged between 46 - 90 days (Appendix

6). Assuming 70 days as the minimum season duration desired for the production of the 90-day maize crop, 10 of the 29 seasons (with their duration ranging between 70 and 90 days) would have enabled production of the 90-day maize crop, and the other 12 seasons with their duration ranging between 60 - 69 days would have suffered from early cessation of rainfall and might have produced some yield. While seven seasons i.e. 1982, 1985, 1991, 1994, 1997-98, and 2001 would have shorter durations (46 - 58 days). These would have failed to produce the 90-day maize crop.

Total seasonal rainfall ranged between 253 - 792 mm (Appendix 6). Gross seasonal water need of the 90-day maize crop was 269 mm. Appendix 4 also lists the calculated seasonal WAR ranging between 0.6 - 0.7 in two of the 30 seasons. This indicates that seasonal water requirements of the 90-day maize crop would have been fairly met and would have enabled harvest of normal yield levels. On the other hand, WAR ranged between 0.8 - 1.8 in 27 of the 29 seasons. Again, this indicates that, the 90-day maize crop seasonal water need would have been sufficiently met. This would have enabled harvest of good maize yield during each of the seasons. Thus, based on WAR values, the 29 seasons would have enabled production of the 90-day maize crop.

Appendix 6 enables the assessments of the degree of water adequacy and evaluation of the historical water supply impacts in different growth stages. For the 90-day maize crop, the initial stage was set to 15 days, rapid vegetative growth period 25 days, the third stage 30 days, and the fourth 20 days. The seedling growth period in these analyses was set at 25 days, followed by 13 periods of five days each.

The results in Appendix 6 show that seasonal water needs in all the seasons were adequate for the 90-day maize crop. However, five of the 29 seasons (1989, 1993-94, 1998 and 2001) encountered dry spells of 15 days towards grain forming and maturation period. This might have some impact on grain sizes and yield although there was adequate to meet crop water needs during the preceding period. Thus, these seasons would have the chance to depend on stored soil water and survive the stress except 1982 season which encountered 20 days dry spell during the same growth period and probably would have produced lower yield.

Taking season duration and WAR into account, the 90-day maize crop would have failed in nine of the 29 seasons, of which 1991, 1993 and 1982 seasons would have failed due to early cessation of rainfall. The rest would have failed due to both early cessation and water stress. Overall, the 90-day maize crop would have been successfully produced in 20 of the 29 seasons. The above results show that at MARC, higher potential for successful production of the 90-day maize crop as compared to the 150- and 120-day maize varieties.

4.1.5.4. The impacts of the date of onset on production of a 150-day maize variety at Adami Tulu

The simulation modelling here was concerned with the evaluation of the dates of onset from April through early July. The simulation assumed production of a 150-day maize crop to physiological maturity on sandy textured soils at ATARC with water holding capacity of 80 mm per 30 cm soil depth. Other model inputs were the first day of February as the first acceptable date of soil water accumulation, an onset criterion of 21.4 mm, with the first acceptable onset on the first day of April, the first normal onset on 10 April, and the last acceptable onset on 10 July. In each of the 32 seasons, planting of the crop was assumed seven dry days following onset with no rainfall allowed on the planting day. The germination criterion was 15 mm. The last search date was tied to crop physiological maturity and the final rainfall criterion was 72.6 mm with a minimum season-end intensity index of 2.4 mm day^{-1}.

The results from the analysis chronologically sorted by the date of germination from earliest to the latest are presented in Appendix 7. Based on the stated conditions, 29 out of the 32 seasons would have met all the requirements except 1979, 1980 and 1988 seasons. Out of the 29 seasons, 23 seasons reached onset during 1 - 27 April, four of the 29 seasons during 4 - 16 May, and another two of the 29 during 3 - 7 June. Out of the 23 seasons reaching onset in April, 12 seasons would have germinated during 13 - 30 April, nine seasons during 5 - 23 May, with only one season on 23 June and another one season on 2 July.

Season duration ranged between 55 - 124 days in 17 of the 29 seasons (Appendix 7). Out of the 17 seasons, duration of seven seasons ranged between 55 - 99 days. Assuming 125 days as the minimum season duration desired for production of the 150-day maize, the crop would have easily failed from too early cessation of rainfall in seven of the 17 seasons. On the other hand, duration ranged between 106 - 118 days in five of the 17 seasons. These seasons might have produced lower yield levels. Whereas, duration ranged between 122 - 124 days in another five of the 17 seasons and would have produced good yield levels. Thus, about 17 of the 29 seasons with season duration ranging from 122 to 150 days would have enabled production of the 150-day maize crop. However, it can be confidently said that only 12 seasons would have successfully produced the 150-day maize crop.

Total seasonal rainfall ranged from 319 to 814 mm. Gross seasonal water needs of an April planted 150-day maize crop was 447 mm. The water adequacy ratio was 0.4 in one of the 29 seasons (Appendix 7). Thus, the crop would have failed, whereas WAR ranged between 0.5 - 0.7 in 17 of the 29 seasons. This would have enabled poor to normal yield levels. On the other hand, WAR was between 0.8 and 1.1 in 11 of the 29 seasons, and thus water available to the crop would have enabled higher maize yield.

The assessments of the degree of water adequacy and evaluation of the historical water supply impacts in the different crop growth sequences are presented in Appendix 7. Terminal drought (during the last 40 days) was encountered in 1994 and 2004 crop seasons, and season 2002 also suffered a 30-day terminal stress. Moreover, 1992 suffered a 30-day drought during pollination period and then received 54 mm water, but again it experienced another 40-day terminal drought. Thus, all these seasons would have failed to produce the 150-day maize crop. On the other hand, 2003 which germinated latest received insignificant rainfall during pollination and suffered a 30-day drought during maturation period and would have clearly failed to produce the 150-day maize crop. In 1991, the crop also encountered a 60-day dry spell and would have failed to produce the 150-day maize crop. Four seasons viz. 1977, 1983, 1997 and 2005 failed due to too short season duration whereas eight seasons i.e. 2002-04, 1984, 1987, 1991-92 and 1994 failed due to both too short season duration and terminal droughts. Overall, the 150-day maize crop would have been successfully produced in 17 of the 29 seasons.

4.1.5.5. The impacts of the date of onset on production of a 120-day maize variety at Adami Tulu

The simulation modelling here assumed the production of a 120-day maize crop to physiological maturity on sandy textured soils at ATARC with water holding capacity of 80 mm per 30 cm soil depth. Model inputs were the first day of February as the first acceptable date of soil water accumulation, an onset criterion of 23 mm, with the first acceptable onset on the first day of May, the first normal onset on 15 May, and the last acceptable onset on 10 July. In each of the 32 seasons, planting of the crop was assumed seven dry days following onset with no rainfall allowed on the planting day. The germination criterion was 15 mm. The last search date was tied to crop physiological maturity and the final rainfall criterion was 82.3 mm with a minimum season-end intensity index of 2.7 mm day^{-1}.

The results from the analysis chronologically sorted by the date of germination from earliest to the latest are presented in Appendix 8. Out of the 32 seasons, 1979, 1980 and 1988 never got started, and were non-crop seasons. Thus, only 29 out of the 32 seasons met the above stated onset and germination requirements. Out of the 29 seasons, 26 seasons reached onset during 1 - 28 May, two seasons during 3 - 7 June, and one season on the third day of July. Out of the 26 seasons that reached onset during May, 13 germinated during 1 - 27 May, 12 during 4 - 29 June, and one season on the fourth day of August.

Appendix 8 again lists season duration in each of the 29 seasons ranging between 45 - 120 days. Season duration ranged between 45 - 90 days in 11 of the 29 seasons and between 91 - 99 days in three of the 29 seasons. Assuming 100 days as the minimum season duration desired for production of a 120-day maize crop, 15 of the 29 seasons would have easily produced the 120-day maize, with 3 seasons producing subsistence level yields and definite failure encountered in 11 seasons.

On the other hand, TSW supply ranged between 269 - 746 mm. Gross seasonal water needs of the May planted 120-day maize crop was 338 mm. Appendix 8 lists WAR for each season ranging between 0.5 - 0.7 in nine of the 29 seasons. This would have enabled harvest of poor to normal yields. On the other hand, WAR ranged between 0.8 - 1.3 in 20 of the 29 seasons. Thus, the seasonal water requirements of a 120-day maize crop would have been sufficiently met in each of the 20 seasons. Overall, based on WAR, the 120-day maize crop would have been produced in all of the 29 seasons.

Data presented in Appendix 8 enables the assessments of the degree of water adequacy and evaluation of the historical water supply impacts in the different crop growth stages. It shows adequate water would have been available for the 120-day maize crop in each of the past 29 seasons over the four growth periods. This would have enabled good crop in majority of the seasons. However, 10 of the 29 seasons covering 1978, 1984, 1991-92, 1997, 2000, 2002-03 and 2005-06 would have failed to produce a 120-day maize crop due to early cessation of rainfall. Taking duration and season water supply into account, 12 of the 29 seasons would have failed to produce the 120-day maize crop due to early cessation of rainfall and inadequate seasonal water. Overall, the 120-day maize crop would have been successfully produced in the 17 of the 29 seasons.

4.1.5.6. The impacts of the date of onset on production of a 90-day maize variety at Adami Tulu

The assessment was concerned with simulation modelling that assumed the production of a 90-day maize crop on sandy textured soils at ATARC with water holding capacity of 80 mm per 30 cm soil depth. Model inputs were 20 June as the first acceptable date of soil water accumulation, an onset criterion of 15 mm, with the first acceptable onset on 20 June, the first normal onset on 25 June, and the last acceptable onset on 15 July. In each of the 32 seasons, the crop planting was assumed promptly following onset with no rainfall allowed on the planting day. The germination criterion was 15 mm. The last search date was tied to crop physiological maturity and the final rainfall criterion was 61.3 mm with a minimum season-end intensity index of 3.1 mm day^{-1}.

The results from the simulation analysis using the above stated input factors chronologically sorted by the date of germination from earliest to the latest are as shown in Appendix 9. Out of the 32 seasons, 30 seasons met the criteria stated above except year 1977 and year 1980. Out of the 30 seasons, 26 seasons that reached onset during 1 - 21 June, 12 seasons germinated during 23 - 29 June and the rest 14 seasons germinated during 1 - 17 July. Four out of the 30 seasons that reached onset during 1 - 12 July germinated during 1 - 16 July.

Season duration in each of the 30 seasons ranged between 35 - 65 days (Appendix 9). Out of the 30 seasons, 15 seasons would have duration in the range of 35 - 65 days, whereas the rest 15 seasons would have duration in the range of 70 - 90 days. Assuming 70 days as the minimum season duration desired for the production of the 90-day maize, only 15 of the 30 seasons would have easily produced the 90-day maize crop, and the rest of 15 seasons would have failed to produce the 90-day maize crop.

On the other hand, TSW supply ranged between 209 - 654 mm. Gross seasonal water needs of the 90-day maize was 261 mm. Appendix 9 shows that WAR ranged between 0.5 - 0.7 in seven of the 30 seasons. This would have enabled harvest of poor to normal maize yield levels. On the other hand, WAR ranged from 0.8 - 1.5 in 23 of the 30 seasons. Thus, the seasonal water requirements of the 90-day maize crop would have been sufficiently met and this would have enabled harvest of good maize yield. Over all, the 90-day maize crop would have been produced in each of the 30 seasons.

Water available in each of the crop growth sequences was as shown in Appendix 9. Water needs during all the seasons were adequate for the 90-day maize crop. However, 16 seasons were too short and encountered terminal droughts and thus would have completely failed to produce a 90-day maize crop. One season (1998) would have had poor yield. Overall, only 13 of the 30 seasons would have produced the 90-day maize crop successfully.

4.1.6. Probabilities of success from production of three maize varieties

The above results imply that starting of crops late in the season in and around ATARC (as is currently prescribed by research establishment) would be very risky. Late onset causes considerable loss of opportunity for higher yields from sowing of the 150- and 120-day maize varieties during early and median onset seasons. The overall results suggest that it is better for farmers to employ appropriate agronomic practices and start their seasons as early as possible. Development of drought tolerant early maturing non-conventional higher yielding maize varieties should be given priority by breeding programs.

The simulation modelling results presented above indicate that, the 150-day maize variety at MARC could have been successfully produced in 12 of the 32 seasons, whereas each of the 120- and 90-day maize varieties could have been produced in 20 of the 32 seasons. On the other hand, each of the 150- and 120-day maize varieties at ATARC could have been successfully produced in 17 of the 32 seasons, whereas the 90-day maize crop could have been successfully produced in 13 of the 32 seasons. The main reason for failure of short maturating 90-day maize crop at ATARC is due to too late onset and hence late planting which uses shorter season duration and early cessation of rainfall.

Probabilities of success from production of each of the three maize varieties are summarized in Table 19. The highest success rate at MARC was for the 120-day maize followed by the 90- and 150-day maize varieties. In contrast, ATARC would have the least rate of success for production of the 90-day maize, and moderate rate of success for production of both 120- and 150-day maize varieties.

Table 19: Comparison of probabilities of success from production of maize varieties at Melkassa and Adami Tulu

Maize variety (days)	Probability (%) at Melkassa		Probability (%) at Adami Tulu	
	for planting maize	success	for planting maize	success
150	100.0	37.5	90.6	58.6
120	78.1	80.0	90.6	58.6
90	90.6	69.0	93.8	43.3

The overall simulation modelling results presented above shows great potential for flexible combination production of the three maize varieties as compared to the growing of a 90-day maize variety in any given season. Thus, it differs with the recommendations of Simane and Struick (1993).

4.1.7. Predictors for the date of onset and seasonal rainfall characteristics

Under this section, results of the assessments of the main characteristics of pre-onset rainfall behaviour parameters are presented and discussed focusing on their significance for use as predictors for the identified date of onset.

Characteristics of pre-onset rainfall parameters

Under the analytical assumptions presented in Table 7, Section 3.3.2.1, results from

WHARF program rainfall analyses are presented in Table 20 for pre-onset rainfall behaviour parameters. The Table shows that at both locales, all pre-season rainfall parameters listed exhibited great inter-seasonal variability.

Table 20: Characteristics of pre-onset rainfall parameters at Melkassa and Adami Tulu

	MARC			ATARC		
Variable	FRD (Julian day)	POR (mm)	Eact (mm)	FRD (Julian day)	POR (mm)	Eact (mm)
Mean	91	95	53	91	96	45
Earliest /Minimum	18	24	3	35	28	3
Latest/ Maximum	184	243	205	157	225	144
Range	166 days	219	203	122 days	197	141
C.V. (%)	53	63	94	37	63	96

Note: FRD = First effective rainfall date; POR = Pre-onset rainfall; Eact = actual evaporative loss of pre-onset rainfall

The above discussed inter-seasonal variability in the first effective rainfall date and the date of onset are fully displayed in Fig. 7: for MARC and Fig. 8: for ATARC. Both Figures show that, the variation in the first effective rainfall date and the dates of onset closely follow each other. It can also be seen that during some seasons, the date of receipt of the first effective rainfall overlaps with the date onset. The relationships disclosed together with the precedence of the first effective rainfall date to the date of onset in time of occurrence implied that there could be great potential for the first effective rainfall date to be a predictor of the date of onset.

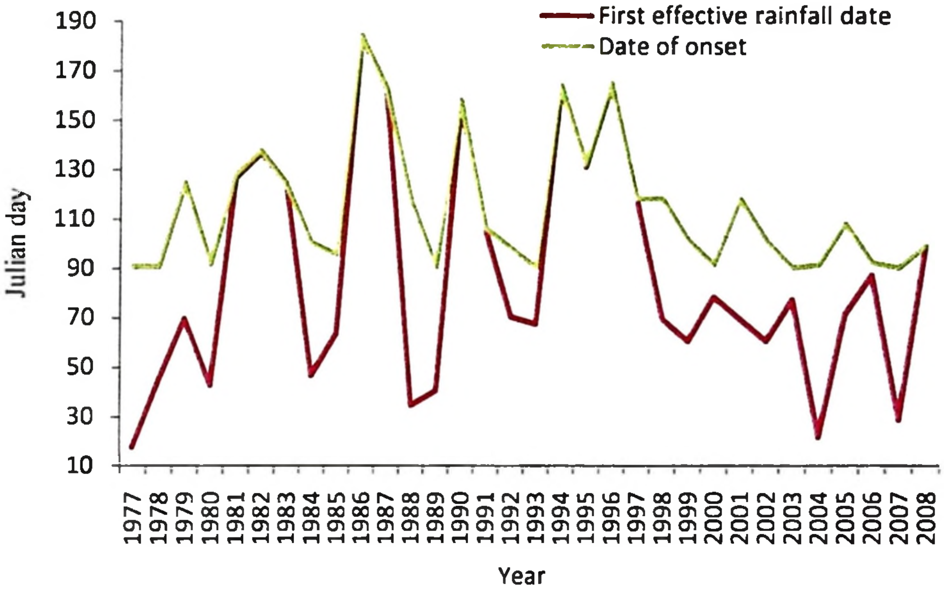

Figure 7: Inter-seasonal variability in the first effective rainfall date and the date of onset at Melkassa during 1977 – 2008

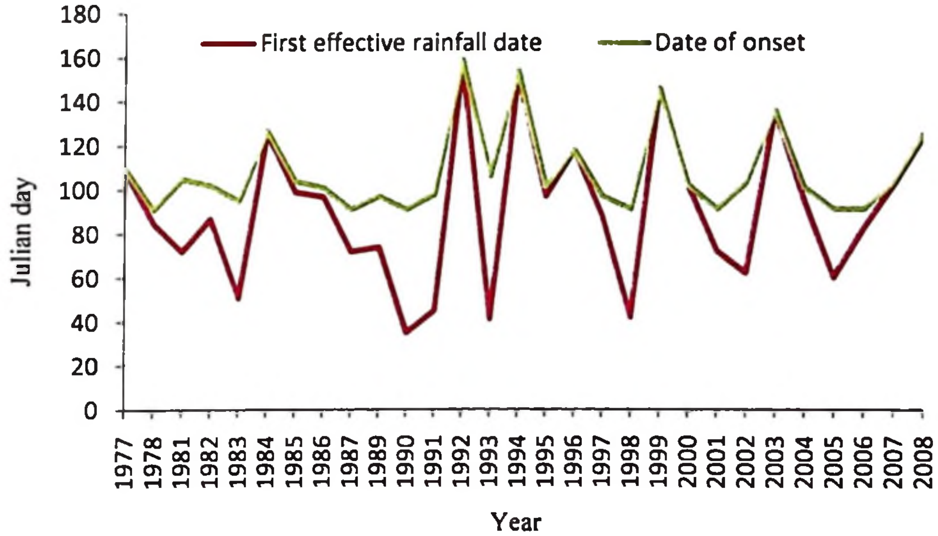

Figure 8: Inter-seasonal variability in the first effective rainfall date and the date of onset at Adami Tulu during 1977 - 2008

The above results imply the need for developing the capacity for determining years during which onset would not at all occur. Moreover, the overall results indicate the need for development of predictive capacity on which to base determination of the most probable dates of onset during any given season. This can facilitate better strategic planning of agronomic operations that leads to efficient use of seasonal rainfall. Accordingly, the above exhibit of higher-inter seasonal variability in pre-onset rainfall parameters implies high potential for the first effective rainfall date, pre-onset rainfall amounts and actual evaporative loss of pre-onset rainfall amounts to serve as predictors for dates of onset and other seasonal rainfall parameters.

4.1.8. Synthesis

The results from this study as presented above established a multi-factor based agronomically risk-wise acceptable dates of onset and corresponding rainfall criteria and predictors for the date of onset and seasonal rainfall parameters. The the multi-factor approach is unique in that it lends itself to the risks that are prevalent in the semi-arid areas than avoid them. It has taken into account rainfall variability, temperature, effective rainfall-evapo-transpiration relations, dry spell and expected rainfall probabilities, farmer's perceptions of rainfall and definition of onset, and crop types and soil characteristics. Moreover, it has taken into account soil types and RF precepts based Stewart's (1988a) definition of onset, and general suitability of rainfall for production of alternative maize varieties applying simulation modelling techniques.

Adopting the multi-factor approach, April onset was found to be the most risk-wise acceptable earliest date of onset for starting of crops at the study sites. The risks from low mean rainfall conditions during early seasons can be terrible unless farmers who are very well aware of the consequences should prevent any runoff employing appropriate agronomic practices. Starting tillage immediately after harvest should be taken seriously to encourage infiltration of all the drops of pre-onset rainfall. The results also revealed that by accepting early onset, failure rate would have been high had a maize variety of 150 days been planted every season. However, there was also great chance of bringing the 120- and 90-day maize varieties and even extra-early maize varieties into play in each of the past seasons. Thus, the low probability of success from growing of a 150-day maize variety could have been compensated by planting of the 120- and 90-day maize varieties during median- and late-onset seasons.

In response to rainfall uncertainty, farmers in the study areas have long ago rejected the notion of a single fixed best-bet maize production system recommended for the two study sites, in which the same cultivar and practices are followed each year. Instead, farmers have over time evolved a number of weather sensitive technical adjustments which are brought into play, particularly during April through late-June depending on the actual rainfall developments (Fujisaka, *et al.*, 1996, ICRA, 1999). Thus, compared to a fixed strategy, flexible combination system of planting of long season maize varieties in early onset seasons (April), medium maturity maize in median onset seasons (May) and an early maturing maize variety in late seasons (late June to mid July) can be superior in stability and potential yield as well as farmer satisfactions.

The multi-factor based definition of onset has fully accommodated the risks that are normally prevalent in semi-arid areas and can be considered more realistic in setting-up risk-wise acceptable dates of onset of rainfall seasons. Thus, onset definition followed in this study differs from the approaches followed by Simane and Struick (1993) that established late June as the desirable time of season onset and the start of cropping for the study sites. Moreover, it differs with FAO (1978) and Sivakumar (1988) criteria for definition of onset that are constrained by single criterion and stringent assumptions that are meant to avoid false onset and tended to ignore the commonly experienced dry periods in the SAT (Kanemasssu *et al.*, 1990). Thus, they roughly result is shorter season duration with lower total seasonal water. Consequently, the approaches result in waste of considerable meagre rainfall resources of the SAT. They also tend to ignore the great inter-seasonal variation in time of season onset that characterizes the SAT (Stewart, 1988a). Thus, the potential of some early and median onset seasons that provide longer and medium season duration and higher seasonal water supply that enable production of higher yielding varieties are merely sacrificed. Their tendency to instruct the farmer to adopt a single fixed-bet production strategy exposes the farmer to a win-or loose game exercises from production of early maturing low yielding varieties regardless of season types. They also fail to account dryland farmers' perceptions and practices (ICRA, 1999) and better risk management opportunity that is possible by employing response farming approach (Stewart, 1991a).

It should be emphasized that successful production of the 90-, 120- and 150-day maize varieties during early, median and late onset dates respectively at both study sites lies in adoption of appropriate agronomic soil and water management practices. Thus farmers should adopt rigid water conservation measures, weed control, and run-off diversion measures for improving the overall rate of success. Practicing tillage following harvest of preceding crop and adoption of early season tillage directed to conserve soil water and to control weeds, use of in-situ moisture conservation practices are pre-requisites for successful production of the different maize varieties. The advantages of these agronomic practices are amply discussed by Reddy and Kidane (1994).

The need to breed for drought tolerant higher yielding long and medium maturing varieties of maize should also be addressed to overcome the identified risks. Rain water harvesting and run-off diversion should also form an integral part of the agronomic risk management strategies. Farmers can also minimize risks by allocating maize to fields which receive runoff, and by reducing area sown to long season maize varieties during late seasons. All of the above mentioned standard agronomic strategies should be adopted by farmers in any given season in order to minimize risks (Stewart, 1991b). Given that farmers prefer the grain quality and yield of longer maturity cultivars, the chance of success for producing them can be improved if farmers are provided with information on the potential of impending season so that they can make informed decisions. The overall results points to the need for predictive capacity for dates of onset of the up-coming season at MARC and ATARC in order to stabilize and enhance maize production.

At Melkassa and Adami Tulu, pre-onset rainfall behaviour parameters exhibited great inter-annual variability. Particularly, the date of onset was found to closely vary with the first effective rainfall date. This implied high potential of the first effective rainfall date for use as predictors for the dates of onset and other season rainfall parameters.

4.2. Prediction Models for the Date of Onset and Duration of Next Rainfall Season

In the study sites, the high inter-annual variability in the date of onset in any given season presents major strategic agronomic decision challenges to resource poor farmers. Such challenges include the types of pre-season water conservation tillage modes to adopt, the type of crops to emphasize or de-emphasize, and whether credit for buying fertilizer and improved seeds, and improved farm implements and herbicides should be sought or not (Stewart, 1991b). Hence, the ability to estimate the date of onset of the approaching rainfall season is crucial. Under this section, results from the analyses conducted in order to address specific objective two of the study that was aimed at developing prediction functions for the date of onset in order to improve strategic response farming of maize are presented and discussed.

4.2.1. The first effective rainfall date – a predictor of the date of onset

Figure 9 depicts results from the regression of the date of onset on its respective first effective rainfall date for each of the 32 seasons at MARC using individual years as data labels. The developed regression equation is:

Date of onset (Julian day) = $70 + 0.1513x$..(1)

Where x is the first effective rainfall date in Julian day.

The regression results indicate that close to 78% (R^2) of the likely variation in the date of onset at MARC is explained by the variation in the first effective rainfall date. Analyses of variance revealed the R^2 to be highly significant at 1% probability level ($P \leq 0.001$).

The slope of the predictor is 0.5. This indicates that, at MARC, on average, the date of onset is delayed by more than half day per day, beyond the first day of January (first Julian day) that passes without receiving its first effective rainfall.

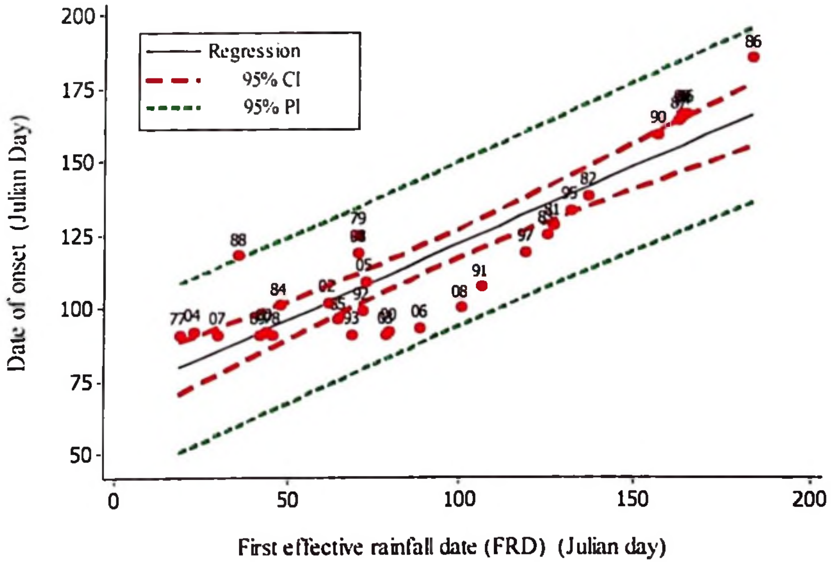

Figure 9: A linear regression function showing the variation of the date of onset with the first effective rainfall date at Melkassa

Figure 10 depicts results from cross validation of the observed with predicted date of onset using the developed model. The correlation coefficient (r) relating both is slightly more than 0.88. This is statistically highly significant at 1% level ($P \leq 0.001$). This indicates that the developed model is good for use in estimating future dates of onset.

Equation 1 is valid to estimate the expected date of onset in the range of 68 to 180 days using the first effective rainfall date in the range of Julian days 91 to 185. The standard error (SE) of predicting the date of onset using the regression equation would be ±14 days. Taking the 32 seasons mean date of onset of 117 Julian into account, the estimation error would have been 12% either above or below it.

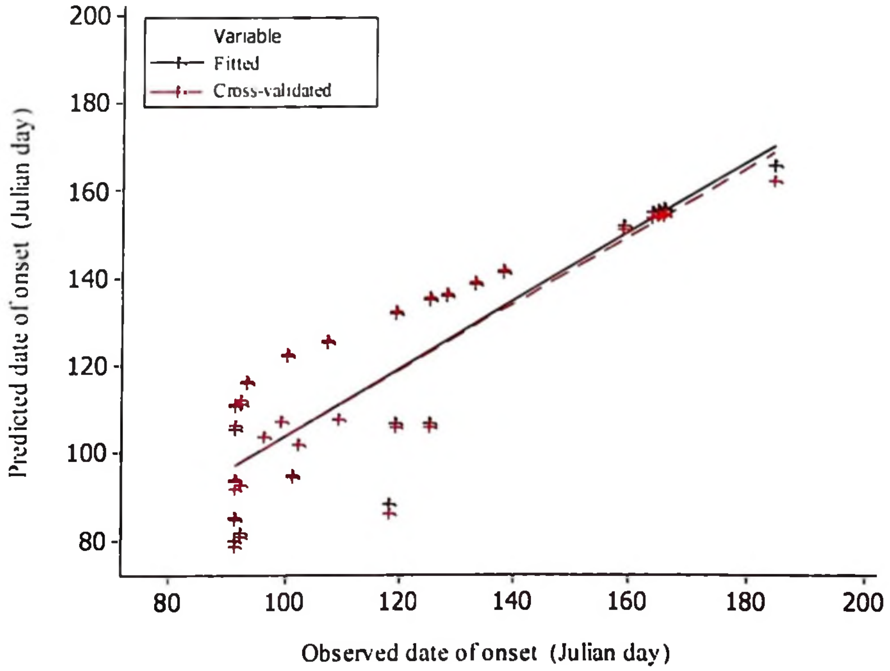

Figure 10: Observed vs. predicted date of onset at Melkassa

Results from the cubic polynomial regression of the date of onset on its respective first effective rainfall date over the past 32 seasons at MARC are depicted in Fig. 11. The resulting regression equation 2 is shown below.

Date of onset (Julian day) = $91.84 + 0.1879x - 0.002292x^2 + 0.000023x^3$.........(2)

Where: x is the first effective rainfall date in Julian day.

The regression explained more than 89% of the variation in the date of onset with the first effective rainfall date (R^2 = 89%). Analyses of variance revealed significance of the regression at 1 % level of significance ($P \leq 0.001$). Thus, significant delay in the date of onset is closely associated with the delay in the first effective rainfall date.

The developed prediction model capability in reproducing future values of the response variable is depicted in Fig.12. The Figure enables assessment of how well the models fit the data and how precisely they can predict. As expected from the large R^2, the fit results for cubic polynomial are very reasonable because the generated data follows a cubic curve. The 95% confidence bounds on the fitted coefficients indicate that they are acceptable because only 9 out of the 32 seasons (28% of the all seasons) were not captured by the model. This implies some degree of uncertainties that should be expected from using the model.

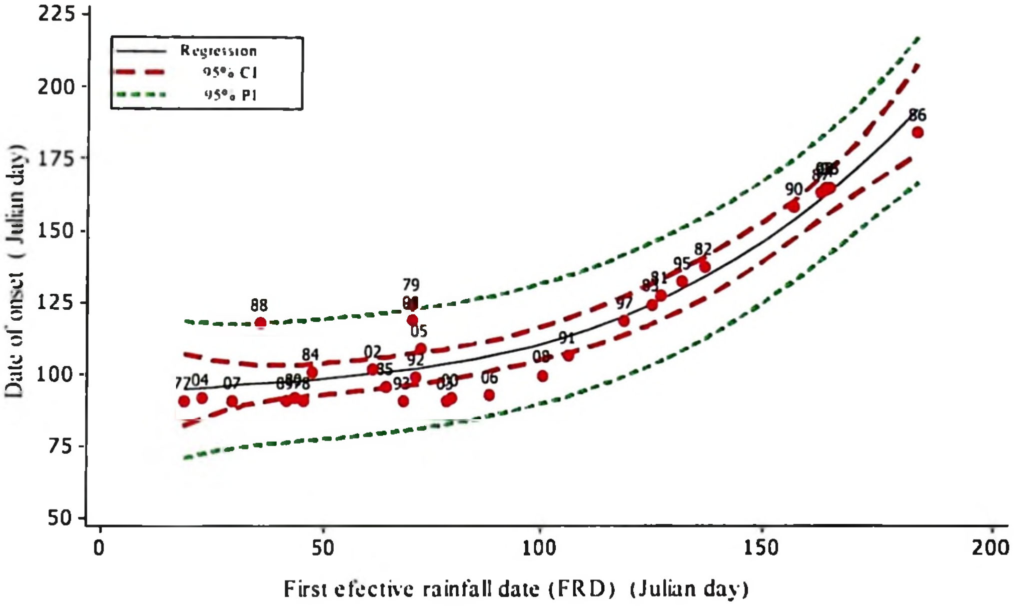

Figure 11: A cubic regression function showing the variation of the date of onset with the first effective rainfall date at Melkassa

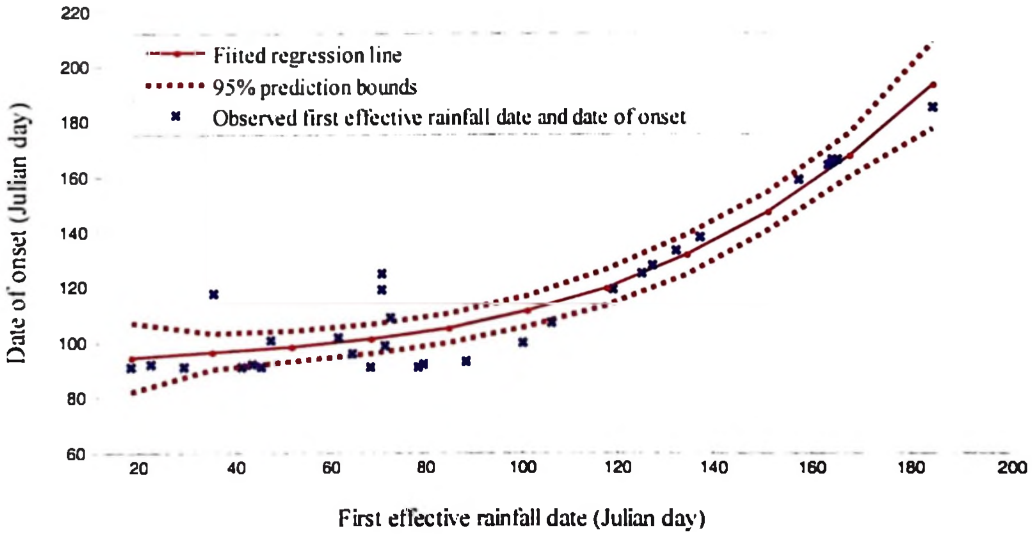

Figure 12: Predictive capability of a cubic regression model developed for determination of the date of onset of next season at Melkassa

Equation 2 is valid to estimate the expected mean date of onset in the range of 68 to 180 days using the date of onset in the range of 91 to 185 Julian days. The SE of predicting the date of onset using the regression equation would be ±10 days. Taking the 32 seasons mean date of onset of 117 Julian into account, the estimation error would have been 8% either above or below it.

Results depicted in Fig. 13: are from the regression of the date of onset on its respective first effective rainfall date for each of the 29 seasons studied at ATARC. The resulting regression equation is shown below.

Date of onset (Julian day) = $63.8 + 0.486x$ ……………………………………………(3)

Where: x is the first effective rainfall date in Julian day.

Regression equation 3 relating both has R^2 close to 72%. This indicates that close to 72% of the likely variation in the date of onset at ATARC is explained by the variation in the first effective rainfall date. Analyses of variance revealed the R^2 to be statistically highly significant at 1% probability level ($P \leq 0.001$). The regression line in the Figure has a slope closer to 0.5. This indicates that, at ATARC, on average, the date of onset is delayed by nearly half day per day, beyond the first day of February (Julian day 32), that passes without its first effective rainfall.

Results from cross validation depicted in Fig. 14: relate the observed with predicted date of onset using the developed model. The r relating both is close to 0.8. This is statistically highly significant at 1% level (P≤0.001). This indicates the developed model to be good for use in estimating future dates of onset.

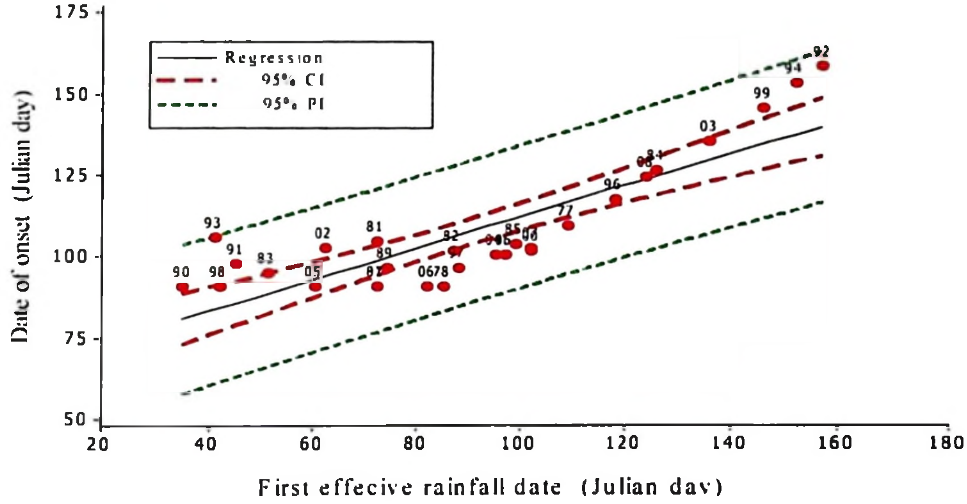

Figure 13: A linear regression function showing the variation of the date of onset with the first effective rainfall date at Adami Tulu

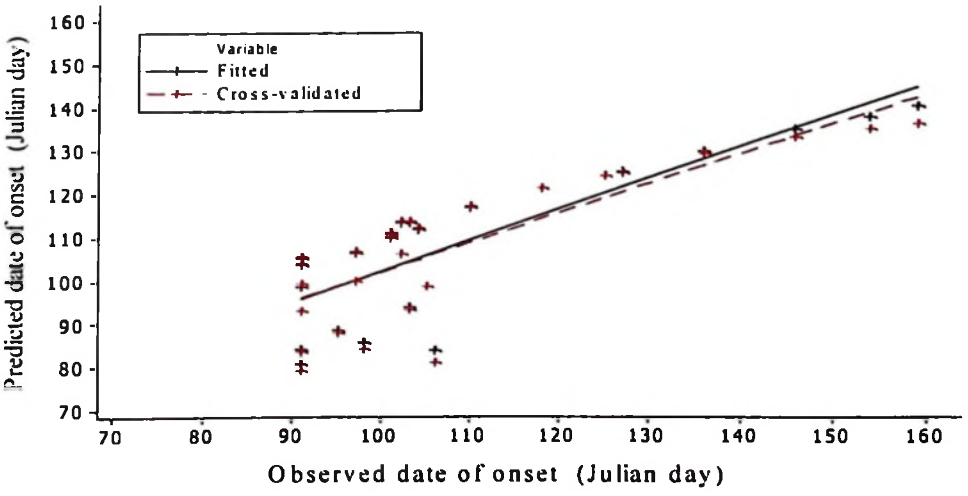

Figure 14: Observed vs. predicted date of onset at Adami Tulu

Equation 3 is valid to estimate the expected mean date of onset in the range of 91 - 159 days using the first effective rainfall date in the range of 35 - 157 Julian days. The SE of predicting the date of onset using the regression equation would be ±11 days. Taking the 29 seasons mean date of onset of 108 Julian into account, the estimation error would have been close to 10% either above or below it.

Results from a polynomial regression analyses is depicted in Fig. 15: with regression Equation 4 relating the date of onset to its respective first effective rainfall date at ATARC over the past 29 seasons has R^2 close to 95%. Equation 4 below is the developed regression model.

Date of onset (Julian day) = $122.3 + 0.9271x - 0.007466x^2$..........................(4)

Where: x is the first effective rainfall date in Julian day.

Analyses of variance revealed significance of the regression at 1% level of significance ($P \leq 0.001$). Thus, at ATARC, the delay in the date of onset is significantly associated with the delay in the first effective rainfall date.

As can be expected from the large R^2, Fig. 16: for ATARC shows the fit results for the quadratic polynomial to be very practical because the generated data follows a quadratic curve.

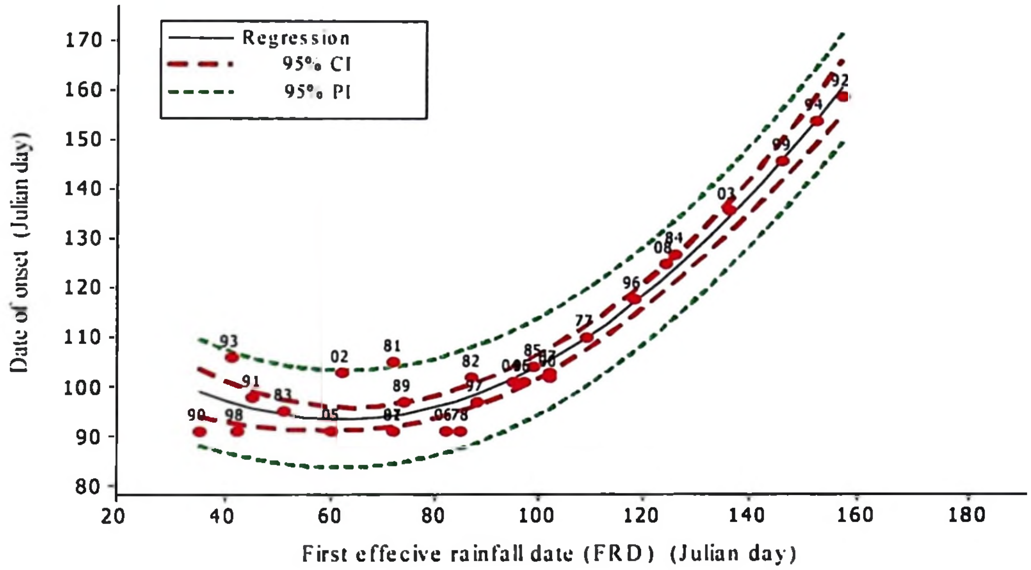

Figure 15: A quadratic regression function showing the variation of the date of onset with the first effective rainfall date at Adami Tulu

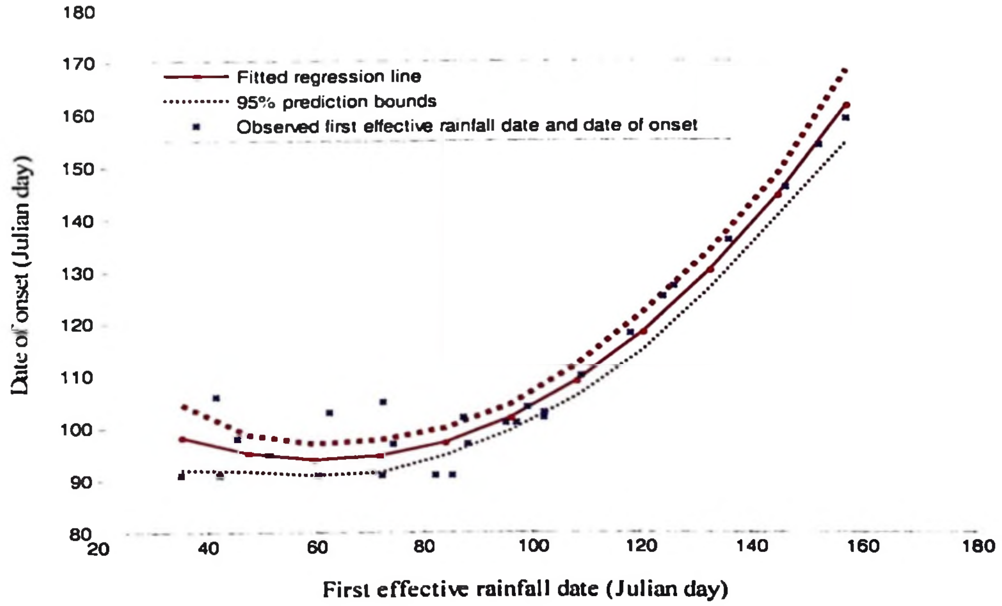

Figure 16: Predictive capability of a quadratic regression model developed for determination of the date of onset of next season at Adami Tulu

Fig. 16: also shows that only five of the 29 seasons (17% of all years) were un-captured by the model. This implies small degree of uncertainties that should be expected from using the first effective rainfall date in predicting the date of onset during some years. The 95% confidence bounds indicate the usefulness of the model for practical strategic decision making.

Equation 4 is valid for predicting the date of onset in the range of 1 to 159 Julian days using the first effective rainfall date in the range of 35 and 157 Julian days. The SE of predicting the date of onset using the regression equation would be ±4 days. Taking the 29 seasons mean date of onset of 107.8 Julian into account, the estimation error would be slightly more than 8.5% either above or below it.

Summary of the linear and polynomial regression models along with detailed statistical values for MARC and ATARC are presented in Table 21 and Table 22 respectively. The two linear and the two polynomial regression models developed for prediction of the date of onset of next season using the first effective rainfall date as a predictor are named *MATOPM-I (Melkassa and Adami Tulu Onset Prediction Model-I)*.

The ability to predict the date of onset is very crucial for farmers in the semi-arid areas, who entirely depend on rainfall for crop production.

Table 21: Linear regression models for prediction of the date of onset using the first effective rainfall date at Melkassa and Adami Tulu

							Constant			Slope			
Location	Prediction model	R^2 (%)	SE (±)	F	P	VIF	SE (±)	T	P	SE (±)	T	P	DW
MARC (Equation 1)	DOS = 70 + 0.1513x	78	14	106^{**}	0.000	1	5	14^{**}	0.000	0.05	10^{**}	0.000	1.84778
ATARC (Equation 2)	DOS = 63.8 + 0.486x	72	11	68^{**}	0.000	1	6	11^{**}	0.000	0.06	8^{**}	0.000	1.50131

Note: DOS = Date of onset (Julian day); x = First effective rainfall date (Julian day); VIF = Variance inflation factor; DW = Durbin-Watson statistic; ** = Highly significant at 1% level; Models are designated by MATOPM-I

Table 22: Polynomial regression models for prediction of the date of onset using the first effective rainfall date at Melkassa and Adami Tulu

						Linear		Quadratic		Cubic	
Location	Prediction model	R^2 (%)	SE (±)	F	P	F	P	F	P	F	P
MARC (Equation 3)	DOS = 91.84 + 0.1879x – 0.002292x^2 + 0.000023x^3	89	10	76^{**}	0.000	106^{**}	0.000	26^{**}	0.000	1.5^{ns}	0.237
ATARC (Equation 4)	DOS = 122.3 + 0.9271x – 0.007466x^2	95	5	232^{**}	0.000	68^{**}	0.000	113^{**}	0.000	-	-

Note: DOS = Date of onset (Julian day); x= First effective rainfall date (Julian day); ** = Highly significant at 1%; ns = Non significant at 5% level; Models are designated by MATOPM-I

As has been shown for both study sites, the date of onset significantly vary with the first effective rainfall date. The apparent reason for the above described strong relationship between the first effective rainfall date and the date of onset can be attributed to the fact that the dates when the first effective rainfall having significant contribution for onset are received are highly variable making the date of onset highly dependent on the first effective rainfall date. The described association between the first effective rainfall date and the date of onset also imply the potential of the former to be used as a predictor of season duration.

The finding from the above analyses clearly contradicts the conclusion by Mamo (2004) who reported a near complete unpredictability of the date onset under semi-arid conditions. The first effective rainfall date as the predictor of the date of onset makes it possible to get good insights about the expected season dates of onset at a lead time of two to three months. This can lay a foundation for strategic selection of crops types to emphasize and credit to be sought for purchase of desired production inputs. Literature review shows no evidence of use of the first effective rainfall date as a predictor of the date of onset of next season. Thus, this is a new finding of the study.

4.2.2. Relationship of the date of onset with the amount of pre-onset rainfall and actual evaporative loss of pre-onset rainfall

Results from a polynomial regression of the date of onset on its respective amount of pre-onset rainfall for each of the 32 seasons studied at MARC are presented in Table 23 (Equation 5). The regression explained more than 55% of the variation in the date of onset with the variation in the amount of pre-onset rainfall (POR). Statistically, the R^2 value is significant at 1% probability level ($P \leq 0.001$). The results suggest tendency of a delay in the date of onset during seasons that receive lower amount of pre-onset rainfall.

Regression equation 5 is valid for predicting the date of onset in the range of 91 - 185 Julian days using the amount of pre-onset rainfall in the range of 23.6 - 242.8 mm. The SE of predicting the date of onset using the regression equation would be ±19 mm. Considering the 32 seasons mean date of onset of 115 Julian, the estimation error would be slightly more than 17% either above or below it.

Results from a polynomial regression analyses in Table 23 (Equation 6) relating the date of onset to its respective pre-onset rainfall at ATARC over the past 29 seasons show little explained variation of the date of onset with the amount of pre-onset rainfall. The apparent reason for the lack of significant variation in the date of onset can be partially attributed to the high evaporative losses due to high temperature and strong winds that are experienced at ATARC during January through March. Thus, the amount of pre-onset rainfall can be regarded as a fair indicator of the date of onset of next season at MARC than at ATARC. The findings for MARC are similar to those reported for Hydrabad in India by Stewart (1988b) who found winter and spring rains to be good predictors of the character of monsoon to come.

Polynomial regression models in Table 24 (Equations 6 and 7) relating the date of onset to its respective amount of the actual evaporative loss of pre-onset rainfall

(Eact) at MARC over the past 32 seasons has R^2 of 47%. Analyses of variance revealed significance of the regression at 1% level of significance ($P \leq 0.001$). On the other hand, results from a polynomial regression analysis presented in Table 24 for ATARC has low R^2 (41%). Analyses of variance revealed significance of the regression at 1% level of significance ($P \leq 0.001$). The results indicate little expected variation in the date of onset with the variation in the amount of the actual evaporative loss of pre-onset rainfall at both MARC and ATARC. The overall results suggest delay in the date of onset is to be expected in season with lower pre-onset rainfall amounts and higher evaporative rates.

Table 23: Polynomial regression models relating the date of onset with the amount of pre-onset rainfall at Melkassa and Adami Tulu

Location	Prediction model	R^2	SE			Linear		Quadratic		Cubic	
		(%)	(±)	F	P	F	P	F	P	F	P
MARC (Equation 5)	$DOS = 147.3 - 0.0488x - 0.005059x^2 - 0.000020x^3$	55	20	11^{**}	0.000	22^{**}	0.000	8*	0.014	1.2^{ns}	0.281
ATARC (Equation 6)	$DOS = 134.0 - 0.4049x + 0.000990x^2$	35	16	7^{**}	0.003	13^{**}	0.001	1^{ns}	0.321	-	-

Note: DOS = Date of onset (Julian day); x = Pre-onset rainfall (mm); ** = Highly significant at 1%; * = Significant at 5%; ns = Non significant at 5% level

Table 24: Polynomial regression models relating the date of onset with the actual evaporative loss of pre-onset rainfall at Melkassa and Adami Tulu

Location	Prediction regression model	R^2	SE			Linear		Quadratic	
		(%)	(±)	F	P	F	P	F	P
MARC (Equation 6)	$DOS = 143.1 - 0.8412x + 0.003602x^2$	48	21	13^{**}	0.000	12^{**}	0.002	10^{**}	0.003
ATARC (Equation 7)	$DOS = 125.3 + 0.6684x + 0.003280x^2$	38	15	8^{**}	0.002	11^{**}	0.002	4^{ns}	0.063

Note: DOS = Date of onset (Julian day); x = Actual evaporative rate (mm); ** = Highly significant at 1% level; * = Significant at 5% level; ns = Non significant at 5% level

4.2.3. The first effective rainfall date – an indicator of the duration of next crop season

The ability to predict the date of onset using the first effective rainfall date as a predictor would imply that seasons that receive their first effective rainfall earliest would have longer duration and vice versa. However, the inference does not provide quantitative expectations of the duration of up-coming season. Therefore, it is important to quantitatively determine the expected length of next season at a reasonable lead time. Accordingly, results from the regression of season duration on its respective first effective rainfall date for MARC is depicted in Fig. 17. The resulting regression model is presented below:

$$\text{Season duration (days)} = 183 - 0.524x \quad \text{..(7)}$$

Where: x is the first effective rainfall date in Julian day.

The regression equation has R^2 of 65% which explain close to 65% of the likely variation in the duration of rainfall seasons with the variation in the first effective rainfall date. Statistically, the R^2 value is highly significant at 1% probability level ($P \leq 0.001$). The median line in the Figure with a slope of -0.5 indicates that, at MARC, on average, season duration is foreshortened by more than half day per day, beyond the first day of January (1 Julian) that passes without its first effective rainfall.

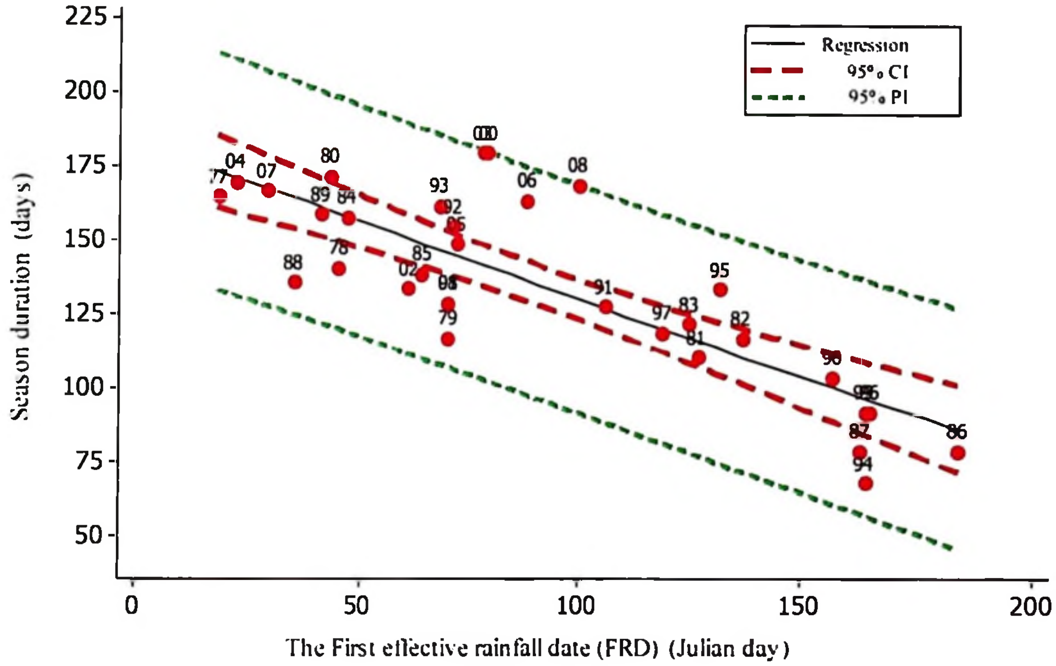

Figure 17: A linear regression function showing the variation of duration of seasonal rainfall with the first effective rainfall date at Melkassa

Results from cross validation depicted in Fig. 18: relate the observed with the predicted date of onset using the developed model. The r relating both is close to 0.8. This is statistically highly significant at 1% level ($P \leq 0.001$). This indicates the developed model to be good for use in estimating future season duration.

Equation 7 is valid to estimate the expected mean season length in the range of 68 - 180 days using the first effective rainfall date in the range of 18 - 184 Julian days. The SE of predicting season duration using the regression equation would be ±19 days. Taking the 32 seasons mean season length of 135 days into account, the estimation error would be close to 14% either above or below it.

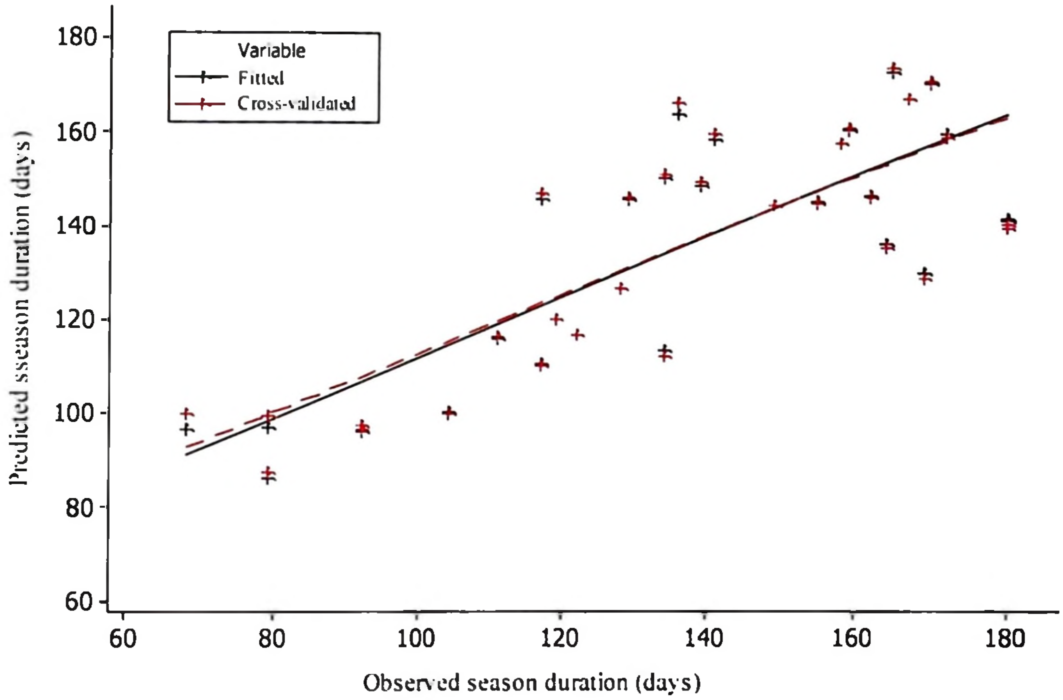

Figure 18: Observed vs. predicted duration of seasonal rainfall at Melkassa

The polynomial regression results depicted in Fig. 19: relating season duration to the first effective rainfall date at MARC has R^2 of 71%. Analyses of variance revealed significance of the regression at 1% level of significance ($P \leq 0.001$). Thus, at MARC, significant delay in the first effective rainfall date would result in shorter season duration.

The developed regression model is as shown below.

Season duration (days) = $154.9 + 0.2043x - 0.003647x^2$..(8)

Where: x is the first effective rainfall date in Julian day.

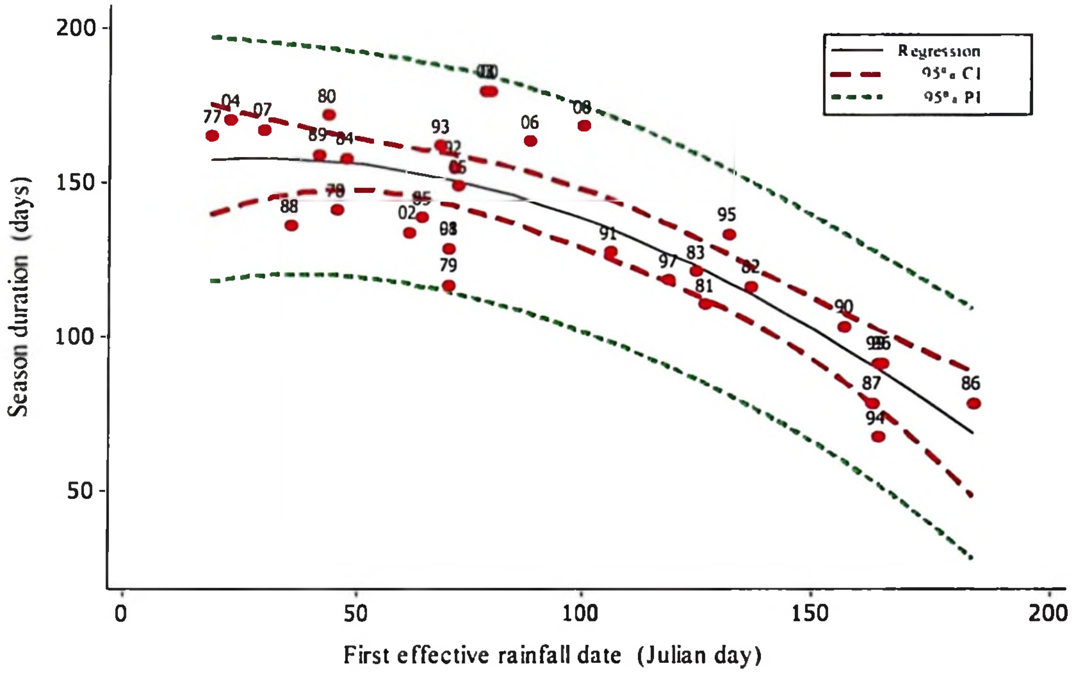

Figure 19: A quadratic regression function showing the variation of the duration of seasonal rainfall with the first effective rainfall date at Melkassa

The prediction bounds for the quadratic regression function in Fig. 20: shows that 14 of the 32 seasons observed values are effectively outside the prediction bounds. This implies that the first effective rainfall date would not have effectively predicted season duration during 44% of all seasons. However, the uncertainty in predicting future season duration using the regression model is fairly acceptable and the model results can be viewed useful as it provides initial insights about expected season duration at a good lead time. Nevertheless, a closer estimator is necessary to more precisely and closely estimate the expected duration of up-coming season before the final decision on crop types and cultivar maturities are reached.

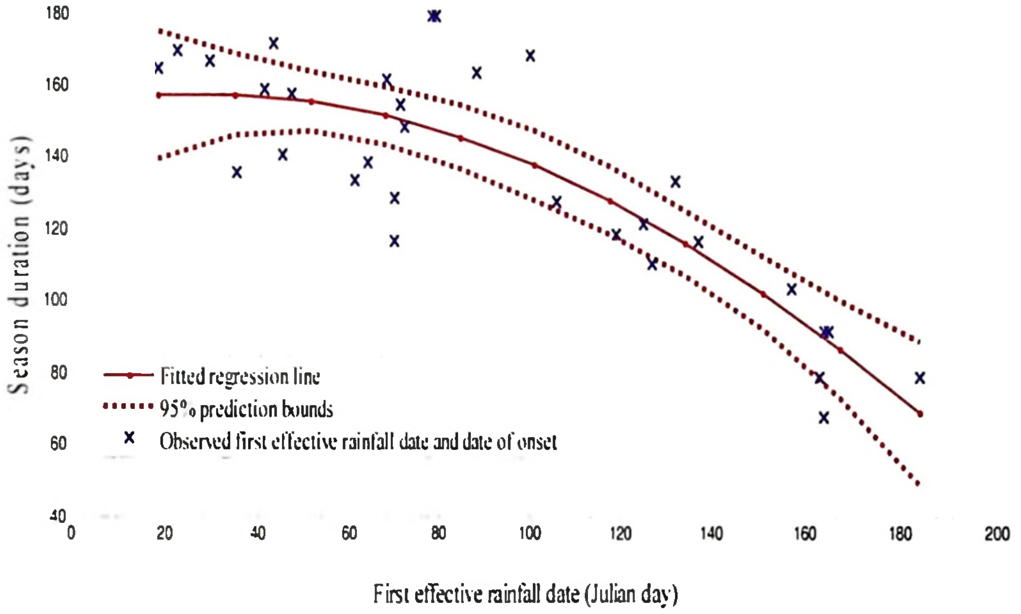

Figure 20: Predictive capability of a quadratic regression model developed for determination of the duration of seasonal rainfall at Melkassa

Equation 8 is valid to estimate the expected season length in the range of 68 - 180 days using the first effective rainfall date in the range of 18 - 184 Julian days. The SE of predicting season length using the regression model would be ±17 days. Taking the 32 seasons mean duration of 135 days into account, the estimation error would be close to 13% either above or below it.

Results from the regression of the duration of rainfall period on its respective first effective rainfall date depicted in Fig. 21: for ATARC fully displays the historical associations between them. The developed regression model is:

Season duration (days) = $191 - 0.509x$ ....(9)

Where: x is the first effective rainfall date in Julian day.

The regression explained close to 51% (R^2) of the variation in season duration with the variation in the first effective rainfall date. Analyses of variance revealed the R^2 value to be statistically highly significant at 1% probability level ($P \leq 0.001$).

The regression line in the Figure with a slope of -0.5 indicates that, at ATARC, on average, season duration is foreshortened by nearly half day per day, beyond the first day of February (32 Julian) that passes without its first effective rainfall.

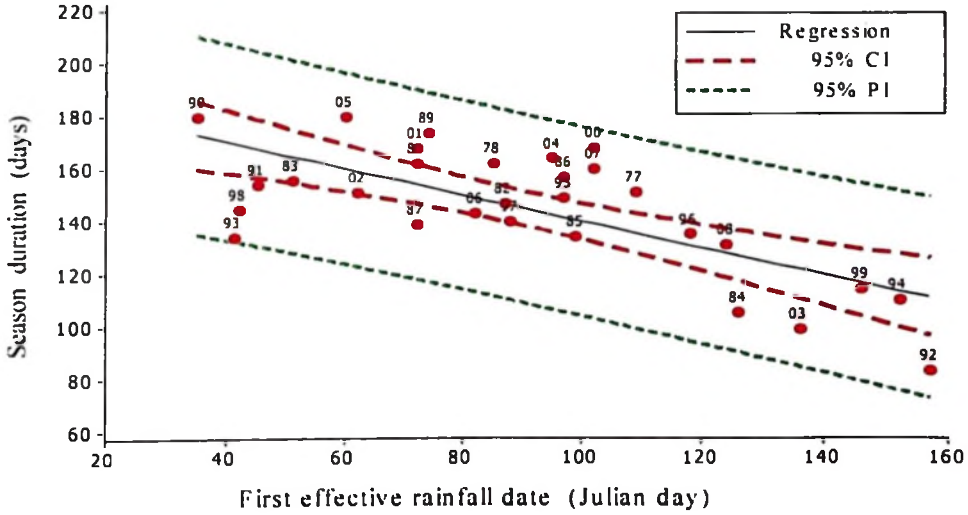

Figure 21: A linear regression function showing the variation of the duration of seasonal rainfall with the first effective rainfall date at Adami Tulu

For ATARC, the results from a polynomial regression of season duration on its respective first effective rainfall date depicted in Fig. 22: and the resulting regression model is shown by Equation 10. The equation has R^2 of 68%. Analyses of variance revealed significance of the variation in season duration with the variation first effective rainfall date at 1% level of significance ($P \leq 0.001$). Thus, significant shortening in season duration is to be expected with delay in the first effective rainfall date. The developed prediction model is:

$$\text{Season duration (days)} = 127.4 + 1.044x - 0.00856x^2 + 0.000002x^3 \ldots\ldots\ldots\ldots\ldots(10)$$

Where: x is the first effective rainfall date in Julian day.

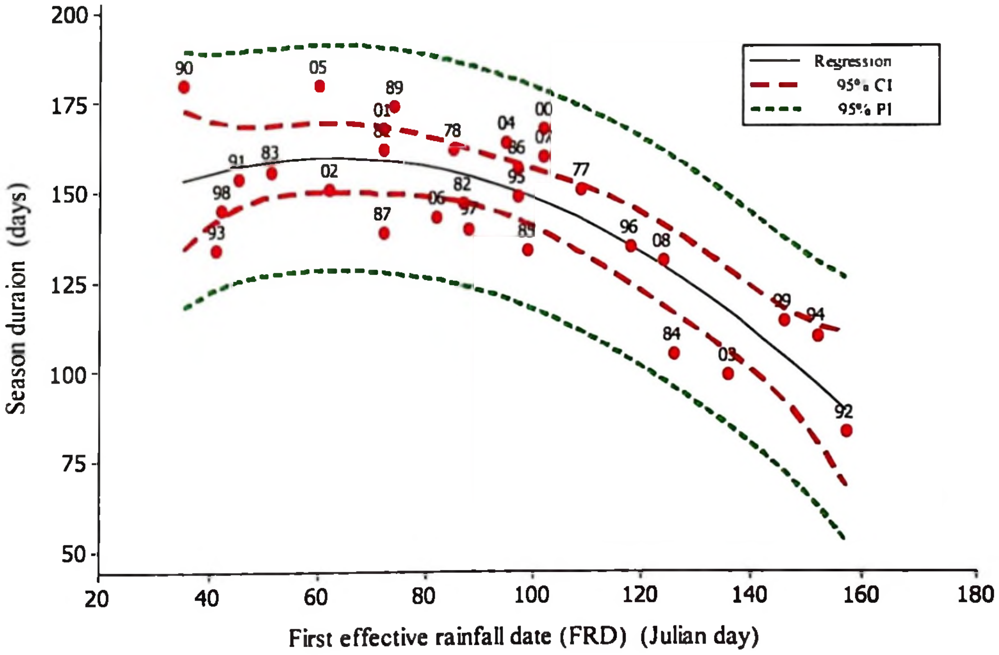

Figure 22: A cubic regression function showing the variation of the duration of seasonal rainfall with the first effective rainfall date at Adami Tulu

For Adami Tulu, the prediction bounds for the cubic regression model depicted in Fig. 23: indicates that the model would have captured season duration during 13 of the 29 seasons (45% of all years). Despite the model uncertainty, the results can be viewed useful to get an indication of the likely season duration at a good lead time. However, like for MARC, a closer estimator is required to estimate expected duration of up-coming season.

Equation 10 is valid to estimate the expected mean season length from 83 - 180 days using the first effective rainfall date from 35 - 157 Julian days. The SE of predicting season length using the regression equation would be ±15 days. Taking the 29 seasons mean season length of 145 days into account, the estimation error would be slightly more than 10% either above or below it.

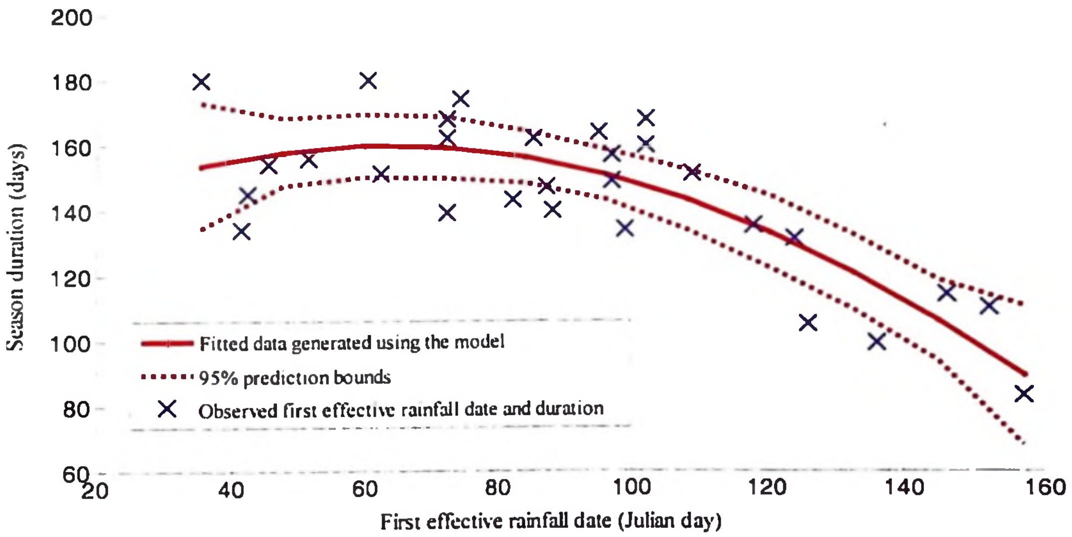

Figure 23: **Predictive capability of a cubic regression model developed for determination of the duration of seasonal rainfall at Adami Tulu**

Table 25 and Table 26 for MARC and ATARC respectively contains summary of the linear and polynomial regression models relating season duration with the first effective rainfall date along with detailed statistical results. The two linear and the two polynomial regression models developed for prediction of the duration of next crop season using the first effective rainfall date as a predictor are collectively named *MATDPM-I* (*Melkassa and Adami Tulu Duration Prediction Model-I*).

The findings show the first effective rainfall date to be a good predictor for the date of onset than for the duration of rainfall season. At MARC and ATARC, significant delay in the first effective rainfall date would result in shorter season duration. The apparent reason for such relationship can be attributed to the fact that the dates of receipt of the first effective rainfall are highly variable making season duration dependent on it. Similarly, as the first effective rainfall date is delayed, the date of onset is delayed implying shortening tendency in season duration. The variation expected in season duration lower than that of the date of onset because of the precedence of the first effective rainfall date in time of occurrence compared to season duration.

The developed prediction models provide good insights about the expected season duration at a lead time of two to three months. These findings are useful in that they lay a foundation for strategic selection of crops types to emphasize and credits for purchase of yield improving inputs. The reviewed literature shows no evidence of use of the first effective rainfall date as a predictor of season duration. Thus, this is also a new finding of the study of practical significance for dryland farmers.

Table 25: Linear regression models for prediction of season duration using the first effective rainfall date at Melkassa and Adami Tulu

		R^2 (%)						Constant			Slope			
Location	Prediction model	Unadjusted	Predicted	SE (±)	F	P	VIF	SE (±)	T	P	SE (±)	T	P	DW
MARC (Equation 7)	DUR = 183 − 0.524x	65	62	19	57^{**}	0.000	1	7	26^{**}	0.000	0.1	-8^{**}	0.000	1.76708
ATARC (Equation 8)	DUR = 191 − 0.509x	51	42	17	28^{**}	0.000	1	9	21^{**}	0.000	0.1	-5^{**}	0.000	1.82238

Note: x = First effective rainfall date (Julian day); DUR = Season duration (days); VIF = Variance inflation factor; DW = Durbin-Watson statistic; ** = Highly significant at 1% level; Models are designated by MATDPM-I

Table 26: Polynomial regression models for prediction of season duration using the first effective rainfall date at Melkassa and Adami Tulu

						Linear		Quadratic		Cubic	
Location	Prediction model	R^2 (%)	SE (±)	F	P	F	P	F	P	F	P
MARC (Equation 19)	DUR = 154.9 + 0.2043x − 0.003647x^2	71	17	36^{**}	0.000	-57^{**}	0.000	6^{*}	0.022	-	-
ATARC (Equation 10)	DUR = 127.4 + 1.044x − 0.00856x^2 + 0.000002x^3	68	15	17^{**}	0.000	28^{**}	0.000	13^{**}	0.001	0.00^{ns}	0.976

Note: x = First effective rainfall date (Julian day); DUR = Season duration (days); ** = Highly significant at 1%; * = Significant at 5% level; ns = non-significant; Models are designated by MATDPM-I

4.2.4. Synthesis

Results presented above show significant variation of the dates of onset of rainfall seasons with the first effective rainfall date as compared to the variation with the amount of pre-onset rainfall and actual evaporative loss of pre-onset rainfall. The results successfully established a predictor for the date of onset and season duration that are locally valid in guiding agronomic planning and decision making under risk. The linear and polynomial prediction models that designated the first effective rainfall date as a predictor of the date of onset are collectively named *MATOPM-I* (Melkassa and Adami Tulu Onset Prediction Model-I), whereas the linear and polynomial prediction models which designated the first effective rainfall date as a predictor of the duration of rainfall period are collectively named *MATDPM-I* (Melkassa and Adami Tulu Duration Prediction Model-I). The predictor enabled determination of highly probable dates of onset and season duration at a lead time of two to three months. Moreover, the predictor brought marked improvements to Stewart's RF that was founded on the date of onset as a strategic predictor of season duration. Thus, the improved RF agronomic decision system which relies on prediction of time of season onset and season duration using the first effective rainfall date as a predictor is called ***enhanced response farming (ERF).*** The enhanced RF enables a multi-staged strategic agronomic planning of farm operations including tactical management of in-season risks. The process begins with prediction of the date of onset and season duration. An initial strategic decision on season's prospect facilitates decision on types of crops to consider and soil and water management technology to adopt for the next season. Moreover, it provides insights for acquiring fertilizer, herbicides and improved seeds of the selected crop and credit for purchase of these inputs.

The scientific community concerned with rainfall prediction using numerical indices and other indicators often have implied a near total unpredictability of date of onset in semi-arid areas (Mamo, 2004). Reviewed literature shows no evidence of success in developing predictors for onset for localized agronomic planning of farm operations and decision making purposes. What is evident in literature is some exhibit of capability for detection of onset at regional scales (Ati *et al.*, 2002; Tadros *et al.*, 2005). Thus, the major challenge of the lack of site specific predictors for the date of onset as well as the problem of time of prediction which usually starts at onset (Stewart, 1988a; Tadros *et al.*, 2005) has been successfully addressed through this study.

The developed predictive capacity has good potential for localized strategic agronomic planning and decision making purposes as compared to the crude down-scaled forecasts that are issued by meteorological service agencies today. In order to make use of the predictors, portable rain gauges can be locally installed and monitored to detect the first effective rainfall dates. These are economically feasible and are less demanding knowledge wise.

The developed predictive capacity encourages resource poor households to look for sources of credit in advance and prepare well to exploit the advantages inherent in early seasons. It also encourages lenders to give credits to farmers, and input suppliers too to deliver the required inputs (seed, fertilizer, herbicides and pesticides) in a very good time. In forecast of too delayed onset which bear high risk of too short season and too low water supply, farmers can be advised early enough to wait and sow lower water demanding short duration crops. In forecast of too delayed onset, they can also be advised to look for other off-farm remittances.

To summarize, ERF responds to the long standing unanswered questions of interest to resource poor dryland farmer in many ways:

(a) With respect to planning time, the forecast is produced two to three months before the actual date of onset. This allows sufficient time to better prepare for the current season;

(b) Agro-meteorological services issued forecasts are almost always issued late and farmers do not have trust on the information because it is too general. The significance of agro-meteorological services issued forecasts for farm level risk management are also yet to be well demonstrated and ascertained. On the other hand, indigenous knowledge based forecast of drought and onset dates are reportedly becoming ineffective. Thus, the enhanced RF has potential to overcome these limitations;

(c) The developed predictors are locally valid as the data source incorporates all the past years of localized topographic features that stand as a limitation to meteorological services issued forecasts (Patt, 2000; Steiner *et al.,* 2004; Vogel and O'Brien, 2006);

(d) Predictors of ERF have potential to improve farmers' traditional RF practices since dryland farmers are adept in applying various forms of the practices that underlie the development of the concept of RF itself (see Stewart, 1988a; Fujisaka *et al.*, 1996; ICRA, 1999). Thus, predictions of ERF can be readily understood and adopted by farmers. This directly implies instant adoption of ERF based agronomic recommendations both in principle and practice. Village based development agents can also easily understand and inform the farmers;

(e) Economic feasibility of RF has been proven (Stewart and Hash, 1982; McCown *et al.*, 1991, Wafula *et al.*, 1992). With the marked advances in time of prediction, significant economic benefits are to be expected from ERF both due to proper advance planning and reduced failure rate that enable exploitation of the advantages inherent in good seasons;

(f) The ERF forecasts are of practical value to ministries of agriculture dealing with early warning of impending drought. Moreover, the value of the ERF should not be under-estimated for urban water planners and irrigation agencies, and hydro-power agencies. Moreover, ERF is also valid for risk insurance, credit and input delivering agencies. It is also vital for pastoral communities in their livestock feed stock management (Stewart, 1988a);

(g) With respect to out-scalability, enhanced RF has most likely a chance of being rapidly adopted and out-scaled as the information is generated for local scale long before the season comes into view and given dryland farmer's universal understanding and knowledge and experience in the practice of various forms of RF (Stewart, 1988a).

4.3. Prediction Models for Seasonal Rainfall Characteristics

Under this section, results of the analyses conducted in order to address specific objective three of the study that was aimed at developing prediction functions for seasonal rainfall parameters so as to improve tactical response farming are presented and discussed.

4.3.1. The date of onset – the predictor of the duration of next crop season

The regression of the duration of rainfall period on its respective date of onset at MARC for each of the 32 seasons studied is as shown in Fig. 20 and the model is Equation 11. The regression explained close to 86% (R^2) of the likely variation in the duration of rainfall period with the variation in the date of onset. Analyses of variance revealed the R^2 to be statistically highly significant at 1% probability level ($P \leq 0.001$). The developed regression model shown below:

$$\text{Season duration (days)} = 255 - 1.02x \quad \text{...} (11)$$

Where: x is the date of onset in Julian day.

The regression line with a slope of the predictor indicates that, at MARC, on average, season duration is foreshortened by more than one day per day, beyond the first day of April (91 Julian) that passes without reaching the state of onset. Results from cross validation depicted in Fig. 25: relate the observed with the predicted season duration using the developed model. The r relating both is more than 0.9. This is statistically significant at 1% level ($P \leq 0.001$). This indicates the developed model to be useful for use in estimating future season duration more closely and precisely than possible by using the first effective rainfall date as a predictor.

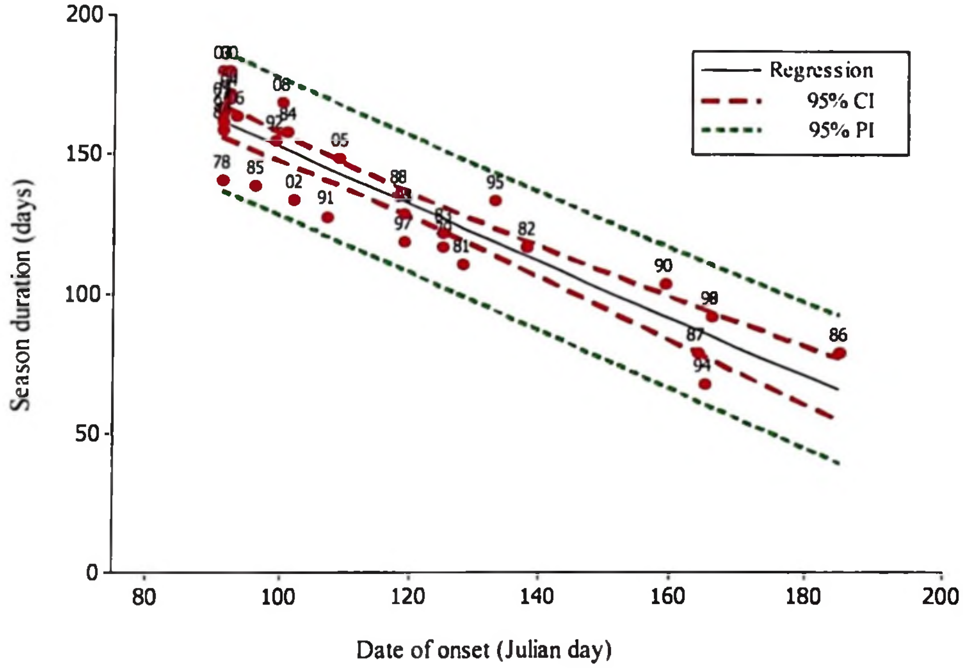

Figure 24: Variation of the duration of seasonal rainfall with the date of onset at Melkassa

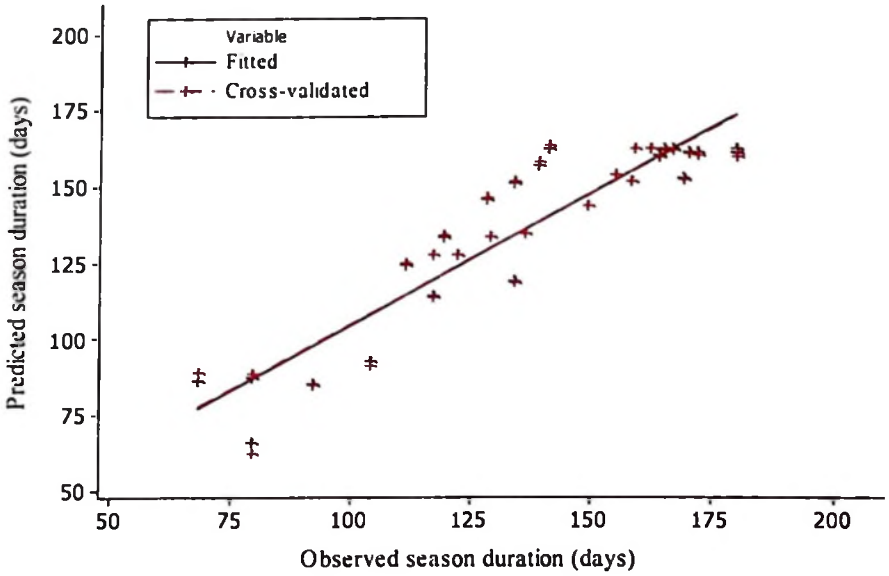

Figure 25: Observed vs. predicted duration of seasonal rainfall at Melkassa

Equation 11 is valid to estimate the expected season length in the range of 83 - 180 days using the date of onset in the range of 91 - 185 Julian days. The SE of predicting season length using the regression equation would be ±12 days. Taking into account the 32 seasons mean season length of 135 days, the estimation error would be close to 9% either above or below it.

Results depicted in Fig. 26: with Equation 12 is from the regression of the duration of rainfall period on its respective date of onset at ATARC for each of the 29 seasons studied. The regression explained close to 71% (R^2) of the likely variation in the duration of rainfall period with the variation in the date of onset. Statistically, the R^2 value is highly significant at 1% probability level ($P \leq 0.001$).

The developed regression model presented below.

Season duration (days) = $258 - 1.05x$..(12)

Where: x is the date of onset in Julian day.

The regression line has a slope of -1 that indicates that, at ATARC, on average, season duration is foreshortened by more than one day per day, beyond the first day of February (32 Julian) that passes without onset.

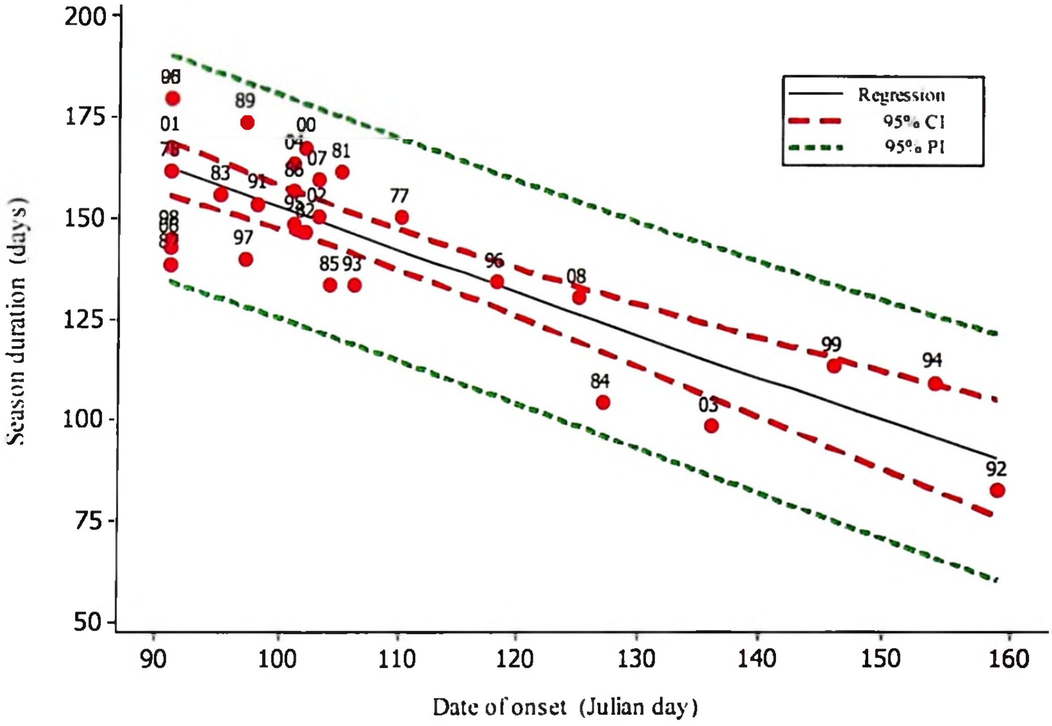

Figure 26: Variation of the duration of seasonal rainfall with the date of onset at Adami Tulu

Results from cross validation depicted in Fig. 27: relate the observed with the predicted season length using the developed model. The r relating both is more than 0.8. This is statistically highly significant at 1% level ($P \leq 0.001$). This indicates the developed prediction model to be useful for use in estimating duration of up-coming season.

Equation 12 is valid to estimate the expected season length in the range of 83 - 180 days using the date of onset in the range of 91 - 185 Julian days. The SE of predicting season duration using the regression equation would be ±13 days. Taking the 29 seasons mean season length of 145 days into account, the estimation error would be about 9% either above or below it.

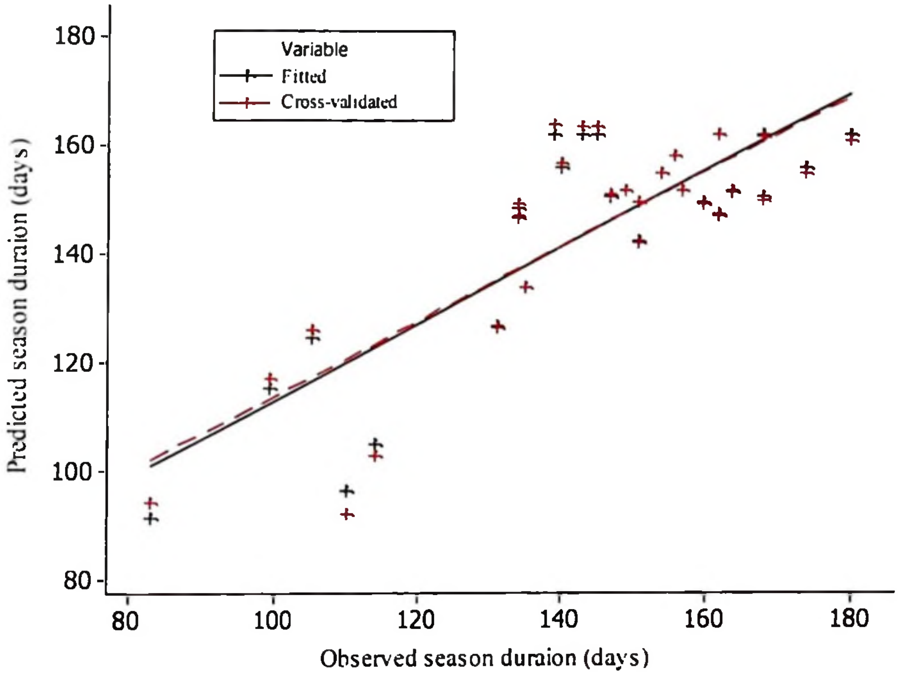

Figure 27: Observed vs. predicted duration of seasonal rainfall at Adami Tulu

Summary of the developed linear regression models for predicting season duration using the date of onset at MARC and ATARC with detailed statistical results is presented in Table 27. The two linear regression models developed for prediction of the duration of next crop season using the date of onset as a predictor are named *MATDPM-II (Melkassa and Adami Tulu Duration Prediction Model-II)*.

It is obvious that the duration of rainfall period is foreshortened with delay in the date of onset as implied by the first effective rainfall date. However, the developed prediction models enable estimation of duration of rainfall seasons to be expected more closely.

Table 27: Linear regression models for prediction of season duration using the date of onset at Melkassa and Adami Tulu

		R^2 (%)						Constant			Slope			
Location	Prediction model	Unadjusted	Predicted	SE (±)	F	P	VIF	SE (±)	T	P	SE (±)	T	P	DW
MARC (Equation 11)	Season duration (days) $= 255 - 1.02x$	86	84	12	185^{**}	0.000	1	10	28^{**}	0.000	0.1	-14^{**}	0.000	1.85487
ATARC (Equation 12)	Season duration (days) $= 258 - 1.05x$	71	66	13	66^{**}	0.000	1	14	18^{**}	0.000	0.1	-8^{**}	0.000	2.35387

Note: x = Date of onset (Julian day); VIF = Variance inflation factor; DW = Durbin-Watson statistic; ** = Highly significant at 1% level; Models are designated by MATDPM-II

The findings presented above are in agreement with those of Stewart (1988a) and Sivakumar (1988) who reported similar relationship for a number of countries in Africa, Asia, Near East and North America (Stewart, 1988a; 1989a; b). According to McCown *et al.* (1991), the apparent reason for such relationship is that the date of cessation of rainfall season is less variable than that of onset, making season duration dependent mainly on the later. Sivakumar (1988) and Stewart (1991b) used onset-duration relationship to develop relay-cropping recommendations for many West African countries. Such experiences and the findings presented above warrant similar efforts to use such relationships in developing agronomic recommendations for use by farmers in the semi-arid areas.

Farmers in the study sites have already understood the above described correlations (Fujisaka *et al.*, 1996; ICRA, 1999) between season date of onset and the subsequent season length. They have used their observation to select type of crops to grow. For seasons with early onset, they plant long and medium maturity cultivars, changing to shorter ones if the perceived season is shorter. In this way, they strive to minimize failure due to too early cessation of rainfall. Hence, the results are useful to strengthen such traditional efforts more scientifically in order to help them make sound agronomic management decisions.

4.3.2. In-season rainfall – the predictor of total seasonal rainfall

Very high variability in the amount of seasonal rainfall and consequently higher risks entails quantified estimate of the amount of rainfall to be expected between onset and the final rainfall date in order to enable initial selection of adapted cultivars according to expected water supplies. It also helps to guide farmers to respond to in-season risks though making rapid changes in on-farm tactics. Moreover, such information can also trigger actions to prevent possible problems due to water-logging through draining of excess water. To this end, total seasonal water (TSW) was regressed on its respective in-season rainfall amount at MARC. The results from the regression are depicted in Fig. 28. The developed regression model (Equation 13) explained more than 98% (R^2) of the likely variation in TSW supply with the variation in the amount of in-season rainfall. Statistically, the R^2 is highly significant at 1% probability level ($P \leq 0.001$).

$$\text{Total seasonal water (mm)} = 27.6 + 1.02x \quad \text{.......................................}(13)$$

Where: x is in-season rainfall (mm).

Results from cross validation depicted in Fig. 29: relate the observed with the predicted TSW using the developed model. The r relating both is close to 1. This is statistically highly significant at 1% level ($P \leq 0.001$). This indicates the developed model to be the best estimator of TSW.

Regression model 13 is valid for predicting TSW in the range of 308 - 958 mm using in-season rainfall in the range of 274 - 914 mm. The SE of predicting TSW using the regression equation would be ±19 mm. Taking the 32 seasons mean TSW of 616 mm into account, the estimation error would be slightly more than 3% above or below it.

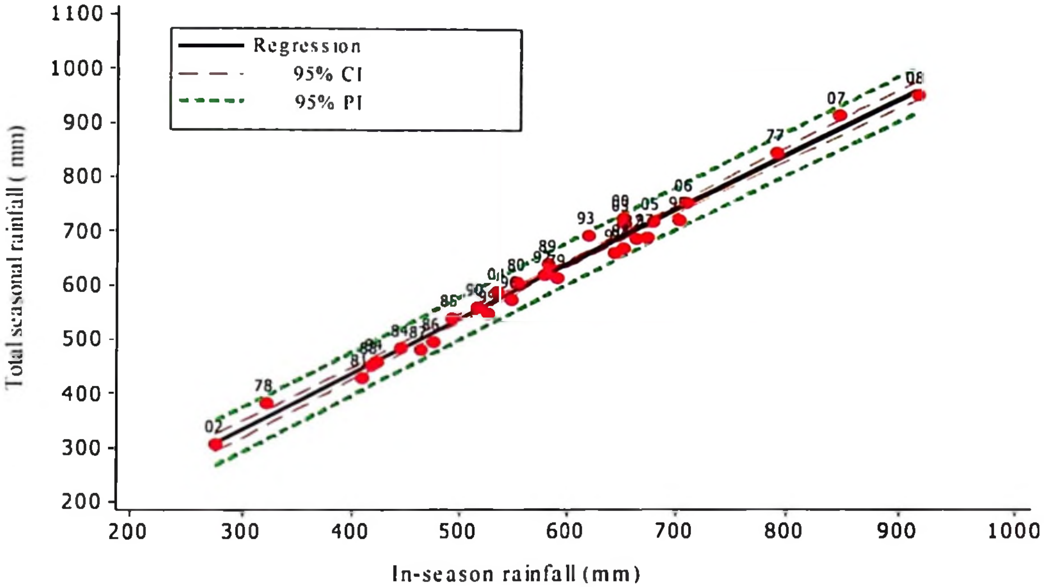

Figure 28: Variation of total seasonal rainfall with the amount of in-season rainfall at Melkassa

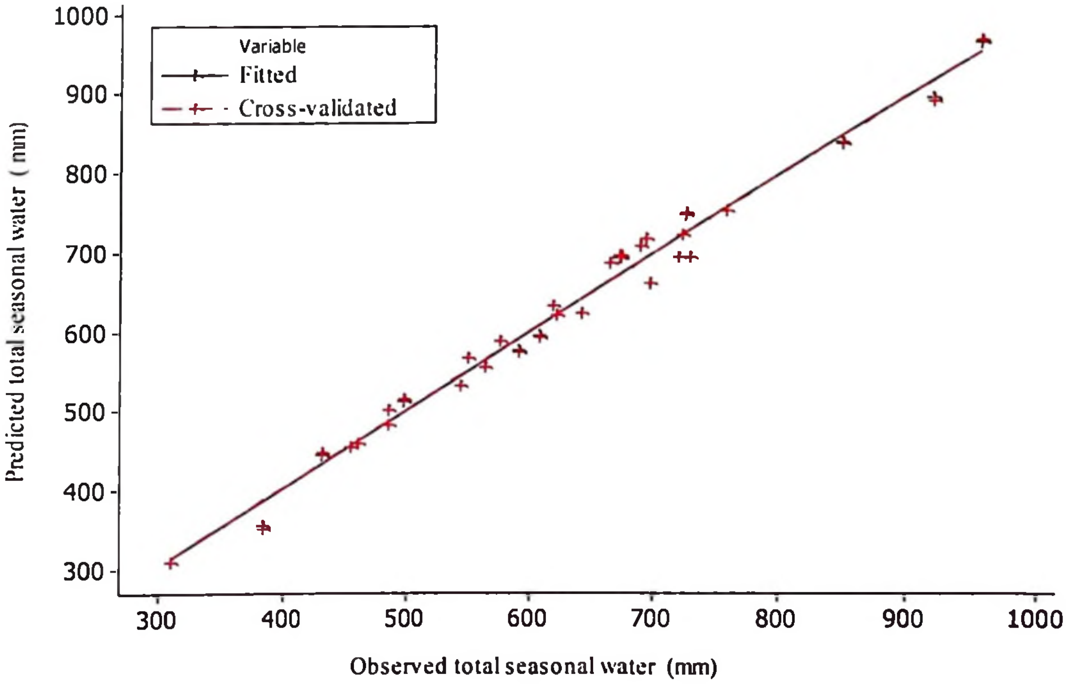

Figure 29: Observed vs. predicted total seasonal rainfall at Melkassa

At ATARC, the results from the regression of TSW on the amount of its respective in-season rainfall are depicted in Fig. 30. The developed regression model (Equation 13) explained about 95% (R^2) of the likely variation in TSW supply with the variation in the amount of in-season rainfall. Statistically, the R^2 is highly significant at 1% probability level ($P \leq 0.001$). Equation 14 is the developed regression model.

Total seasonal water (mm) = $26.8 + 1.05x$..(14)

Where: x is in-season rainfall (mm).

Results from cross validation depicted in Fig. 31: relate the observed with the predicted TSW using the developed model. The r relating both being close to 1 is statistically highly significant at 1% level ($P \leq 0.001$). Like for MARC, this indicates the developed model to be the best estimator of TSW supply.

Equation 14 is valid for predicting TSW in the range of 434 - 544 320.5 mm using in-season rainfall amount in the range of 433 - 498 mm. The SE of predicting TSW using the regression equation would be ±29 mm. Taking the 29 seasons mean TSW of 565 mm into account, the estimation error would have been about 5% above or below it.

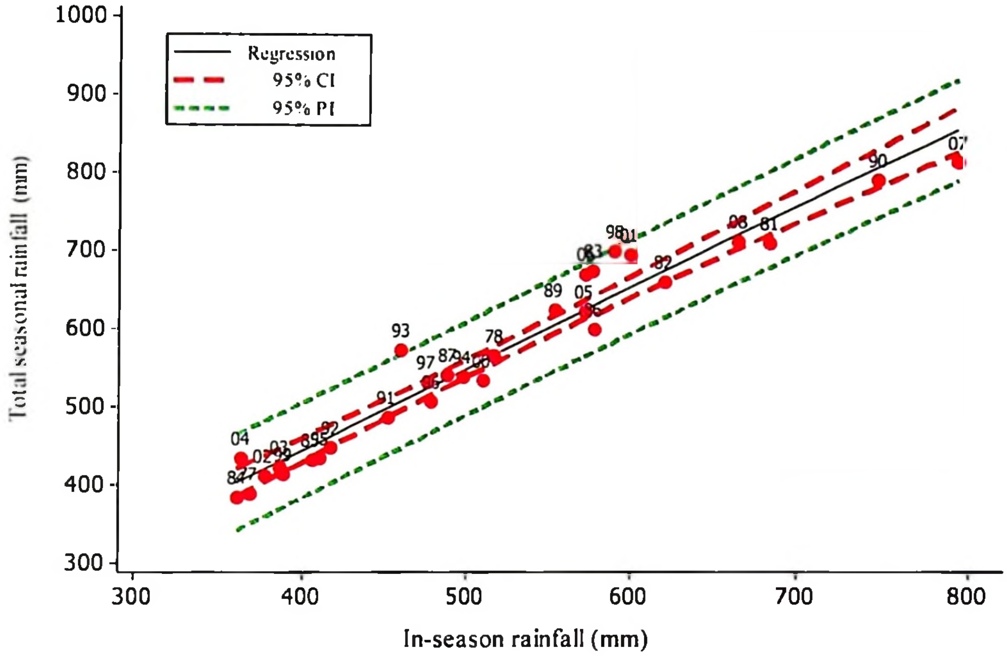

Figure 30: Variation of total seasonal rainfall with the amount of in-season rainfall at Adami Tulu

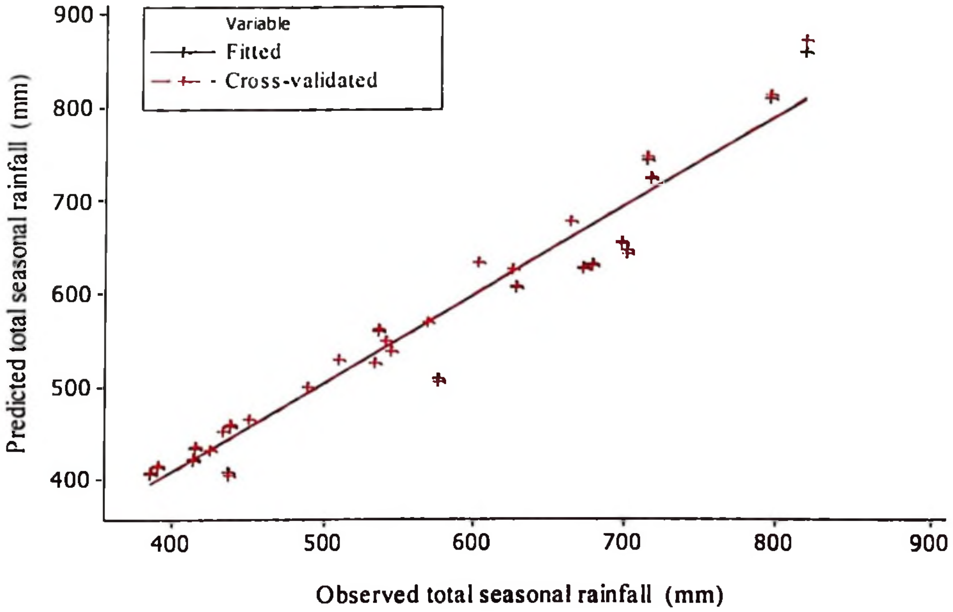

Figure 31: Observed vs. predicted total seasonal rainfall at Adami Tulu

The linear regression models developed for predicting TSW at both MARC and ATARC are presented in Table 28. It is worth mentioning that the results from the above regression analyses are not directly applicable. However, they imply the potential of in-season rainfall for use as an indicator of expected rainfall on shorter time intervals. These can facilitate determination of thinning time rainfall (35 to 44 days after sowing) for use in making tactical adjustments to plant stand and fertilizer.

Table 28: Linear regression models for prediction of total seasonal water supply using the amount of in-season rainfall at Melkassa and Adami Tulu

Location	Prediction model	R^2 (%)		SE	F	P	VIF	Constant			Slope			DW
		Unadjusted	Predicted	(±)				SE (±)	T	P	SE (±)	T	P	
MARC (Equation 13)	TSW = 27.6 + 1.02x	98	98	17	1 857**	0.000	1	14	2^{ns}	0.062	0.02	43**	0.000	0.5124
ATARC (Equation 13)	TSW = 26.8 + 1.05x	95	94	29	515**	0.000	1	24	1^{ns}	0.280	0.05	23**	0.000	1.8398

Note: TSW = Total seasonal water (mm); x = In-season rainfall (mm); VIF = Variance inflation factor; DW = Durbin-Watson statistic; ** = Significant at 1% level of significance; * = Significant at 5% and, ns = Non-significant at 5% level of significance

4.3.3. The date of onset – a practical indicator of the amount of total seasonal rainfall

Total seasonal rainfall was regressed on its respective date of onset at MARC. The resulting regression model (Equation 15 in Table 29) with detailed statistics is resented in Table 29.

The regression model relating total seasonal water and the date of onset has low R^2 (13%), but it is still statistically significant at 5% level ($P \leq 0.040$). Moreover, the regression coefficient for the constant intercept is statistically significant at 1% level ($P \leq 0.001$). Although the low R^2 indicates little variation of TSW with the date of onset, the large intercept indicates that seasons with earliest onset dates would have still significant amount of TSW. On the other hand, the slope of the predictor is also statistically significant at 5% level of significance ($P \leq 0.001$). This indicates a good example of the dichotomy, which can occur between the practical and the statistical in that a slope of -2 means that rainfall expectation is reduced by close to 2 mm for each day that onset is delayed beyond the first day of April (Julian day 91). Thus, this equation can be used to gain initial insight about TSW expectation.

The regression results for ATARC like for MARC shows significant variation of TSW with the variation in the date of onset at 5% level ($P \leq 0.018$). Moreover, the regression coefficient for the constant intercept is statistically significant at 1% level ($P \leq 0.001$). The large intercept indicates that seasons with earliest onset dates would have significant amount of TSW. On the other hand, the slope of the predictor is also statistically significant at 1% level of significance ($P \leq 0.018$). The slope of the predictor indicates that rainfall expectation is reduced by about 3 mm for each day that onset is delayed beyond the first day of April (91 Julian).

The above results suggest that the date of onset can be used as an indicator of expected seasonal water supply on which to base final decision on the type of cultivar maturity to emphasise. Moreover, it can be used as an indicator for the type of soil and moisture conservation practice to adopt either to conserve or drain the excess water to prevent damage to sown crop due to drought or water-logging and erosion. For Kenya, Stewart (1988a) used the date of onset as a predictor of total season water and found strong correlation between the two particularly in early onset seasons of long rains (Stewart, 1988a).

Table 29: Linear regression models for prediction of total seasonal rainfall using the date of onset at Melkassa and Adami Tulu

		R^2 (%)						Constant			Slope			
Location	Prediction model	Unadjusted	Predicted	SE (±)	F	P	VIF	SE (±)	T	P	SE (±)	T	P	DW
MARC (Equation 15)	TSW, mm = $837 - 1.82x$	12.5	3	139	4^{*}	0.047	1	106	8^{**}	0.000	0.9	-2.1^{*}	0.047	2.4216
ATARC (Equation 16)	TSW, mm = $871 - 2.8x$	18.9	9	116	6^{*}	0.018	1	124	7^{**}	0.000	1.1	-2.5^{*}	0.018	1.9843

Note: Total seasonal water (mm); x = Date of onset (Julian day); VIF = Variance inflation factor; DW = Durbin-Watson statistic; ** = Significant at 1%; * = Significant at 5% level of significance

4.3.4. Prediction models for the amount of post-onset rainfall

The above discussed rainfall expectation based on the date of onset is not adequate, but indicative of the ranges of expectations and the amount that would be lost with delayed onset. As have been established earlier, at both locales, the cropping season starts on the first day of April and ends by 30 September. Pre-onset rainfall is the amount of rainfall that is received as of the first effective rainfall date to the date of onset. In this study, for MARC, pre-onset rainfall was rainfall received between January and March, whereas for ATARC, pre-onset rainfall was rainfall received during February and March. Thus, at both sites, rainfall received during the months of October through March is effectively out of the growing seasons and are thus off-season rainfall. Off-season rainfall was used for developing prediction model for post-onset rainfall amount in order to be able to determine the amount of expected rainfall more closely. Accordingly, results presented in Table 30 for MARC and Table 31 for ATARC contain the regression models developed to predict dekadal post-onset rainfall amount based on dekadal off-season rainfall amount.

It can be seen from the Tables that, the expected amount of rainfall during April through June can be effectively estimated using off-season rainfall. This predictive capacity would therefore facilitate revision of earlier decisions concerning the type of soil and water conservation mode to be adopted, cultivar maturity to be sown, field type (flat areas or well-drained fields) where the selected crop cultivar should be sown, sowing time, seed rate as well as the type and amount of initial fertilizer to be used at sowing.

The eight polynomial regression models developed for prediction of dekadal post-onset rainfall amount using dekadal off-season rainfall amount as predictors and labelled Equation 17 to 20 in Table 30 for MARC and Equation 17 to 24 in Table 31 for ATARC are collectively named *MATP-ORFPM-I* (*Melkassa and Adami Tulu Post-Onset Rainfall Prediction Model-I*).

The above results confirm the work of Stewart (1988a, b) who, for Hydrabad in India found winter/spring rainfall to be good predictors of the character of monsoon to come. For Kusum in Nepal, extremely light or heavy rainfall was reported to be good predictors of the amount of monsoon rainfall. According to Stewart (1988b), intermediate off-season rainfall also predict rainfall amount, but only weakly. This implies that it would be possible to improve predictability at the time of actual onset using early season cumulative rainfall.

Table 30: Essential polynomial regression models for prediction of the amount of post-onset rainfall using the amount of dekadal off-season rainfall at Melkassa

Prediction equation number	Prediction model	R^2 (%)	SE (±)	F	P	Sequential ANOVA Linear F	 P	 Quadratic F	 P	 Cubic F	 P
Equation 17	Apr-Jun rainfall (mm) $= 4.50 + 5.949x - 0.6467x^2 + 0.01850x^3$	81	3	7^*	0.030	2^{ns}	0.218	6^{ns}	0.056	6^{ns}	0.062
Equation 18	Apr–Jun, rainfall (mm) $= 23.28 - 4.020x + 0.5560x^2$	77	3	10^*	0.012	6^*	0.048	9^*	0.026	-	-
Equation 19	Apr-Jul rainfall (mm) $= 24.40 - 4.579x + 0.7804x^2$	68	12	10^{**}	0.006	12^{**}	0.006	4^{ns}	0.089	-	-
Equation 20	Apr-Aug rainfall (mm) $= 20.79 - 3.480x + 0.9686x^2 - 0.03166x^3$	77	12	12^{**}	0.001	21^{**}	0.000	3^{ns}	0.096	3^{ns}	0.095

Note: For equation 17, x is January-March rainfall (mm); for equation 18, x is November-January rainfall (mm); for equation 19, x is November-February rainfall (mm); for Equation 20, x is November-March rainfall (mm); ** = Highly significant at 1% probability; * = Significant at 5% probability, ns = non-significant at 5% probability; d.f. for regression equations 17 to 20 are 8, 8, 11 and 14 respectively; The models are designated by MATP-ORFPM-I

Table 31: Essential polynomial regression models for prediction of the amount of post-onset rainfall using the amount of dekadal off-season rainfall at Adami Tulu

						Sequential ANOVA					
						Linear		Quadratic		Cubic	
Prediction equation number	Prediction model	R^2 (%)	SE (±)	F	P	F	P	F	P	F	P
Equation 21	May-Aug rainfall (mm) = $33.56 - 2.725x + 0.3142x^2 - 0.006876x^3$	73	7	7^{*}	0.012	10^{**}	0.009	1^{ns}	0.293	5^{ns}	0.061
Equation 22	Jun-Aug rainfall (mm) = $-43.58 + 6.433x - 0.1128x^2$	65	8	6^{*}	0.044	7^{*}	0.036	3^{ns}	0.152	-	-
Equation 23	May-Jul rainfall (mm) = $14.88 + 1.120x - 0.00234x^2$	67	7	6^{*}	0.036	14^{**}	0.007	1^{**}	0.00	-	-
Equation 24	Apr-Aug rainfall (mm) = $22.82 + 0.008x + 1.154x^2 - 0.08441x^3$	69	7	6^{*}	0.023	3^{ns}	0.147	10^{**}	0.014	-	-

Note: For equation 21, x is January-April rainfall (mm); for equation 22, x is March-May rainfall (mm); for equation 23, x is February-April rainfall (mm); for Equation 24, x is November-February rainfall (mm); ** = Highly significant at 1% probability; * = Significant at 5% probability; ns = non-significant at 5% probability; d.f. for regression equations 21 to 24 are respectively 11, 8, 8 and 11; The models are designated by MATP-ORFPM-I

4.3.5. Prediction models for the amount of thinning time, and mid- to late-season rainfall

In Stewart's response farming (Stewart, 1988a), the selection of the level of variable input is made at two stages, namely (i) at onset of the rainfall season, in response to forecast of either good (early), or poor (late) season; and (ii) at 30 or 40 days after planting, in response to the forecast of type of season provided by cumulative rainfall since onset. In order to optimally match crop yield potential with season type, options for adjusting production inputs can be kept open as long as possible. Hence plant density and fertilizer input are initially high to provide maximum flexibility for tactical adjustments to be made at the second stage decision point (30 to 35 days after sowing) (Stewart and Faught, 1984).

To facilitate in-season tactical adjustments (both at thinning and during the various growth stages of the crop), cumulative early season rainfall was regressed on its respective in-season rainfall amount. Cumulative rainfall listed in Appendix 10 for MARC and Appendix 11 for ATARC were used to develop prediction model for thinning and post-thinning time rainfall that can be used to facilitate tactical adjustments to plant stand and fertilizer. Table 32 for MARC and Tables 33 for ATARC contain the regression models and detailed statistical results. All the developed prediction models are statistically significant at 1% probability level ($P \leq 0.001$).

For MARC, the prediction models can be used to inform and regularly update farmers about in-seasonal rainfall expectations on shorter time scales. Unfortunately, cumulative early-season rainfall at ATARC are poor predictors of thinning time rainfall, although post-thinning time, and mid- to late season rainfall are well predicted by cumulative 40-day rainfall amount.

The nine linear regression models developed for prediction of early, mid- and late-season rainfall amount using cumulative early season rainfall as predictors as predictors and labelled Equation 25 to 29 in Table 32 for MARC and Equation 30 to 33 in Table 33 for ATARC are collectively named *MATP-ORFPM–II* (*Melkassa and Adami Tulu Post-Onset Rainfall Prediction Model-II*).

Table 32: Essential prediction models for tactical response farming at the time of thinning and during mid-season at Melkassa

Prediction equation number	Prediction model	R^2 (%)		SE	F	P	VIF	Constant			Slope			DW
		Unadjusted	Predicted	(±)				SE (±)	T	P	SE (±)	T	P	
Equation 25	30-day rainfall (mm) = $-7.0 + 1.3x$	84	82	31	163^*	0.000	1	13	-0.5^*	0.000	0.1	13^{**}	0.000	1.3720
Equation 26	40-day rainfall (mm) = $2.5 + 1.62x$	66	60	63	58^*	0.000	1	26	0.1^*	0.000	0.2	8^{**}	0.000	1.5656
Equation 27	50-day rainfall (mm) = $23.1 + 1.77x$	59	52	80	43^*	0.000	1	33	0.7^{ns}	0.492	0.3	7^{**}	0.000	1.0314
Equation 28	50-day rainfall (mm) = $12.8 + 1.44x$	85	82	48	168^*	0.000	1	18	0.7^{ns}	0.488	0.1	13^{**}	0.000	1.2137
Equation 29	60-day rainfall (mm) = $40.9 + 1.16x$	83	81	57	145^*	0.000	1	20	2^{ns}	0.052	0.1	12^{**}	0.000	1.1547

Note: For equation 25 to 27, x is cumulative 20 days rainfall (mm); for equation 28, x is 30-day rainfall (mm); for equation 29, x is 40-day rainfall (mm); VIF = Variance inflation factor; DW = Durbin-Watson statistic

** = Highly significant at 1% probability; * = Significant at 5% probability; ns = Non significant at 5% level; d.f. for the 5 regression equations is 31; The models are designated by MATP-ORFPM–II

Table 33: Essential prediction models for tactical response farming during mid- and late-season at Adami Tulu

Prediction equation number	Prediction model	R² (%) Unadjusted	R² (%) Predicted	SE(±)	F	P	VIF	Constant SE (±)	Constant T	Constant P	Slope SE (±)	Slope T	Slope P	DW
Equation 30	70-day rain (mm) $= 79.2 + 1.08x$	67	62	53	54^{**}	0.000	1	30	3^{*}	0.013	0.1	7^{**}	0.000	1.63714
Equation 31	80-day rain (mm) $= 125 + 1.02x$	56	49	62	35^{**}	0.000	1	35	4^{**}	0.001	0.2	6^{**}	0.000	1.96894
Equation 32	90-day rain (mm) $= 152 + 1.08x$	62	56	58	44^{**}	0.000	1	33	5^{**}	0.000	0.2	7^{**}	0.000	1.79381
Equation 33	100-day rain (mm) $= 205 + 1.01x$	51	43	67	28^{**}	0.000	1	39	5^{**}	0.000	0.2	5^{**}	0.000	1.81675

Note: For equation 30 to 33, x is cumulative 40 days rainfall (mm); VIF = Variance inflation factor; DW = Durbin-Watson statistic; ** = Highly significant at 1% probability; * = Significant at 5% probability; ns = Non significant at 5% level; d.f. for the regression equations from 30 to 33 is 28; The models are designated by MATP-ORFPM–II

The above results are very similar to those reported by Stewart and Faught (1984) for Kenya who used cumulative early season rainfall to predict thinning time rainfall for early and late season types for use in making tactical adjustments to plant stand and use of fertilizer.

For Kenya, Stewart (1988a) found positive correlation between cumulative early season rainfall and TSW supply. The correlations were stronger for late season as compared to early season. Based on early season rainfall, three classes of seasons termed by Stewart and Faught (1984) as good, fair and poor are determined. Accordingly, the season is perceived good if the water supply expected is in the upper range, medium (fair) in the middle range and poor if it is on the lower range. If in the upper range, original plant stand is maintained and additional fertilizer is considered aiming at higher yield range. When the water supply is in the middle range, the plant stand is reduced by a third of the original and half the original fertilizer dose is applied. When the expected water is in the lower range, no additional fertilizer is applied and plant number is reduced by a third. These agronomic response tactics are very crucial in economic terms because there is evidence that the high risk of in-seasonal rainfall and resultant poor crop response to fertilizer is a major disincentive limiting its use (McCown *et al.*, 1991).

4.3.6. Synthesis

With objective to improve tactical RF through better management of in-season on-farm risks, two prediction models collectively named *MATDPM-II* was developed. The models are useful to closely determine expected season duration. *MATDPM-II* improved predictability for season duration than possible by *MATDPM-I* (Melkassa and Adami Tulu Duration Prediction Model-II). *MATDPM-II* facilitates selection of crop varieties that better match the expected duration of rainfall season.

Total seasonal water supplies exhibited little variation with the date of onset at MARC and ATARC. However, each day that the date of onset was delayed beyond the first day of April, TSW supply expectation was found to decrease. At both locations, fairly large amount of TSW can be expected during early seasons. TSW exhibited considerable variation with in-season rainfall at both locations. This was found a useful indicator of the potential of cumulative early season as well as mid- to late-season rainfall amount for developing prediction models for thinning and cultivation time rainfall for use in adjusting plant stand and fertilizer.

Accordingly, eight prediction models collectively named *MATP-ORFPM-I* enable in-season tactical management of rainfall risks through making rapid changes in on-farm tactics were developed. The prediction models designated off-season rainfall as a predictor of post-onset rainfall amount. Moreover, nine prediction models which designated cumulative early season rainfall as a predictor of thinning time, mid- and late-season rainfall amount collectively named *MATP-ORFPM-II* were developed. Unlike for MARC, cumulative early season rainfall at ATARC was found to be poor predictor of thinning time rainfall. However, at both locations, off-season rainfall was found to be good predictor of post-onset rainfall amount. Nevertheless, all the developed prediction models enable determination of highly probable post-onset thinning time, mid- and late-season rainfall expectations. The prediction models are used through real time monitoring of off-season rainfall and early- to mid- to late-season rainfall amount to determine post-onset rainfall expectations.

Farmers in the vicinity of MARC and ATARC make incremental changes in input use by observing early season rainfall developments. They make decision concerning use of urea based on their observation of in-season rainfall developments. By so doing they always strive to minimize losses from use of costly fertilizer inputs due to low rainfall conditions that follow cultivation and thinning (ICRA, 1999). Hence, the findings above are useful to guide farmers to better manage post-onset rainfall related risks.

The steps and actions required for application of ERF technique are summarized in Fig. 32. The application of farm yard manure and tillage after harvest, field preparation, preparation of run-off diversion and drainage channels, rain water harvesting structures, soil and water conservation structures, and regular maintenance of soil bunds (Reddy and Kidane, 1994) should be an integral part of the enhanced RF technique.

Application of ERF requires closer working relationship between farmers who need the information, agronomists and agro-meteorologists who produce the forecasts and devise management options and extension workers who disseminate them. Researchers use modern tools to formulate RF forecasts and corresponding packages and communicate extension workers. Village based extension workers and farmers document rainfall and regularly relay the information to researchers. A platform, a consultation ground, is necessary where these actors meet at village level for exchange of forecast information, identification of RF strategy, regular updating, and application. Initial interactions of actors draw tentative outlooks and agronomic packages corresponding to the forecasts. Farmers remain contingent to apply the advice. Seasonal rainfall developments are monitored, and meetings are again held where observed is compared against the predicted and initial plans are revised. At onset, feasible plans are fixed, and farmers are informed to implement them. Researchers regularly monitor rainfall and update extension workers about in-season rainfall expectations.

Training of farmers and development workers in rainfall measurement is therefore required to get reliable data from locally installed rain gauges. Moreover, researchers and agro-meteorologists should be trained in RF analytical methodologies and in formulation of agronomic packages that can be guided by ERF forecasts including its field application methods.

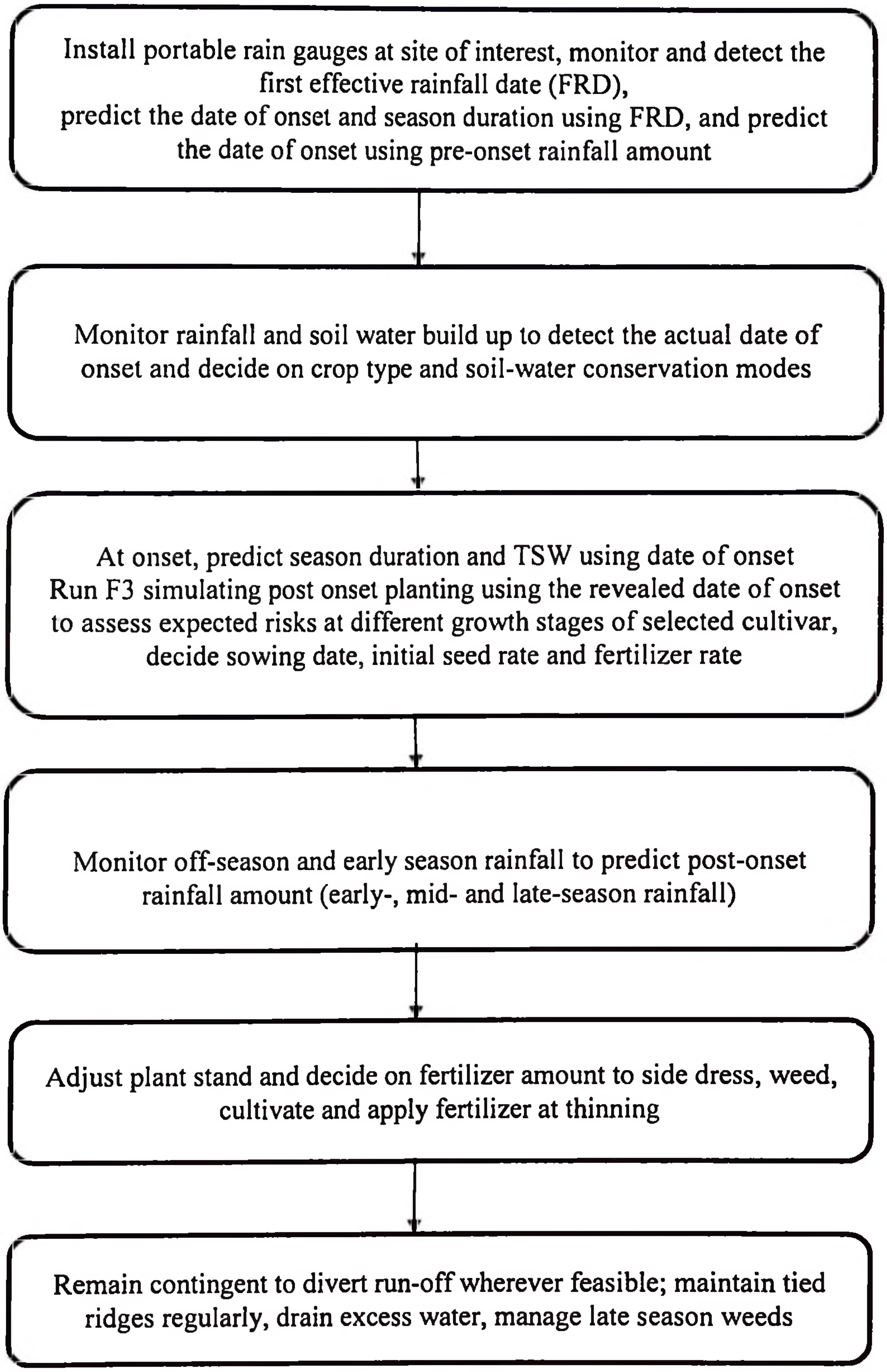

Figure 32: Schema for application of enhanced response farming agronomic decision system

4.4. On-farm Performance of Maize Production Strategies

Results of the analyses conducted in order to address specific objective four of the study that was aimed at evaluation of on-farm performance of the developed predictors in guiding strategic and tactical agronomic decisions and in improving maize yields are presented and discussed in this section.

4.4.1. Performance of enhanced response farming rainfall predictors

The steps followed and results of evaluation of the enhanced response farming are presented below.

4.4.1.1. Predicted and the actual time of season onset

Observed first effective rainfall dates and rainfall amount recorded on those dates during 2010-11 cropping seasons at MARC are presented in Table 32. The recorded dates were used to estimate the mean, earliest and latest dates of onset using the prediction model relating the first effective rainfall date and the date of onset. Table 34 shows that the estimated dates of onset fall under early category (Admassu, 2004). Thus, the sowing of early and medium as well as late maturing maize varieties was possible. The last column of Table 34 shows the actual time of recorded season onset dates. The Table shows a near accurate prediction for onset at MARC during 2010 cropping season. However, during 2011 crop season, the actual onset was detected three days after the predicted onset date. Given the seven days waiting time for sowing following onset, the predictions were useful.

Similarly, Table 35 shows that at ATARC and surrounding areas the estimated dates of onset using the prediction model relating the first effective rainfall date with the date of onset during 2010 ranged from 27 March to 14 April. The actual season onset was on 13 April. This shows high level of model performance. On the other hand, the actual season date of onset during 2011 was detected 13 days after the latest predicted onset. Early onset season have wider window. Moreover, farmers in the area wait for seven days for onset to manifest itself before sowing. Thus, the predictions can be taken to be practically valid.

Table 34: Actual first effective rainfall date, predicted and actual time of season onset at Melkassa during 2010-11 crop seasons

Crop season	Actual FRD (Julian day)	Rainfall amount (mm)	Predicted DOS (Julian day)			Actual DOS (Julian day)
			Mean	Earliest	Latest	
2010	Julian day 46	25.8	98	88	108	89
2011	Julian day 67	34.5	101	91	111	114

Note: FRD = First effective rainfall date; DOS = Date of onset

Table 35: Actual first effective rainfall date, predicted and actual time of season onset at Adami Tulu during 2010-11 crop seasons

Crop season	Actual FRD (Julian day)	Rainfall amount (mm)	Predicted DOS (Julian day)			Actual DOS (Julian day)
			Mean	Earliest	Latest	
2010	41	63	95	86	104	103
2011	66	29	94	85	103	115

Note: FRD = First effective rainfall date; DOS = Date of onset

4.4.1.2. Predicted and the actual duration of rainfall seasons

Table 36 shows estimated versus observed season duration at MARC during 2010-11 cropping seasons using the prediction model relating season duration with the first effective rainfall date. The estimated season duration for 2010 cropping season was shorter than the actual season duration. However, it could have been possible to grow crops maturing within 90 to 150 days. The observed season duration during 2010 cropping season being longer would have had no effect on the crop. On the other hand, during 2011 cropping season, the actual season duration was effectively within the prediction interval. The overall result shows the model to be of good predictive capacity, as has been shown in theory (in previous sections) now in practice.

Table 36: Actual first effective rainfall date, predicted and actual season duration at Melkassa during 2010-11 crop seasons

Crop season	Actual FRD (Julian day)	Predicted season duration (days)			Actual
		Mean	Shortest	Longest	
2010	46	148	130	165	180
2011	67	152	134	169	156

Note: FRD = First effective rainfall date

Table 37 shows estimated vs. observed season duration during 2010-11 cropping seasons at ATARC estimated using the prediction model relating season duration with the first effective rainfall date. It shows that at ATARC, the actual season duration was effectively within the prediction interval during both cropping seasons. This shows the model to be of good predictive capacity.

Table 37: Actual first effective rainfall date, predicted and actual season duration at Adami Tulu during 2010-11 crop seasons

Crop season	Actual FRD (Julian day)	Predicted season duration (days)			
		Mean	Shortest	Longest	Actual
2010	41	167	145	180	171
2011	66	156	139	172	157

Note: FRD = First effective rainfall date

4.4.1.3. Revised expectations in the duration of rainfall seasons using the date of onset

Table 38 shows predicted season duration at MARC using the date of onset as a predictor and the actual season duration during 2010-11 cropping seasons. During both seasons, the model slightly underestimated season duration compared to the actual. However, this would have had no effect on the crop as long as the crop water needs during the later growth period could also be met from stored soil water.

Table 38: Actual date of onset, and predicted and actual season duration at Melkassa during 2010-11 crop seasons

Crop season	Actual DOS (Julian day)	Predicted season duration (days)			
		Mean	Shortest	Longest	Actual
2010	89	167	155	179	180
2011	114	132	120	144	156

Note: DOS = Date of onset

Table 39 shows estimated season duration at ATARC during 2010-11 cropping seasons based on prediction model developed using date of onset as a predictor, and the actual season duration. Again, there is only slight under-estimation of season duration with no practical impact on crops provided the crops water needs during the later growth period are met from stored soil water.

Table 39: Actual date of onset, and predicted and actual season duration at Adami Tulu during 2010-11 crop seasons

Crop season	Actual DOS (Julian day)	Predicted season duration (days)			
		Mean	shortest	longest	Actual
2010	103	150	136	163	171
2011	115	137	123	152	157

Note: DOS = Date of onset

4.4.1.4. Crop variety selected and sowing time decisions

The estimated season duration was useful for cultivar selection. Guided by the ERF predictions, Melkassa II was selected and grown on ERF plots during 2010-11 cropping seasons at MARC, and during 2010 at ATARC. Sowing dates were adjusted to allow the medium maturing maize to mature before effective end of the rainfall season. In 2010, sowing of ERF guided strategy was made on 8 May at MARC, whereas the crop was planted on 15 May in 2011. At ATARC, sowing was conducted during 2010 on 12 May. All ERF plots matured well in the growing season as predicted. Fertilizer was used at the rate of 100 kg DAP ha^{-1} at the time of sowing. Based on actual monitoring of early season rainfall after sowing, the cumulative early season rainfall amount to thinning time was used to estimate expected season water supply.

Table 40 shows estimates for TSW for MARC using the prediction model relating 40 day rainfall with TSW during 2010-11 cropping seasons. Table 38 shows that cumulative rainfall amount over the 40 days following onset were all in the medium to upper range. Hence, the seasons were categorized as good. Accordingly, decision was made to maintain the original plant population, and to add additional nitrogen fertilizer (50 kg urea ha^{-1} at thinning). At Adami Tulu, the decision was to maintain the original plant stand and reduce fertilizer amount to 35 kg urea ha^{-1} because of the low rainfall expectations.

Table 40: Predicted seasonal water supplies based on 40 days cumulative rainfall totals at Melkassa and Adami Tulu during 2010-11 cropping seasons

Crop season	Site	40 day rainfall (mm)	Predicted total seasonal water supplies (mm)			
			Least	Highest	Mean	Actual
2010	MARC	188	396	678	537	913
2010	ATARC	213	589	815	702	574
2011	MARC	120	532	758	645	720

4.4.2. On-farm performance of maize production strategies

4.4.2.1. On-farm performance of maize production strategies at Adami Tulu during 2010 crop season

Table 41 shows maize grain yield from maize production strategies that were evaluated at four testing sites during 2010 cropping season at ATARC. Analyses of variance (Appendix 12) revealed highly significant differences between the three strategies at 1% level of significance ($P \leq 0.001$). Differences among the three strategies across the four sites were also significant at 5% level ($P \leq 0.022$). Pair comparison of the mean maize grain yield revealed statistically significant differences between farmers' and the other two maize production strategies ($P \leq 0.001$). The enhanced RF strategy raised maize grain yield by about 70% as compared to farmers' strategy. In contrast, farmers' strategy with enhanced RF forecast raised maize grain yield by 49.4% over farmers' strategy.

Table 41: On-farm maize grain yield (t ha^{-1}) from three production strategies tested at the vicinity of Adami Tulu during 2010 crop season

	Site				
Strategy	1	2	3	4	Mean
FP	1.3	1.6	1.4	1.3	1.4
ERF+FP	2.3	3.5	3.2	2.6	2.9***
ERF	3.7	4.6	4.5	3.7	4.7***

Note: FP = Farmers strategy; FP+ERF = RF improved farmer strategy; ERF = Enhanced RF strategy; C.V. = 8.9%; *** = Highly significant at 1% level ($P \leq 0.001$); $LSD_{0.01}$ = 0.66 t ha^{-1}

4.4.2.2. On-farm performance of maize production strategies tested at Dibibissa during 2010-11 crop seasons

Table 42 shows maize grain yield from the 14 testing sites at Dibibissa during 2010 cropping season. Analyses of variance (Appendix 11) revealed highly significant differences between the three strategies at each and across the sites at 1% level of significance ($P \leq 0.001$). Pair comparison of the mean maize grain yield revealed statistically significant differences between farmers' and the other two strategies ($P \leq 0.001$). Overall, the enhanced RF increased maize grain yield by about 76% over farmers' strategy. Farmers' strategy with enhanced RF forecast also raised maize grain yield by more than 46% as compared to farmers' strategy.

Table 43 shows maize grain yield from the 17 testing sites at Dibibissa during 2011 cropping season. Analyses of variance (Appendix 14) revealed highly significant differences between the three strategies across the testing sites at 1% level of significance ($P \leq 0.001$). Pair comparison of the maize grain yield revealed statistically significant differences between farmers and the other two strategies ($P \leq 0.001$). Overall, ERF forecast increased maize grain yield by over 75% as compared to farmers' strategy. Farmers' strategy with ERF forecast also raised maize grain yield by about 47% over farmers' strategy.

The overall results shows that maize grain yield from ERF strategy exceeded those of traditional farmers' maize production strategy during both seasons across all the testing sites. Enhanced RF forecast increased maize grain yield by more than 76%, whereas farmers' strategy with ERF forecast information raised maize grain yield by more than 46% over farmers' traditional maize production strategy.

Table 42: On-farm maize grain yield (t ha^{-1}) from three production strategies at Dibibissa during 2010 cropping season

	Site														
Strategy	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**Mean**
FP	0.9	1.6	2.1	2.3	2.5	2.2	1.7	1.9	2.1	2.5	1.8	2.8	1.8	2.2	2.0
ERF+FP	3.7	2.4	4.6	4.6	4.6	4.8	3.9	3.9	4.7	5.3	4.3	5.5	4.8	4.7	4.4***
ERF	4.8	3.8	5.9	6.3	6.4	6.3	4.7	5.6	5.9	6.6	5.6	6.6	6.1	5.7	5.7***

Note: FP = Farmers strategy; FP+ERF = RF improved farmer strategy; ERF = Enhanced RF strategy; C.V. = 8.2%; *** = Highly significant at 1% level ($P \leq 0.001$); $LSD_{0.01}$ = 3.6 t ha^{-1}

Table 43: On-farm maize grain yield (t ha^{-1}) from three production strategies at Dibibissa during 2011 cropping season

	Site																	
Strategy	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**Mean**
FP	2.8	3.4	2.4	1.6	1.7	1.6	2.3	2.7	1.9	1.8	2.4	1.8	1.7	1.8	1.5	2.1	1.8	2.1
ERF+FP	5.4	5.4	4.6	5.1	3.2	3.4	4.7	5.5	3.9	5.1	4.3	4.2	4.1	4.8	3.9	4.2	3.9	4.5***
ERF	7.1	7.1	6.1	6.5	5.8	5.7	6.2	6.5	5.7	4.7	5.5	5.5	5.8	5.9	5.6	6.3	4.7	5.9***

Note: FP = Farmers strategy; FP+ERF = RF improved farmer strategy; RF = Enhanced RF strategy; C.V. = 9.7%; *** = Highly significant at 1% level ($P \leq 0.001$); $LSD_{0.01}$ = 3.8 t ha^{-1}

4.4.2.3. On-farm performance of maize production strategies tested at Marmarssa during 2010-11 crop seasons

Table 44 shows maize grain yield from nine testing sites at Marmarssa during 2010 cropping season. Analyses of variance (Appendix 15) revealed highly significant differences between the three strategies at 1% level of significance ($P \leq 0.001$). In addition, differences across sites among the strategies were also significant at 5% level ($P \leq 0.001$). Pair comparison of the mean maize grain yield revealed statistically significant differences between farmers' and the other two strategies ($P \leq 0.001$). Overall, ERF forecast increased maize grain yield by more than 71% as compared to farmers' strategy. Farmers' strategy with ERF forecast also raised maize grain yield by about 30% as compared to farmers' traditional maize production strategy.

Table 44: On-farm maize grain yield (t ha^{-1}) from three production strategies at Marmarssa during 2010 cropping season

	Site									
Strategy	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Mean**
FP	1.7	5.5	7.3	1.4	0.54	1.4	1.2	0.7	0.8	1.0
ERF+FP	4.1	1.5	4.4	3.4	4.1	4.6	2.3	3.7	1.8	3.3***
ERF	6.0	3.2	5.8	4.3	5.6	5.3	2.8	6.0	26.0	4.6***

Note: FP = Farmers strategy; FP+ERF = RF improved farmer strategy; ERF = Enhanced RF strategy; C.V. = 26.4%. *** = Highly significant at 1% level ($P \leq 0.001$); $LSD_{0.01}$ = 10.8 t ha^{-1}

Table 45 shows maize grain yield from the 11 testing sites at Marmarssa during 2011 cropping season. Analyses of variance (Appendix 16) revealed highly significant differences between the three strategies at 1% level of significance ($P \leq 0.001$). In addition, differences across sites among the strategies were also significant at 1% level ($P \leq 0.001$). Pair comparison of the maize grain yield revealed statistically significant differences between farmers' and the other two strategies ($P \leq 0.001$).

Table 45: On-farm maize grain yield (t ha^{-1}) from three production strategies at Marmarssa during 2011 cropping season

	Site											
Strategy	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**Mean**
FP	2.8	0.6	0.9	0.7	2.1	0.2	2.7	0.9	1.6	2.4	0.6	1.4
ERF+FP	4.2	3.3	3.0	4.0	3.2	1.4	4.3	1.6	4.1	4.8	3.1	3.4***
ERF	4.7	4.4	4.1	5.8	4.0	5.2	5.9	3.7	5.6	6.7	4.5	4.9***

Note: FP = Farmers strategy; FP+ERF = RF improved farmer strategy; ERF = Enhanced RF strategy; C.V. = 19.9%. *** = Highly significant at 1% level ($P \leq 0.001$); $LSD_{0.01}$ = 7.9 t ha^{-1}

Overall, ERF increased maize grain yield by about 68% as compared to farmers' strategy. Farmers' use of ERF forecast also raised maize grain yield by about 42% as compared to farmers' traditional maize production strategy.

The overall results from evaluation of the three strategies at 20 on-farm sites at Marmarssa during 2010-11 cropping seasons shows that grain yield of maize from ERF strategy exceeded those of farmers' traditional maize production strategy during both seasons across all the testing sites. Enhanced RF increased maize grain yield by about 70%, whereas use of ERF forecast information with farmers' traditional maize production strategy raised maize grain yield by more than 36% over farmers' traditional maize production strategy.

Maize grain yield results from the three production strategies that were evaluated at 51 on-farm testing sites at Dibibissa and Marmarssa during 2010-11 cropping seasons are depicted in Fig. 33. The Figure shows that grain yield of maize from

ERF strategy exceeded those of traditional farmers' strategy during both seasons across all the testing sites. Overall, ERF increased maize grain yield by about 70%, whereas use of ERF forecast information with traditional farmers' strategy raised maize grain yield by more than 49% over farmers' traditional maize production strategy. The results demonstrate the potential of ERF to improve traditional maize production strategy. Similarly, it implies considerable potential of ERF forecast to blend with and improve farmers' traditional maize production strategy and to boost the overall current low level maize yield.

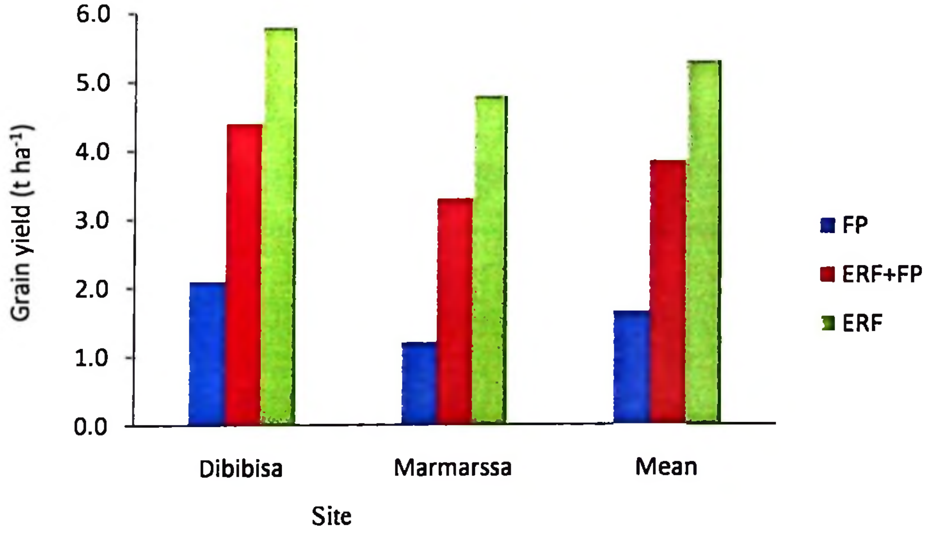

Figure 33: Maize grain yield from three production strategies tested at 51 on-farm sites during 2010-11 cropping seasons

4.4.3. Synthesis

The results presented above demonstrate superiority of ERF over both strategies. At all sites, 2010 season was good in terms of seasonal water supply. Thus, maize grain yield were generally higher. The use of ERF forecasts with traditional strategies holds great promise. Since farmers in the study areas flexibly adjust their management practices according to their perceptions of season date of onset, there is great potential for farmer adoption of ERF forecasts. The overall results show the benefits from ERF strategy most likely to have come from the matching of varieties to season length in addition to use of fertilizer and good soil and water management practices adopted. In terms of average yields, ERF forecast over farmers' traditional maize production strategy is apparently great indicating a good potential for improving traditional maize production strategy and to enhance the current low maize yield in the study sites.

On-farm valuation of RF strategy by Stewart (1988a), and extensive validation of the methodology by Wafula (1989), McCown *et al.* (1991), Wafula *et al.* (1992) and Admassu *et al.* (2010) show similar considerable benefits of RF strategy as compared to fixed strategies. The benefits from ERF can be considerable given the advances made to the time of prediction of the date of onset and season duration which allows the farmer to be well prepared to look for sources of credit to purchase yield improving inputs in forecast of good seasons. Thus, this warrants further efforts for developing ERF packages and testing in other sites to confirm the benefits and ultimately assist farming families living in the wider semi-arid areas in meeting their goals of food security.

CHAPTER FIVE

5.0 CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusions

The study was conducted using 32 years of daily climatic data for MARC and ATARC, high risk agricultural areas located in the Central Rift Valley of Ethiopia where predictive capability for onset was critical. The climate of the study areas exhibited great inter-annual variation. At the two study sites, maximum temperatures are uniformly high. Hence, efforts to conserve pre-onset rainfall are crucial for early starting of crops.

Considering the uncertainty in rainfall expectations in study sites, the study adopted a multi-factor approach for establishing the date of onset. Accordingly, April dates of onset were found the most risk-wise acceptable date onset of growing maize seasons. This allows farmers to make flexible combination of production of a 150-, 120- and 90-day maize varieties as compared to the growing of a single variety every season. This will raise the overall production and ensure food security.

Of all pre-onset rainfall parameters, the first effective rainfall date exhibited great inter-seasonal variation much more than the variation in the date of onset. Thus, the first effective rainfall date is the best signal of the expected dates of onset and good indicator of season duration. Prediction information based on the first effective rainfall date facilitates strategic planning of agronomic operations.

The date of onset was also found to be a good predictor of expected season duration that facilitates tactical management decisions. The date of onset which fairly indicates total seasonal water supply expectation is also useful to match crop water needs to expected seasonal water supply. Off-season rainfall holds great potential for determining post-onset rainfall expectations that can facilitate in-season agronomic response tactics. Similarly, cumulative early season rainfall following onset are useful in facilitating tactical decisions on plant stand and fertilizer at thinning and mid- and late-season agronomic corrective measures such as conservation of mid- and late-season rainfall to tackle the problems of mid-season dry-spells.

The strategic and tactical agronomic decision system which designates the first effective rainfall date, the date of onset, off-season rainfall and early season cumulative rainfall as predictors named enhanced RF (ERF) was proven to be of high potential in improving maize production. Enhanced RF predictors can bring in credit into picture for low resource farmers in dryland areas. In early onset seasons, credit will allow the production of much greater yields of more desired crops, using essential inputs such as nitrogen fertilizers. In late seasons such choices would actually lead to higher failure rates, so farmers can be advised to pull back to their present positions, avoiding both crop failure and cash outflow. When combined with adoption of climate smart options such as rainfall risk insurance schemes and prudent management of natural resources, ERF can contribute to sustainable agronomic adaptation to seasonal rainfall variability. This can in turn stabilize and enhance maize production and lead to achievement of food security under semi-arid conditions. This way vulnerable rural population may be able to capitalize on yield opportunities in good rainfall seasons and cut failure in bad seasons, and adapt to seasonal rainfall variability and future climate change.

The overall result will be improved average production of crops to consume and to sell, thus economic betterment for the family. Equally, enhanced crop growth and its root will maintain the soil organic matter - its fertility, state of aggregation and its condition for supporting plant growth, preventing its erosion and making farming sustainable.

5.2. Recommendations

The overall assessments of predictability suggest high potential for improving strategic and tactical RF to support planned agronomic adaptation to seasonal rainfall variability. Enhanced RF substantially increased maize yield. It is therefore recommended that risk management decisions need to be organized in a multi-staged decision array: first, for strategic planning purposes, using the first effective rainfall date to predict the date of onset and season duration, and second tactically according to what the date of onset closely informs us about expectations of total seasonal water and duration of up-coming season. Enhanced RF enables farmers to better prepare, better respond, and reduce failure from rainfall variability induced risks. Further research is recommended to confirm the benefits of ERF in similar agro-ecologies.

Together with ERF forecast information, improved agricultural technology, particularly more productive drought tolerant varieties are important to reduce crop failure and raise yields in semi-arid areas. Thus, plant breeders need to pay more attention to the development of high yielding drought tolerant maize varieties and non-conventional hybrids. Fertilizer use should be adjusted according to the date of onset total seasonal water supply expectations, and in-season rainfall developments.

In order to reduce rainfall risks, more efficient use of rainfall should be made by reducing run-off, increasing infiltration and reducing deep percolation losses. Any management practice which influences run-off, infiltration, and evapo-transpiration also influences the effectiveness of rainfall. Soil bunds, terraces, contour-ploughing, ridging and mulching reduce run-off and increase effectiveness of rainfall while the current, sometimes arbitrary farmer's traditional practices may reduce it. For such practices to be instantly adopted by farmers under semi-arid conditions, it is crucial that they are well demonstrated and popularized. Community based soil-water management practices, rain water harvesting, use of improved farm implements and management of natural resources should form integral part of ERF technique. Moreover, climate smart agricultural options such as rainfall risk insurance schemes are highly required to ensure further benefits of ERF technology. Climate change due to enhanced rainfall variability in the semi-arid areas may make the current management strategies very vulnerable. More robust adaptive mechanisms should therefore be sought and refined for adaptation to both current variability and projected changes.

The national meteorological agencies presently issue seasonal outlook information, but the outlooks are crude in nature and wider in coverage making location specific use very difficult. Traditional risk management strategies have helped people manage drought risk, but they are becoming ineffective in the event of widespread, major droughts. Obviously, the predictive capability developed through this study will never be total, but there is some risk in every agricultural enterprise everywhere. ERF strategic and tactical agronomic decision systems can be made robust if coupled with seasonal outlooks which are of proven skill and reliability. Therefore, research aimed at calibration of the ERF forecasts for use together with regularly updatable meteorological forecasts is required so as to improve on strategic and tactical management of risks. The need for such integration is more important now than ever due to the anticipated negative impacts of climate change.

Forecasts derived from RF analyses are location specific, and once developed, may remain valid for years to come until probably additional data sets are accumulated to change the equations. Thus, with availability of more data, the models should be updated. Research institutions in the country should consider funding research on ERF in order to develop ERF packages for the wider semi-arid areas of Ethiopia. Policy interventions are also required to facilitate rapid scaling up of the ERF technology wherever it is found feasible. They should invest on development of capacity of researchers in RF analytical methodology, interpretation of results, development and communication of ERF packages.

Research aimed at development of efficient methods for timely communication of ERF forecasts are recommended in order to find out how best to present the information and corresponding agronomic guidelines to the farming community before and at the start of each new season, in forms easy to understand and follow in practice. Efforts to develop decision support tools which can aid farm advisory services in guiding farmers in their seasonal decision making are also recommended.

Effective and sustainable agronomic adaptation to seasonal rainfall variability depends on the quality climate data. High quality data will also enhance credibility of climate analyses results, which will contribute to improving farm level decision-making. Thus, there is a need to establish more meteorological stations across the semi-arid areas in order to collect location specific data that can be used for development of site-specific prediction models and corresponding ERF packages.

REFERENCES

Admassu, H., Reddy, M. S., Teshale, A. and Jibril, M. (1996). Maize based cropping systems for sustainable agriculture in semi-arid areas of Ethiopia. In: *Proceedings of the first inaugural conference of agronomy and crop physiology society of Ethiopia.* (Edited by Weldeyesus, S. *et al.*), 30 - 31 May 1995, Addis Ababa, Ethiopia. 74 - 82pp.

Admassu, H. (2004). Assessing the impacts of historical water supplies on alternative maize production packages in the Central Rift Valley of Ethiopia. Thesis for Award of MSc Degree at Alemaya University of Agriculture, Alemaya, Diredawa, Ethiopia, 132pp.

Admassu, H., Rwehumbiza, F. B., Mahoo, H. F. and Siza, D. T. (September 2010). The role of response farming rainfall forecasts in improving the performance of agronomic adaptation strategies. [http://www.dewpoint.org.uk/Asset%20Library/ICID18/1-ADMASSU_et_al_ICID+18.pdf] site visited on 8/4/2011.

Admassu, H., Erenso, D., Mesay, B., Emana, G., Estifanos, H. M. and Mesfin, H. (2011a). *Participatory Action Research for Climate Change Adaptation in Boset Area.* Ethiopian Institute of Agricultural Research, Addis Ababa, Ethiopia. 30pp.

Admassu, H., Daniel, B. and Ashebir, T. (2011b). *Participatory Action Research for Climate Change Adaptation in Miesso Area.* Ethiopian Institute of Agricultural Research, Addis Ababa, Ethiopia. 22pp.

Admassu, H., Solomon, J., Getachew, A., Aman, A. and Temam, A. (2011c). *Participatory Action Research for Climate Change Adaptation in Adama Area.* Ethiopian Institute of Agricultural Research. Addis Ababa, Ethiopia. 27pp.

Admassu, H., Getinet, M., Timothy, S. T., Waithaka, M., Kyotalime, M. and Nelson, G. (2012). Crop Production and Climate Change in Ethiopia: Analyses of current and future scenarios and actions for adaptation. In: *Proceedings of 14th Biennial Conference of Crop Science Society of Ethiopia.* (Edited by Wegary, D. and Lijalem, K.), 28 - 29 April 2011, Addis Ababa, Ethiopia. 1 - 29pp.

Adugna, L. (2005). Rainfall probability and agricultural yield in Ethiopia. *Journal of Eastern Africa Social Science Research Review* 21(1): 57 - 96.

Allen, R. G., Pereira, L. S., Raes, D. and Smith, M. (1998). *Crop Evapotranspiration: Guidelines for computing crop water requirements.* Irrigation and Drainage Paper No. 56 of the Food and Agriculture Organization of the United Nations (FAO), FAO, Rome, Italy. 300pp.

Araya, A., Keesstra, S. D. and Stroosnijder, L. (2010). A new agro-climatic classification for crop suitability zoning in northern semi-arid Ethiopia. *Journal of Agriculture and Forest Meteorology* 150: 1047 - 1064.

Ati, O. F. (1995). A comparison of methods to detect the onset of the growing season and its trends for some stations in the Sudan Savanna of Northern Nigeria. Thesis for Award of MSc Degree at Ahmadu Bello University, Department of Geography, Zaria, Nigeria, 113pp.

Ati, O. F., Stigter, C. J. and Olandipo, E. O. (2002). Comparison of methods to determine the onset of the growing season in northern Nigeria. *International Journal of Climate* 22: 731 - 742.

Barron, J. (2004). Dry spell mitigation to upgrade semi-arid rainfed agriculture: water harvesting and soil nutrient management for smallholder maize cultivation in Machakos, Kenya. Thesis for Award of PhD Degree in Natural Resources Management at Stockholm University, Docusy, Stockholm, Sweden, 38pp.

Benoit, P. (1977). The start of the growing season in northern Nigeria. *Journal of Agricultural Meteorology* 18: 91 - 99.

Berger, P. (1989). *Rainfall and agroclimatology of the Laikipia Plateau, Kenya.* African Studies Series, A7. Geographica Bernesia, Berne, Switzerland. 102pp.

Berhane, B., Nigusie, T. and Admassu, H. (1993). Appropriate cultural practices for dryland farming areas of Ethiopia. In: *Proceedings of the First National Workshop on Developing Technologies for Dryland Farming Areas of Ethiopia.* (Edited by Reddy, M. S. and Kidane, G.), 26 - 28 November 1991, Nazreth, Ethiopia. 82 - 94pp.

Boko, M. I., Nyong, A., Vogel, C., Githeko, A., Medany, M., Osman-Elasha, B. R. and Yanda, P. (2007). Africa Climate Change: Impacts, Adaptation and Vulnerability. In: *Fourth Assessment Report of the Inter-governmental Panel on Climate Change.* (*Edited by Parry, M. L. et al.*), Cambridge University Press, Cambridge, UK. pp. 433 - 467.

Broad, K. and Agrawala, S. (2000). The Ethiopia food crisis: uses and limits of climate forecasts. *Science* 289: 1693 - 1694.

Burton, I. (1997). Vulnerability and adaptive response in the context of climate change. *Journal of Climate Change* 36: 185 - 196.

Central Intelligence Agency of the United States of America (CIA) (September 2012). Ethiopian Economy. [http://www.theodora.com/wfbcurrent/Ethiopia/Ethiopia_economy.htm] site visited on 12/9/2013.

Chappell, A. and Agnew, C. T. (2004). Modelling Climate Change in West African Sahel Rainfall (1931 - 90) as an Artifact of Changing Station Locations. *International Journal of Climatology* 24: 547 - 554.

Chmielewski, F. M. and Rötzer, T. (2002). Annual and spatial variability of the beginning of growing season in Europe in relation to air temperature changes. *Journal of Climate Research* 19: 257 - 264.

Conway, D., Mould, C. and Bewket, W. (2004). Over one century of rainfall and temperature observations in Addis Ababa, Ethiopia. *International Journal of Climatology* 24: 77 - 91.

Dastane, N. G. (1974). *Effective rainfall in irrigated agriculture.* Irrigation and Drainage Paper No. 25 of the Food and Agriculture Organization of the United Nations (FAO), FAO, Rome, Italy. 67pp.

Davidson, N. E., McBride, J. L. and McAvaney, B. J. (1983). The onset of the Australian monsoon during winter MONEX: Synoptic aspects. *Monthly Weather Review* 111: 496 - 516.

Davidson, N. E., McBride, J. L. and McAvaney, B. J. (1984). Divergent circulations during the onset of the 1978 - 79 Australian monsoon. *Monthly Weather Review* 112: 1684 - 1696.

Deressa, A. and Seboka, B. (Eds.) (1996). *Research achievements and technology transfer attempts: vignettes from Shoa.* Proceedings of National Workshop on Technology Transfer, Institute of Agricultural Research, Addis Ababa, Ethiopia, 25 - 30 June, 1995. 126pp.

Doorenbos, J. and Pruitt, W. O. (1977). *Crop water requirements.* Irrigation and Drainage Paper No. 24 of the Food and Agriculture Organization of the United Nations (FAO), FAO, Rome, Italy. 144pp.

Durbin, J. and Watson, G. S. (1950). Testing for serial correlation in least squares regression. *Biometrika* 37: 409 - 428.

Easterling, W. E. and Mjelde, J. W. (1987). The importance of seasonal climate prediction lead time in agricultural decision making. *Journal of Agriculture and Forest Meteorology* 40: 37 - 50.

Eltahir, E. and Gong, C. (1996). Dynamics of wet and dry years in West Africa. *Journal of Climate* 9: 1030 - 1040.

Fauchereau, N., Trzaska, S., Richard, Y., Roucou, P. and Camberlin, P. (2003). Sea surface temperature co-variability in the southern Atlantic and Indian Oceans and its connections with the atmospheric circulation in the southern hemisphere. *International Journal of Climatology* 23: 663 - 677.

Fischer, G., Shah, M., Tubiello, F. N. and van Velthuizen, H. (2005). Socio-economic and climate change impacts on agriculture: an integrated assessment. *Journal of Philosophical Transactions - The Royal Society of Biological Sciences* 360: 2067 - 2083.

Food and Agriculture Organization of the United Nations (FAO) (1978). *Agro-ecological zones project: methodology and results for Africa.* World Soil Resources Report No. 48, vol. 1. FAO, Rome, Italy. 158pp.

Fraisse, C. W., Bellow, J. G., Breuer, N., Cabrera, V., Hatch, L., Hoogenboom, G., Ingram, K., Jones, J. W., O'Brien, J. J., Paz, J. and Zierden, D. (2006). AgClimate: A Climate Forecast Information System for Agricultural Risk Management in the South Eastern USA. *International Journal of Computers and Electronics in Agriculture* 53(1): 13 - 27.

Frère, M. and Popov, G. F. (1979). *Agrometeorological crop monitoring and forecasting.* Plant Production and Protection Paper No. 17 of the Food and Agriculture Organization of the United Nations (FAO), FAO, Rome, Italy. 67pp.

Fujisaka, S., Wortmann, C. and Admassu, H. (1996). Resource poor farmers with complex technical knowledge in high risk system in Ethiopia: Can research help? *Journal of Farming Systems Research-Extension* 6(3): 1 - 14.

Gee, G. W. and Bauder, J. W. (1986). Particle-size analysis. In: *Methods of soil analysis. Part 1.* 2nd Ed. (*Edited by Klute, A.*), ASA and SSSA, Madison, WI. pp. 383 - 411.

Glantz, M. H. (Eds.) (2001). *Once Burned, Twice Shy? Lessons Learned from the 1997 - 1998 El Niño*. United Nations University Press, Tokyo. 294pp.

Goddard, L., Mason, S. J., Zebiak, S. E., Ropelewski, C. F., Basher, R. and Cane, M. A. (2001). Current approaches to seasonal-to-inter-annual climate predictions. *International Journal of Climatology* 21: 1111 - 1152.

Graef, F. and Haigis, J. (2001). Spatial and temporal rainfall variability in the Sahel and effects on farmers' management strategies. *Journal of Arid Environments* 48(2): 221 - 231.

Grey, D. and Sadoff, C. W. (2007). Sink or Swim? Water security for growth and development. *Journal of Water Policy* 9: 545 - 571.

Hammer, G. L., Holzworth, D. P. and Stone, R. (1996). The value of skill in seasonal climate forecasting to wheat crop management in a region with high climatic variability. *Australian Journal of Agricultural Research* 47: 717 -737.

Hansen, J. W. (2002). Realizing the potential benefits of climate prediction to agriculture: issues, approaches, challenges. *Journal of Agricultural Systems* 74: 309 - 330.

Hargreaves, G. H. (1975). *Water requirements manual for irrigated crops and rainfed agriculture.* Publication No. 75-D158 of EMBRAPA and Utah State University, Logan, Utah, United States of America. 40pp.

Hargreaves, G. H. and Zamani, Z. A. (1982). Estimating potential evapo-transpiration. *Journal of the Irrigation and Drainage Division of the American Society of Civil Engineers* 108 (3): 225 - 230.

Hendon, H. and Liebmann, B. (1990). A composite study of onset of the Australian summer monsoon. *Journal of Atmospheric Sciences* 47: 2227 - 2240.

Holland, G. J. (1986). Inter-annual variability of the Australian monsoon at Darwin. *Monthly Weather Review* 114: 594 - 604.

Hulme, M., Doherty, R., Ngara, T., New, M. and Lister, D. (2001). African climate change: 1900 - 2100. *Journal of Climate Research* 17: 145 - 168.

ICRA (International Centre for Development Oriented Research in Agriculture) (1999). *Livelihoods and drought coping strategies of households in Central Rift Valley of Ethiopia: Challenges for agricultural research.* ICRA Working Document series no. 73, Wageningen, The Netherlands. 124pp.

Inter-governmental Panel on Climate Change (IPCC) (2001). *Climate Change 2001: The Scientific Basis.* Cambridge University Press, Cambridge, United Kingdom and New York, United States of America. 881pp.

Inter-governmental Panel on Climate Change (IPCC) (2007). *Third Assessment Report (TAR).* Cambridge University Press, Cambridge, New York. 1031pp.

Ioan, F., John, A. F., Joern, F., Kate, S., John, W., Reed, F. and Stephen, R. D. (2007). Adaptive capacity and learning to learn as leverage for social-ecological resilience. *Journal of Ecological Environment* 5(7): 375 - 380.

Itana, F. (In Press). Sulphur distribution in five Ethiopian Rift Valley soils under Humid and Semi-Arid Climate. *Journal of Arid Environment.*

Janicot, S., Harzallah, A., Fontaine, B. and Moron, V. (1998). West African monsoon dynamics and eastern equatorial Atlantic and Pacific SST anomalies (1970 - 88). *Journal of Climate* 11: 1874 - 1882.

Joseph, P. V., Liebmann, B. and Hendon, H. H. (1991). Inter-annual variability of the Australian summer monsoon onset: Possible influence of Indian summer monsoon and El Nin˜o. *Journal of Climate* 5: 529 - 538.

Kaihla, A. H. (1983). A Study of Evaporation Pan Factoring at Katumani, Kenya. Thesis for Award of MSc Degree at University of Nairobi, Nairobi, Kenya, 139pp.

Kanemasu, E. T., Stewart, J. I., Van Donk, S. J. and Virmani, S. M. (1990). Agroclimatic approaches for improving agricultural productivity in Semiarid Tropics. *Advances in Soil Science* 13: 273 - 209.

Konate, M. and Traore, K. (1987). Agro-climatic monitoring during the growing season in semi-arid regions of Africa. In: *Planning for drought: Towards a Reduction of Societal Vulnerability.* (*Edited by Donald A. W., et al.*), Westview Press, Boulder and London. pp. 113 - 129.

Kousky, V. E. (1988). Pentad outgoing longwave radiation climatology for the South American sector. *Brazilian Journal of Meteorology* 3: 217 - 231.

Kowal, J. M. and Knabe, D. T. (1972). An Agroclimatological Atlas of the Northern states of Nigeria with explanatory notes. In: *Yields of millet between shelterbelts in semi-arid northern Nigeria, with a traditional and a scientific method of determining sowing date, and at two levels of organic* *manuring*. (*Edited by Onyewotu, L. O. Z. et al.*), Ahmadu Bello University Press, Zaria, Nigeria. pp. 11 - 25.

Kruger, A. C. and Shongwe, S. (2004). Temperature trends in South Africa: 1960 - 2003. *International Journal of Climatology* 24: 1929 - 1945.

Lamb, P. J. and Peppler, R. A. (1992). Further case studies of tropical Atlantic surface atmospheric and oceanic patterns associated with sub-Saharan drought. *Journal of Climate* 5: 476 - 488.

Laux, P., Kunstmann, H. and Bárdossy, A. (2008). Predicting the Regional Onset of the Rainy Season in West Africa. *International Journal of Climatology* 28(3): 329 - 342.

Lehmann, J., Willert, F. V., Wulf, S. and Zech, W. (1998). Influence of Runoff Irrigation on Nitrogen Dynamics of *Sorghum bicolour* (L.) in Northern Kenya. *Advances in Geoecology* 31(2): 1255 - 1260.

Lemma, Z., Reddy, M. S., Admassu, H., Berhane, B., Tsegaye, H. and Etagegnehu, G. M. (1995). Agronomic research to alleviate moisture stress, poor soil fertility and weed problems in the semi-arid areas of Ethiopia. In: *Proceedings of fourth eastern and southern Africa regional maize workshop*. (Edited by Jwell, D. C. *et al.*), March 28 - April 1, 1994.

International Maize and Wheat Improvement Centre (CIMMYT), CIMMYT, Mexico. 242 - 246pp.

Lenters, J. and Cook, K. (1995). Simulation and diagnosis of the regional summertime precipitation climatology of South America. *Journal of Climate* 8: 2298 - 3005.

Makridakis, S., Wheelbright, S. C. and McGee, V. E. (1983). *Forecasting Methods and Applications*. John Wiley and Sons, New York. 923pp.

Malhi, Y. and Wright, J. (2004). Spatial patterns and recent trends in the climate of tropical rainforest regions. *Journal of Philosophical Transactions - The Royal Society of Biological Sciences* 359: 311 - 329.

Mamo, G. (2004). Using seasonal climate outlook to advise on sorghum production in the Central Rift Valley of Ethiopia. Thesis for Award of PhD Degree in Agrometeorology at the University of the Free State, Bloemfontein, South Africa, 188pp.

Marengo, J. A., Brant, L., Vernon, E. K., Naziano, P. F. and Ilana, C. W. (2001). Onset and End of the Rainy Season in the Brazilian Amazon Basin. *Journal of Climate* 14: 833 - 852.

McCown, R. L., Wafula, B. M., Mohammed, L., Ryan, J. G. and Hargreaves, J. N. G. (1991). Assessing the value of a seasonal rainfall forecast to agronomic decisions: The case of response farming in Kenya. In: *Proceedings of the International Symposium on Climatic Risk in Crop Production: Models and Management for the Semi-Arid Tropics and Sub-Tropics.* (Edited by Muchow, R. C. and Bellamy, J. A.), 2 - 6 July 1990, Brisbane, Australia. 383 - 410pp.

Meinke, H., Stone, R. C. and Hammer, G. L. (1996). Using SOI phases to forecast climatic risk to peanut production: A case study for northern Australia. *International Journal of Climatology* 16: 783 - 89.

Michigan State University (1993). MSTAT-C: *A micro-computer software program for the design, management and analysis of agronomic research experiments.* Michigan State University, Michigan, USA. 152pp.

Mideksa, T. (2011). A multivariate time series analysis of agro-meteorological data to assess the effect of climate variability on production of sorghum: The case of Melkassa, Ethiopia. Thesis for Award of MSc Degree at Addis Ababa University, Addis Ababa, Ethiopia, 70pp.

Ministry of Finance and Economic Development (MOFED) of the Federal Democratic Republic of Ethiopia (2010). Growth and Transformation Plan of Ethiopia, Volume 1 Main Text. MoFED, Addis Ababa, Ethiopia. 135pp.

MINITAB Incorporated (March 2008). MINITAB Statistical Software ver. 14: A software for statistics, process improvement, six sigma, quality. [http://www.minitab.com/en-US/academic/] site visited on 11/11/ 2009.

Murakami, T. and Sumi, A. (1982). Southern Hemisphere summer monsoon circulation during 1978 - 79 WMONEX. Part I: Onset, active and break monsoon. *Journal of Meteorological Society of Japan* 60: 649 - 671.

Nicholls, N., McBride, J. L. and Ormerod, R. J. (1982). Predicting the onset of the Australian wet season at Darwin. *Monthly Weather Review* 110: 14 - 17.

Nicholls, N. (1999). Cognitive illusions, heuristics, and climate prediction. *Bulletin of the American Meteorological Society* 80: 1385 - 97.

Nicholls, N. (2000). Opportunities to improve the use of seasonal climate forecasts. In: *Applications of seasonal climate forecasting in agricultural and natural ecosystems: the Australian experience* (*Edited by Hammer, G. L., Nicholls, N. and Mitchell, C.*), Kluwer Academic Publishers. pp. 309 - 327.

Nicholson, S. E., Some, B. and Kone, B. (2000). An analysis of recent rainfall conditions in West Africa, including the rainy season of the 1997 El Niño and the 1998 La Niña years. *Journal of Climate* 13: 2628 - 2640.

Olaniran, O. J. (1983). The onset of the rains and the start of the growing season in Nigeria. *Nigerian Geographical Journal* 26: 81 - 88.

Omotosho, J. B. (1990). Onset of thunderstorms and precipitation over northern Nigeria. *International Journal of Climatology* 10: 849 - 860.

Omotosho, J. B. (1992). Long-range prediction of the onset and end of the rainy season in the West African Sahel. *International Journal of Climatology* 12: 369 - 382.

Omotosho, J. B., Balogun, A. A. and Ogunjobi, K. (2000). Predicting monthly and seasonal rainfall, onset and cessation of the rainy season in West Africa using only surface data. *International Journal of Climatology* 20: 865 - 880.

Patt, A. (September 2000). Communicating Probabilistic Forecasts to Decision Makers: A Case Study of Zimbabwe. [http://environment.harvard.edu/geapp] site visited on 13/06/2008.

Patt, A. (2001). Understanding uncertainty: forecasting seasonal climate for farmers in Zimbabwe. *Risk Decision and Policy* 6(2): 1 - 15.

Phillips, J. G., Cane, M. A. and Rosenzweig, C. (1998). ENSO seasonal rainfall patterns and simulated maize yield variability in Zimbabwe. *Journal of Agriculture and Forest Meteorology* 90: 39 - 50.

Punyawardena, B. V. R. (2002). Identification of the potential of growing seasons by the onset of seasonal rains: a study in the dll region of the north central dry zone. *Journal of Science Foundation of Sirilanka* 30 (1 and 2): 13 - 21.

Ramage, C. S. (1971). *Monsoon Meteorology*. New York. Academic Press. 296pp.

Ransom, J. K., Regassa, T. and Nugussie, M. (1997). Use of simulation models to predict the optimum duration of maize cultivars adapted to the Rift Valley of Ethiopia. In: *Proceedings of a Symposium on Developing Drought- and Low-N Tolerant Maize*. (Edited by Edmeades, M. *et al.*), 25 - 29 March 1996, International Maize and Wheat Improvement Centre (CIMMYT), CIMMYT, El Batan, Mexico. 96 - 98pp.

Rao, G. V. and Erdogan, S. (1989). The atmospheric heat source over the Bolivian Plateau for a mean January. *An International Journal of Physical, Chemical and Biological Processes in the Atmospheric Boundary* 46: 13 - 33.

Rao, K. P. C., Ndegwa, W. G., Kizito, K. and Oyoo, A. (2011). Climate variability and change: Farmer perceptions and understanding of intra-seasonal variability in rainfall and associated risk in semi-arid Kenya. *Experimental Agriculture* 47: 267 - 291.

Reddy, M. S. and Kidane, G. (1994). *Dryland farming research in Ethiopia: Review of past and thrust in the nineties.* Institute of Agricultural Research, Addis Ababa, Ethiopia. 107pp.

Richard, J. T. K. and Donald, C. M. (May 1999). Adaptation to climate variability and change: methodological issues. [http://www.macis-project.net/MACIS-deliverable-2.2-2.3.pdf] site visited on 15/7/2008.

Sadras, V., Roget, D. and Krause, M. (2003). Dynamic cropping strategies for risk management in dry-land farming systems. *Journal of Agricultural Systems* 76: 929 - 948.

Sarria-Dodd, D. E. and Jolliffe, I. T. (2001). Early detection of the wet season in semiarid tropical climates of western Africa. *International Journal of Climatology* 21: 1251 - 1262.

Simane, B. and Struick, P. C. (1993). Agroclimatic analyses: a tool for planning sustainable Wheat (*Triticum turgidum var. durum*) production in Ethiopia. *Journal of Agricultural Economics and Environment* 47: 31 - 46.

Sivakumar, M. V. K., Virmani, S. M. and Reddy, S. J. (1979). *Rainfall climatology of West Africa: Niger.* International Crops Research Institute for the Semi-Arid Tropics, Patancheru, India. 66pp.

Sivakumar, M. V. K. and Gnoumou, F. (1987). *Agroclimatology of Burkina Faso.* International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Patancheru, India. 192pp.

Sivakumar, M. V. K. (1988). Predicting rainy season potential from the onset of rains in southern Sahelian and Sudanian climatic zones of West Africa. *Journal of Agriculture and Forest Meteorology* 42: 295 - 305.

Sivakumar, M. V. K. (1990). Exploiting rainy season potential from the onset of the rains in the Sahelian zone of West Africa. *Journal of Agriculture and Forest Meteorology* 51: 321 - 332.

Sivakumar, M. V. K. (1992). Empirical analysis of dry spells for agricultural application in West Africa. *Journal of Climate* 5: 532 - 539.

Smith, M. (1992). *CROPWAT, a computer program for irrigation planning and management.* Irrigation and Drainage Paper No. 46 of the Food and Agriculture Organization of the United Nations (FAO), FAO, Rome, Italy. 126pp.

Smit, B., Burton, I., Klein, R. J. T. and Wandel, J. (2000). An anatomy of adaptation to climate change and variability. *Journal of Climatic Change* 45(1): 233 - 251.

Steiner, J. L., Schneider, J. M., Garbrecht, J. D. and Zhang, X. J. (2004). Climate Forecasts: Emerging Potential to Reduce Dryland Farmers' Risks. *Journal of Crop Science Society of America.* 32: 47 - 65.

Stephen, N. N., Hubert, H. G. S., Josephine, N. T., Rockstrom, J. and Penning de Vries, F. W. T. (2005). Agro-hydrological evaluation of on-farm rainwater storage systems for supplemental irrigation in Laikipia district, Kenya. *Agricultural Water Management* 73: 21 - 41.

Stern, R. D., Dennett, M. D. and Garbutt, D. J. (1981). The start of the rains in West Africa. *Journal of Climatology* 1: 59 - 68.

Stern, R., Knock, J., Rijks, D. and Dale, I. (2002). *Instat+ (Interactive Statistics Package).* Statistical Services Centre, University of Reading, Reading, Berkshire, United Kingdom. 530 pp.

Stewart, J. I. and Hash, C. T. (1982). Impact of weather analysis on agricultural production and planning decisions for the semiarid areas of Kenya. *Journal of Applied Meteorology* 21(4): 477 - 494.

Stewart, J. I. and Kashasha, D. A. R. (1984). Rainfall criteria to enable response farming through crop-based climate analysis. *East African Agriculture and Forestry Journal* 44: 58 - 79.

Stewart, J. I. and Faught, W. A. (1984). Response farming of maize and beans at Katumani, Machakos District, Kenya: Recommendations, yield expectations and economic benefits. *East African Agriculture and Forestry Journal* 44: 29 - 51.

Stewart, J. I. (1985). Response farming: a scientific approach to ending starvation and alleviating poverty in drought zones in Africa. In: *Proceedings of International Conference on African Agriculture Development: Technology, Ecology, and Society*. (Edited by Yolanda, T. M.), 28 May to June 2, 1985, California State Polytechnic University, Pomona, Kellogg West Conference Center, California, United States of America. 45 - 58pp.

Stewart, J. I. (1988a). Response Farming in Rainfed Agriculture. The WHARF Foundation Press, Davis, California, United States of America. 103pp.

Stewart, J. I. (1988b). Development of Management Strategies for Minimizing the Impact of Seasonal Rainfall Variation. In: *Drought Research Priorities for the Dryland Tropics. (Edited by Bidinger, F. R. and Johansen, C.)*, International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Patancheru, Andhra Pradesh, India. pp. 131 - 150.

Stewart, J. I. (1989a). Mediterranean-type climate, wheat production and response farming. In: *Proceedings of the Workshop on Soil, Water, and Crop/Livestock Management Systems for Rainfed Agriculture in the Near East Region.* (Edited by Whitman, C. E. *et al.*), 18 - 23 January 1986, Amman, Jordan. 5 - 19pp.

Stewart, J. I. (1989b). Response farming for improvement of rainfed crop production in Jordan. In: *Proceedings of the Workshop on Soil, Water, and Crop/Livestock Management Systems for Rainfed Agriculture in the Near East Region.* (Edited by Whitman, C. E. *et al.*), 18 - 23 January 1986, Amman, Jordan. 288 - 308pp.

Stewart, J. I. (1989c). Potential for response farming in Sub-Saharan Africa. In: *Proceedings of an International Workshop on Soil, Crop and Water Management Systems for Rainfed Agriculture in the Sudano-Sahelian Zone.* (Edited by Renard, C., *et al.*), 11 - 16 January 1987, Niamey, Niger. 255 - 264pp.

Stewart, J. I. (1991a). Managing climatic risk in agriculture. In: *Proceedings of the Tenth Agriculture Sector Symposium on Risk in Agriculture.* (Edited by Dennis, H. *et al.*), 9 - 10 January 1990, Washington, DC, United States of America. 17 - 37pp.

Stewart, J. I. (1991b). Principles and performance of response farming. In: *Proceedings of the International Symposium on Climatic Risk in Crop Production: Models and Management for the Semi-Arid Tropics and Sub-Tropics*. (Edited by Muchow, R. C. and Bellamy, J. A.), 2 - 6 July 1990, Brisbane, Australia. 361 - 382pp.

Stewart, J. I. (1991c). Developing Guidelines for Early Warning and Response Farming Based on Agriculturally Relevant Analyses of Historical Daily Rainfall Data. In: *Proceedings of Workshops on Famine Mitigation*. (Compiled by the Office of Arid Lands Studies of University of Arizona), 20 - 23 May 1991, Tucson, Arizona, and July 31 - August 2, 1991, Berkeley Springs, West Virginia, United States of America. 245 - 264 pp.

Stewart, J. I. (1995). WHARF computer programs to determine rainfall probabilities for crop seasons and growth stages, define and quantify risk factors in rainfall behaviour, and design cropping systems and response farming decision packages for risk management. In: *Proceedings of an Expert Consultation on Coordination and Harmonization of Databases and Software for Agro-climatic Applications.* Agro-meteorology Working Paper Series No. 13 of the Food and Agriculture Organization of the United Nations (FAO). (Edited by Sustainable Development Department), 29 November to December 3, 1993, FAO, Rome, Italy. 261 - 289pp.

Stone, R. C. and Meinke, H. (2005). Operational seasonal forecasting of crop performance. *Journal of Philosophical Transactions - The Royal Society of Biological Sciences* 360: 2109 - 2124.

Taddesse, T. (2000). Drought and its predictability in Ethiopia. In: *Drought: A Global Assessment, Volume 1. (Edited by Wilhite, D. A.)*, Rougtledge, United States of America. pp. 135 - 142.

Tadros, M. A., Hewitson, B. C. and Usman, M. T. (2005). The inter-annual variability of the onset of the maize growing season over South Africa and Zimbabwe. *Journal of Climate* 18: 3356 - 3372.

Tesfaye, K. F. (2004). Field comparison of resource utilization and productivity of three grain legumes under water stress. Thesis for Award of PhD Degree in Agrometeorology at the University of the Free State, Bloemfontein, South Africa, 237pp.

Teshale, A., Teshome, R., Admassu, H., Reddy, M. S., Chanyalew, T. and Legese, T. (1996). On-farm evaluation of maize fertilizer response with and without moisture conservation practices. In: *Proceedings of the first inaugural conference of agronomy and crop physiology society of Ethiopia.* (Edited by Sinebo, W. *et al.*), 30 - 31 May 1995, Addis Ababa, Ethiopia. 98 - 106pp.

The MathWorks Incorporated (March 2013). MATLAB software Version R2013a. [http://www.mathworks.com/academia/student_version/?s_v1=56673931] site visited on 7/09/2013.

Troll, C. (1965). Seasonal climates of the earth. In: *World Maps of Climatology, Second Edition.* (*Edited by Rodenwaldt, E. and Jusatz, H. J.*), Springer-Verlag, Berlin, pp. 2 - 25.

Troup, A. J. (1961). Variations in upper tropospheric flow associated with the onset of the Australian summer monsoon. *Indian Journal of Meteorology and Geophysics* 12: 217 - 230.

United States Department of Agriculture (USDA) (1975). *Soil Taxonomy. A basic system of soil classification for making and interpreting soil surveys.* USDA Hand book No. 436. Washington, DC. 754pp.

Unites States Department of State (USDS) (June 2007). Background Note: Ethiopia. Bureau of African Affairs. [http://www.state.gov/r/pa/ei/bgn/2859.htm] site visited on 8/7/2008.

Vogel, C. and O'Brien, K. (2006). Who can eat information? Examining the effectiveness of seasonal climate forecasts and regional climate-risk management strategies. *Journal of Climate Research* 33: 111 - 122.

Wafula, B. M. (1989). Evaluation of the concepts and methods of response farming using crop growth simulation models. Thesis for Award of MSc Degree of School of Agriculture and Forestry at the University of Melbourne, Melbourne, Australia, 123pp.

Wafula, B. M., McCown, R. L. and Keating, B. A. (1992). Prospects for Improving Maize Productivity through Response Farming. In: *Proceedings of a Symposium on A Search for Strategies for Sustainable Dryland Cropping in Semi-arid Eastern Kenya.* (Edited by Probert, M. E.), 10 - 11 December 1990, Nairobi, Kenya. 26 - 33pp.

Walter, M. W. (1967). Length of the rainy season in Nigeria. *Nigerian Geographical Journal* 10: 123 - 128.

Wilks, D. S. (1995). *Statistical Methods in Atmospheric Sciences.* Academic Press, New York. 467pp.

APPENDICES

Appendix 1: Soil characteristics in the vicinity of Melkassa

Soil depth, cm	B.D (g/ cm³)	pH	Texture class, USDA	N (%)	O. C. (%)	C/N	FC (% Vol)	PWP (% Vol)
0-10	1.13	6.7	Sandy loam	0.04	0.7	11.7	23.96	11.44
10-30	1.3	7.0	Sandy clay loam	0.06	0.7	11.7	30.84	14.5
30-60	1.13	6.7	clay loam	0.04	0.12	12	30.37	16.1

Note: FC = field capacity; PWP = permanent wilting point

Appendix 2: Soil characteristics in the vicinity of Adami Tulu

Soil depth, cm	B.D (g/ cm³)	pH	Texture class, USDA	N (%)	O. C. (%)	C/N	FC (% Vol)	PWP (% Vol)
0-10	0.95	7.3	Sandy loam	0.15	1.7	11.6	37.8	15.9
10-30	1.18	7.5	Sandy loam	0.14	1.6	11.6	46.5	19.2
30-60	1.17	7.8	Silt loam	0.08	0.9	11.6	43.8	20.4

Note: FC = field capacity; PWP = permanent wilting point

Appendix 3: Description of MINITAB ver 14 regression analyses techniques, analytical outputs and cross-validation techniques

MINITAB assumes the dependent variable *y* as a linear function of an independent variable *x* plus an error ε introduced to account for all other factors. Using the 'least squares methodology' (Middleton, 2000) which minimizes the sum of squares of the error term in the equation. The fitted line is: $\hat{y}_i = b_0 + b_1 x_i$, where $\hat{y}_i$ are the values of y estimated from the fitted line and ε are the differences between the observed values of y and the estimated values, b_0 is the intercept of the y axis and b_1 is the slope of the regression line and, simultaneously, the trend value of the dependent variable. In order to test the null hypothesis when the slope $b_1 = 0$, the total variances $S^2_y = (yi - y)^2/(N - 1)$ of the dependent variable is divide into two independent parts: the variance due to the regression and the error variance $\sum\varepsilon^2/(N-2)$. These calculations are indicated by the Analysis of Variance (ANOVA) table for linear regression. Under the null hypothesis of there being no effect due to the regression, the mean squares due to regression and the mean squares due to the variance result in the variance due to the error. Hence, the ***MSR/MSE*** ratio is expected to follow the F distribution, and the calculated value is compared with the tabulated value for a certain level of significance ($\alpha = 0.5$ and 1) at $(N-2)$ degrees of freedom. Under the null hypothesis of there being no effect due to the regression, the mean squares due to regression and the mean squares due to the variance result in the variance due to the error. If the calculated value is larger than the tabulated value, the null hypothesis is rejected and the regression is declared to be significant.

MINITAB outputs values that provide information of the resulting regression equation relating the predictand with the predictor. These are Standard Error (SE) of the regression or the root mean squared error (RMSE), Coefficient of Determination (Variation) or correlation of determination (R^2), Analysis of Variance (ANOVA) table listing Degrees of Freedom (DF), the total DF, Sum of Squares (SS) for each source of variation due to regression, residual errors (and its sub-sets - lack of fit and pure error), F-statistic and corresponding P-values. In addition, it outputs SE of estimates for the coefficients of the predictand, the predictors and for the constant terms along with their T-statistic and corresponding P-values.

MINITAB outputs the Variance Inflation Factor (VIF) as a measure of how much the variances of estimated regression coefficients are inflated. VIF value of 1 shows absence of multi-co-linearity; VIF > 1 but <5 shows moderate correlation, and VIF >5 - 10 show predictors are highly correlated. In the latter case, the regression coefficients are poorly estimated. VIF > 10 indicates multi-co-linearity is excessively influencing the regression results.

MINITAB outputs the Durbin-Watson (DW) statistic which tests for the presence of autocorrelation (Durbin and Watson, 1950). Autocorrelation means that adjacent observations are correlated. If they are correlated, then least squares regression underestimates the standard error of the coefficients. Thus, the predictor may appear to be significant when they may not be. To reach a conclusion from the test, the displayed DW statistic is compared with lower and upper bounds in a DW significance table. If DW > upper bound, no correlation exists; if DW < lower bound, positive correlation exists; if DW is in between the two bounds, the test is inconclusive. DW statistic towards 2 is an indication of small or non-autocorrelation, while DW values of ≥2 indicates definite autocorrelation. DW towards 4 indicates negative autocorrelation, and DW toward 0 indicates positive autocorrelation (Makridakis, *el al.*, 1983). DW statistic < 1 indicates difficulty of concluding regarding the presence of auto-correlation.

MINITAB enables assessments of model's predictive ability via testing the goodness of fit between predicted and observed values of the predictand using the developed model. It thus enables potential of the model for use in operational forecasting. A one-year-out cross validation technique (Wilks, 1995) in partial least square regression analyses technique was applied for cross-validation.

Accordingly, assessments of prediction model's capability in reproducing the observed series were carried out to determine the potential of the model for use in operational forecasting. A one-year-out cross validation technique (Wilks, 1995) in partial least square regression analysis technique was applied for cross-validation. In this method, MINITAB computes the new predicted observation by systematically removing each observation from the data set one at a time, estimating the regression equation using the remaining ***n-1*** partition to train the model. The analyst specifies components (predictors) to evaluate. If there is more than one component, the analyses will determine the components that best describe the developed model. It performs analysis of variance for the predictand, and outputs source of variation due to the regression and residual error along with their respective DF, SS, MS, the total DF and F statistic and P-value for the regression. It also outputs the Predicted R^2 which indicates how well the model predicts responses for new and the removed observation. Predicted R^2 prevents over-fitting of models and to avoid artificial forecast skills. It is more useful than adjusted R^2 for comparing models. Its values range between 0 and 100%. Larger values suggest models of greater predictive ability. Thus, whenever significance of regression models is confirmed with F statistic, cross-validation technique was applied to assess the predictor's capacity in capturing the future values of the predictand. At the end, a response plot relating the fitted and the predicted values using the model are output. Coefficient of correlation (r) is computed to enable assessments of the goodness of fit of the observed and predicted observations of the predictand. Based on the r-value relating the observed with predicted value of the predictand, a conclusion was reached about model capability in capturing the predictands future values and its potential for use in operational agronomic decisions.

Appendix 4: Impacts of water supplies in different growth stages of a post-onset planted 150-day maize variety at Melkassa (1977 - 2008)

		ETc	150	15.8	15.7	19.7	27	37.9	41.8	44.1	42.9	41.8	40.7	44.9	35.5	28	16.8			ETc	464.5
	DOS	GERM Date		Initila	Seedling	Rapid vegetative growth				Tasseling/silking/grain forming					Maturation and harvest					0.6*TSW	ETa/ETc
Year	J	J	Soil water at GERM	Period 1 (20)	2	3	4	5	6	7	8	9	10	11	12	13	14	TSW	DUR	ETa	WAR
1993	91	99	69.3	55.9	14.5	22.8	34	52.8	31.5	10.5	25.5	61.4	21	54.7	40.5	32.5	76.1	599	146	359.4	0.8
2003	91	99	54.1	70.8	0	4	0	4.2	2.3	41.4	30.3	62.2	89.4	41.4	32.1	86.8	77.8	596.8	149	358.1	0.8
2000	92	100	63.1	70.8	0	4	0	4.2	2.3	41.4	30.3	62.2	89.4	41.4	32.1	86.8	77.8	605.8	149	363.5	0.8
1989	91	100	45.5	7.6	0	13.3	0	0	10.6	48.5	70.8	43.3	89.5	90.7	55.2	101.8	47	623.8	150	374.3	0.8
1980	92	103	47	36.5	0	1.2	0	0.3	0	2.5	35	78.4	117.5	40.6	75.7	33.5	43	511.2	149	306.7	0.7
1978	91	104	77.1	16.3	1.3	2.3	0	2.6	39.8	10.8	45.6	3.5	15	48.6	94.5	21.5	25	355.7	128	213.4	0.5
1977	91	104	134.8	71.2	15.8	16.6	4.5	67.4	71.8	79.5	45.8	53.7	57.5	30.5	27.3	63.7	48.4	788.5	148	473.1	1.0
1992	99	107	51	50.9	0	3.4	7.2	0	36.2	42.5	111.9	46.9	3.2	110.9	37.4	58.5	43	603	147	361.8	0.8
1985	96	108	37	12	25.6	102	9	3.2	0	36.4	46.6	16	26.4	115.3	88.8	20.8	9.2	518.3	127	311.0	0.7
2004	92	109	51.1	4.5	0	0.1	0.1	7.3	38.1	40.2	94.2	10.4	97	69	31	15.4	76.4	534.8	149	320.9	0.7
2007	91	109	129.9	0.1	29.8	61.4	24.1	14.9	32.6	14.7	44.1	82.8	109.5	54.4	40.3	137.7	111.1	885.8	149	531.5	1.1
2008	100	111	26.3	45.4	26.9	35.3	10	10.7	28.2	52.2	145.6	137.8	21.5	167.3	95.5	23.2	53.6	876	145	525.6	1.1
1991	107	117	29.6	139.2	37.6	31.2	5.2	0	65.4	138	56.2	32.4	48.3	54	10	13	32	637.1	118	382.3	0.8
2002	102	123	31.4	16.2	0	12.1	2.2	5.9	17.5	14	43.2	66.1	47.5	40.1	10.5	30.1	0	276.8	113	166.1	0.4
2001	119	134	62.4	49	33.5	66.9	28.3	83.4	63.7	54.1	58.9	42.9	54.7	28.7	19.5	1.4	0	623.7	114	374.2	0.8
1998	119	134	63.2	49	33.5	66.9	28.3	83.4	63.7	54.1	58.9	42.9	54.7	28.7	19.5	1.4	0	624.5	114	374.7	0.8
1979	125	136	32.1	52.9	56.8	45.8	66.3	85.3	77.2	66.6	19.5	46.7	41.8	26.4	31.2	26.3	0	591	106	354.6	0.8
1997	119	136	51.8	0	14.4	3.4	60.1	130	105	24.2	133.6	104.7	24.2	34.9	7	47.6	19.5	685.6	118	411.4	0.9

Appendix 4: Continued

		ETc	150	15.8	15.7	19.7	27	37.9	41.8	44.1	42.9	41.8	40.7	44.9	35.5	28	16.8			ETc	464.5
	DOS	GERM Date		Initila	Seedling	Rapid vegetative growth				Tasseling/silking/grain forming					Maturation and harvest					0.6*TSW	ETa/ETc
Year	J	J	Soil water at GERM	Period 1 (20)	2	3	4	5	6	7	8	9	10	11	12	13	14	TSW	DUR	ETa	WAR
2005	109	137	89.1	30	9.6	22.6	50.5	16.7	51.8	102.7	36.4	99.1	30	87.7	17.3	19.7	3.9	630.8	121	378.5	0.8
1984	101	140	31.9	14.8	19.3	46.6	89.3	5.7	74.2	10.9	54.8	8.7	22.4	59.4	10.8	9.8	0	437	119	262.2	0.6
1983	125	140	43.5	3.8	21.9	4.2	57.4	47.2	122.4	138.2	65.1	89.9	52.9	31.2	13	0.6	0	640.8	107	384.5	0.8
1981	128	142	17.7	0	18.7	9.7	21.1	27.7	86.4	76.8	36.3	108.4	27.6	5.7	8.9	47.7	20.1	422	106	253.2	0.5
2006	93	145	69.8	8.3	19.3	35	101.6	57.3	60.3	95.8	85.8	22.3	84	49.5	5.1	0	1.9	684.5	112	410.7	0.9
1982	138	158	156.1	0	21.3	49.4	68.1	40.4	23.2	145	31.2	108.5	10.1	0	0	10.3	0	637.8	97	382.7	0.8
1990	159	168	29.2	56.8	43.3	77.8	41	24.6	125.5	62	39.9	42.7	2.2	45	0	0	0	541.3	95	324.8	0.7
1994	165	178	45.3	105.9	99.4	75.2	30.7	72.5	19.6	49.4	4	1.3	6.3	100.6	33.1	1.5	10.2	643.3	125	386.0	0.8
1999	166	178	53	133.7	41.6	78.1	79	8	81.2	39.9	9.7	29.6	81.6	41.8	0	0	0	677.2	116	406.3	0.9
1996	166	178	20.1	148.1	80.7	75.6	79	8	89.9	39.9	11.3	29.2	81.6	41.8	0	0	0	705.2	116	423.1	0.9
1987	164	181	33.7	122.9	24.5	39.1	98.5	111.9	43.7	21.2	19.5	5.7	1.3	8.2	0	0	0	453.3	62	272.0	0.6
1995	133	189	15.8	176	144.4	184.8	54.2	34.7	28.8	35.1	29.7	102.3	0	0	0	0	0	805.1	95	483.1	1.0
1988	118	200	37	109.7	117.3	48.5	54.1	15	38	21.2	1.9	0	0	0	0	0	0	379.8	54	227.9	0.5
1986	185	203	103.2	114	75.8	31.1	74.3	26.9	30.9	1	13	0	0	0	0	0	4.5	449.8	61	269.9	0.6

Appendix 5: Impacts of water supplies in different growth stages of post-onset planted 120-day maize variety at Melkassa (1977 - 2008)

			ETc	9.4	9.4	15.6	19.8	27.5	36.9	42.7	41.8	40.7	44.8	36.4	30.8	27.2	11.9			0.6*TSW	
			GS	Initial	Seedling	Rapid vegetative growth				Tasseling/silking/grain forming					Maturation and harvest					ETc	383.5
									Period												
Year	DOS	GERM Date	Soil water at GERM	1 (20)	2	3	4	5	6	7	8	9	10	11	12	13	14	Total	DUR	ETa	WAR
1991	121	129	98.7	112.5	5.2	0	19.8	45.6	115.5	23	56	32	24	51	28	5.3	9.9	625.9	106	375.5	1.0
1977	121	132	160.7	78.2	10.3	71.8	71.9	33.2	28.3	46	24	43	21	12	51	28.9	48.4	727.4	120	436.4	1.1
1993	121	133	76	96.1	31.5	10.5	5.6	43.3	3	56	0	55	33	19	21	73.1	87	609.8	120	365.9	1.0
1979	127	136	32.1	83.2	72.3	1.2	65.1	68.4	34.9	59	67	4	29	33	42	20.6	5.8	617.4	106	370.4	1.0
2007	121	136	131.1	99.7	19.2	14.2	2.1	21.8	34.9	79	36	78	47	28	85	72.8	51.4	799.1	119	479.5	1.3
1997	124	137	50.8	14.4	0	53.2	12.3	76.6	97.2	78	5	34	104	100	24	17.9	21.5	689.6	101	413.8	1.1
1998	125	139	60.4	68.3	66.9	27.1	80.4	30.4	34.1	39	42	35	27	54	20	26	18.3	628.6	109	377.2	1.0
2001	125	139	59.6	68.3	66.9	27.1	80.4	30.4	34.1	39	42	35	27	54	17	28.7	18.3	627.8	109	376.7	1.0
1983	127	140	43.5	25.7	4	11.8	45.8	41.2	25.3	104	99	62	85	44	29	35	23.7	677.7	107	406.6	1.1
1980	132	141	40.6	0.3	0.7	1.8	20	66	91.9	53	32	12	73	12	36	28.4	57.1	524.2	118	314.5	0.8
1981	135	143	16.8	18.7	2.5	25.2	3.1	27.7	44.9	87	22	43	63	48	19	8.8	5.3	435.2	96	261.1	0.7
2006	121	145	69.8	27.6	35	56.6	45	33.9	63.1	21	95	28	72	9	68	60.7	4.5	689	112	413.4	1.1
2008	132	145	27.9	55.9	28.2	44.1	71.1	82.6	66.2	72	61	125	45	52	23	50.1	15	820.2	111	492.1	1.3
2005	121	146	92.1	22.7	52.4	12.6	16.5	30.5	22.4	102	16	56	71	21	29	64.9	12.7	621.3	112	372.8	1.0
1985	135	154	96.1	3.4	46	37	15	1	26.4	76	101	28	12	10	9	17.2	12.2	489.4	81	293.6	0.8
1982	138	158	156.1	16.1	13.1	45	64.6	40.2	14.8	20	67	93	6	108	6	4.5	0	653.3	97	392.0	1.0
1992	126	168	55.4	160.4	46.9	0	13.2	84.6	21.3	54	27	43	26	8	0	0	0	540.2	86	324.1	0.8
1990	159	168	29.2	98.1	79.8	2	39	24.6	82	66	40	35	5	43	0	2.2	45	590	95	354.0	0.9
2004	128	173	55.4	155.3	7.6	71.2	90.4	14.2	18.5	6	12	76	15	1	30	11.2	0	563.7	89	338.2	0.9
2003	121	173	55.1	150.6	62.3	37.8	7.3	29.9	68.7	46	75	11	15	54	3	0	0	616	98	369.6	1.0
1978	121	174	87.4	59.9	3	25.3	35.3	74	35	7	25	28	6	9	37	2.3	8	442.5	83	265.5	0.7
2000	122	174	64.1	150.6	62.3	37.8	7.3	29.9	68.7	46	75	11	15	54	3	0	0	625	98	375.0	1.0
1994	165	178	45.3	205.3	68.3	19.2	18.4	64.2	17	11	8	45	2	0	6	79.3	21 3	610.2	115	366.1	1.0
1996	166	178	20.1	219.3	83.6	7.9	72.6	2.8	20.8	74	10	31	10	26	84	15.5	27.5	705.2	116	423.1	1.1
1987	164	181	33.7	147.4	17.5	46.4	73.7	79.1	57	20	13	8	24	1	0	9.5	0	530.2	62	318.1	0.8

Appendix 6: Impacts of water supplies in different growth stages of post-onset planted 90-day maize variety at Melkassa

(1977 - 2008)

			ETc, mm	8.7	14.1	18.2	25.6	15	20	23	23	21	21	21	21	17	17	3.9			
DOS	GERM Date			Initila	Seedling	Rapid vegetative growth	Tasseling/silking/grain forming										ETc	269			
Year J	J		Soil water at GERM	Period 1 (20)	2	3	4	5	6	7	8	9	10	11	12	13	14	DUR	TSW	ETa	WAR
1977	174	176	51.9	179	17.2	8.2	35	10.3	28.8	0	31.5	24.6	29.7	32.6	33.5	3	0	80	482	289.2	1.1
1978	174	176	20.3	59.9	0	3	19.7	23.8	53.8	37.3	20.9	21.1	2.8	9.5	25.5	15.2	5.9	62	253	151.8	0.6
1984	177	179	29.7	123	47.6	0.5	10.4	39.8	15	4.7	4	16	6.4	25.4	33	3.8	8	80	355	213	0.8
1999	178	180	35.2	160	86.7	3.4	10.1	50.1	22.5	2.8	5.2	76.3	4.9	8.3	32.8	6.1	2.4	63	450	270	1.0
1997	178	180	41.9	245	21.2	3	9.3	72.8	79.9	52.5	42.9	5.1	17.9	17	5.1	1.9	11.4	58	568	340.8	1.3
2006	178	180	24.7	159	43	17.3	95.5	0.3	27.8	58	16.5	5.8	34.3	49.7	45.8	3.7	3.9	77	577	346.2	1.3
1996	179	181	51.7	158	87.3	3	7.4	60.6	12	2.8	14.2	76.9	4	10.3	30.8	5.9	4.2	62	472	283.2	1.1
1992	180	182	30.3	159	0	3.2	73.1	37.8	5	32.4	42	16.5	32.7	10.3	19	5.5	0	69	432	259.2	1.0
1991	179	182	16.3	230	14.4	18	24	24.3	35.3	18.7	5.3	4.7	6.8	6.2	6.5	25.5	7.8	53	381	228.6	0.8
1989	180	182	25	188	44.2	23.7	49	22.6	28.2	83.3	22.2	4.2	33.2	0	0	0	8.1	68	520	312	1.2
2005	180	182	26.5	80.9	31.8	70.9	2.4	34	35.2	63.9	23.4	6.6	27.4	60.3	14.9	2.4	19.7	76	468	280.8	1.0
1990	180	182	25.7	133	2	39	22	2.6	82	42	27	36.5	34.8	5.1	21.2	21.5	0	81	493	295.8	1.1
1979	181	183	58.7	163	66.6	0	3.7	29.3	16.5	27.3	31.2	12.8	9.9	10.1	8.3	16.5	26.3	66	416	249.6	0.9
1987	181	183	27.2	135	11.3	23.5	40.4	35.7	45.6	71.5	55.5	11.5	9.5	13.2	8	7.5	16.5	60	446	267.6	1.0

Appendix 6: Continued

			ETc, mm	8.7	14.1	18.2	25.6	15	20	23	23	21	21	21	21	17	17	3.9			
	DOS	GERM Date	Initila	Seedling	Rapid vegetative growth			Tasseling/silking/grain forming								ETc		269			
Year J	J		Soil water at GERM	Period 1 (20)	2	3	4	5	6	7	8	9	10	11	12	13	14	DUR	TSW	ETa	WAR
2004	178	183	20.5	124	63.5	13.9	84.2	0.9	27	6.7	4.3	11.8	43.5	33	15	0.1	0.6	75	433	259.8	1.0
2003	179	183	19.6	155	35.2	21	3.9	28.4	20.2	66.2	29.3	48.9	26.2	11.4	6.7	34.3	31.3	88	535	321	1.2
1998	182	184	16	178	22.8	33.2	25.7	26.7	16.2	50.5	4.2	25.9	2.8	18.3	1.2	0	1.4	55	370	222	0.8
2001	182	184	16	178	22.8	33.2	25.7	26.7	16.2	50.5	4.2	25.9	2.8	18.3	1.2	0	1.4	55	370	222	0.8
2000	180	184	19.6	155	35.2	21	3.9	28.4	20.2	66.2	29.3	48.9	26.2	11.4	6.7	34.3	31.3	88	535	321	1.2
1994	184	186	63.1	157	42.6	19.2	12.9	30.7	41.7	12.5	8.2	4.5	7.8	44.6	1	1.3	0	53	378	226.8	0.8
1983	185	187	36	228	48.6	42	61.7	42.7	32.3	32.9	29.2	13.2	3.5	25.6	7.6	0	0.2	60	554	332.4	1.2
2008	178	187	32.2	304	8.9	52.9	0.2	138	32	52	2.6	52.2	18.5	11	5.8	32	0	68	690	414	1.5
1986	185	188	39.4	135	34.1	45.2	47.9	27.9	10.9	20.2	33.3	41	11.4	15.5	28.9	2	0	76	486	291.6	1.1
1985	187	189	31.8	77	19.1	34	77.8	68.2	14.4	0	20.6	4	6	0	26.6	2.8	0.4	46	322	193.2	0.7
1993	190	192	18.3	82.2	52.5	19.5	11.8	13	50.1	30.7	33	66.2	12.1	10.2	0.6	0	0	61	365	219	0.8
1995	189	194	17.1	306	132	53.3	32	22.2	20	14.7	8	20.8	8.8	26.3	0	29.7	102	90	792	475.2	1.8
1980	192	196	36.1	206	8.3	71.7	8.6	22	17.5	11.7	17.6	57.1	19.5	16.2	0	9.6	0.1	68	476	285.6	1.1
2007	196	198	25.7	219	20	20.4	26.3	65.9	72.8	23.9	85.6	6.4	0	12.2	27.9	0	0.5	60	560	336	1.2
1982	196	198	31.3	130	1.8	25.5	120	25.8	5.4	80.7	27.8	5	5.1	0	0	0	0	57	442	265.2	1.0

Appendix 7: Impacts of water supplies in different growth stages of a post-onset planted 150-day maize variety at Adami Tulu (1977 - 2008)

		ETc	mm/dec	16	25	18	25	35	38	43	41	39	37	41	36	29	26			ETc	433
	DOS	GERM Date		Initila	Seedling	Rapid vegetative growth				Tasseling/silking/grain forming											
Year	J	J	Soil water at GERM	Period 1 (20)	2	3	4	5	6	7	8	9	10	11	12	13	14	TSW	DUR	ETa	WAR
1978	91	103	71.8	30	34	0	9.1	13	46	7.9	36	77	2.5	65	53	63	33	541	150	324.6	0.7
1990	91	104	80.5	22	32	0	44	29	15	9.1	25	101	56	28	71	57	18	586	146	351.6	0.8
2001	91	109	97.7	68	34	49	4.7	21	29	50	64	3	61	18	50	46	85	679	150	407.4	0.9
1997	97	110	70.3	61	11	1.6	3.1	73	7.4	56	34	106	36	14	32	16	11	459	109	275.4	0.6
2005	91	110	105.3	130	70	0	3.1	15	5.6	34	44	32	45	23	7.7	19	30	483	106	289.8	0.7
2006	91	110	182.4	92	0	6	4.5	17	48	37	39	111	35	26	30	20	19	617	124	370.2	0.9
1998	91	111	143.4	106	31	2.2	22	0	50	48	72	45	54	32	67	14	0	672	125	403.2	0.9
1989	97	112	73.5	9.9	1.4	0	40	59	41	82	30	11	34	33	48	42	28	530	146	318.0	0.7
1985	104	115	50.2	77	3.5	0	0	14	13	66	19	44	70	20	22	15	41	392	123	235.2	0.5
1993	106	117	100.6	84	43	34	19	15	44	62	52	25	19	29	17	13	3.3	542	123	325.2	0.8
2000	102	119	28.5	106	0	5.3	0	18	28	36	37	28	59	20	3.3	47	49	466	149	279.6	0.6
1995	101	120	36.8	69	0	16	30	19	31	28	0	36	17	63	30	17	0	373	130	223.8	0.5
1982	102	128	38.4	56	0	38	30	33	5.9	67	35	72	177	48	11	27	64	701	149	420.6	1.0
1996	118	129	24.2	73	9.1	54	20	6.1	48	41	26	15	76	62	33	7.3	0	482	124	289.2	0.7
1986	101	130	16.5	89	13	66	3.2	51	28	26	28	33	109	0	63	29	30	583	147	349.8	0.8
2008	125	134	43.6	40	39	33	21	146	69	89	33	48	78	2.5	57	16	0	697	122	418.2	1.0
1983	95	136	93.5	168	0	1.7	15	47	97	12	26	64	16	62	12	3.8	0	597	115	358.2	0.8
2007	103	136	74	147	32	39	131	45	3.5	75	39	48	36	39	70	37	0	814	139	488.4	1.1

Appendix 7: Continued

		ETc	mm/dec	16	25	18	25	35	38	43	41	39	37	41	36	29	26			ETc	433
	DOS	GERM Date		Initila	Seedling	Rapid vegetative growth				Tasseling/silking/grain forming											
Year	J	J	Soil water at GERM	Period 1 (20)	2	3	4	5	6	7	8	9	10	11	12	13	14	TSW	DUR	ETa	WAR
1981	105	137	110	11	8.4	4.8	14	22	4.7	0	155	47	86	74	71	0	0	607	130	364.2	0.8
2002	103	138	45.5	34	23	36	3.6	69	18	10	36	24	34	36	0	0	0	368	116	220.8	0.5
1987	91	139	109	193	0	0	1.7	43	28	0.8	76	9.2	7.8	11	16	9.9	0	458	91	274.8	0.6
1984	127	139	23.3	54	27	88	15	71	16	34	10	25	4.1	38	2.2	10	0	358	93	214.8	0.5
1977	110	143	20.7	42	12	17	6.2	15	24	45	25	39	31	61	15	22	17	337	118	202.2	0.5
1999	146	159	44.6	26	63	26	47	2.8	45	40	32	29	29	67	19	91	0	563	134	337.8	0.8
1994	154	165	33	116	35	6.5	44	125	19	19	29	80	0	0	0	0	2.5	506	99	303.6	0.7
1992	159	173	33.6	95	71	54	33	76	48	0	7	0	59	0	0	0	0	410	69	246.0	0.6
2004	101	175	100.6	48	4	44	36	18	3	18	83	0.4	20	0	0	0	0	355	90	213.0	0.5
2003	136	180	24.5	129	0	26	35	111	11	2.8	3.6	2.5	6.1	8.6	0	0	0	319	55	191.4	0.4
1991	98	183	52.6	85	54	73	29	63	35	1.4	12	0	0	0	0	0	0	389	69	233.4	0.5

Appendix 8: Impacts of water supplies in different growth stages of a post-onset planted 120-day maize variety at Adami Tulu (1977 - 2008)

				ETc, mm/dec	1.6	17.1	15.2	17.5	25.3	32.4	36.5	41.2	38.2	38.4	36.4	25.8	12.1			ETc	337.7
	DOS	GERM Date		Initila	Seedling	Rapid vegetative growth				Tasseling/silking/grain forming					Maturation and harvest					0.6*TSW	
Year	D	J	Soil water at GERM	Period 1 (29)	2	3	4	5	6	7	8	9	10	11	12	13	14	DUR	TSW	ETa	WAR
1993	11	131	124.3	119	0	14.8	10.2	33.3	42.1	36.1	35.2	23.4	15.3	19.8	14.3	16.7	0.1	109	504.6	302.8	0.9
2001	12	132	111.5	84.5	4.6	14.6	35.9	28.3	37.1	28.8	1.5	57	10.1	28.8	30.9	40.3	26.1	108	540	324.0	1.0
1998	12	132	198.1	45.5	0	44.2	10	43.2	41.7	56.9	18	14.6	59.2	12.5	67.3	4.8	9.5	104	625.5	375.3	1.1
1990	12	132	89.3	72.5	0	14.8	3.5	22.5	24	81.2	47.1	20.3	19.6	50.4	28.2	49.6	17.6	118	540.6	324.4	1.0
1995	13	133	63.1	16	29.5	4	14.9	30.6	27.5	0.1	0	34.4	18.4	0.2	61	17.3	14.3	117	331.3	198.8	0.6
2008	13	134	43.6	78.5	5	28.1	20.5	106.2	39.5	69	89.1	9	23.5	47.5	62	16	2.5	110	640	384.0	1.1
1983	16	136	93.5	168.3	0	9.9	7	8.1	53.7	82.9	11.8	20.1	17.4	53.1	16.3	21.7	40	115	603.8	362.3	1.1
1981	17	137	110	10.7	12	5	9.7	0	24.6	2.2	0	97.2	62.3	42.2	31.6	66.5	61.8	116	535.8	321.5	1.0
1985	17	137	74.5	0	5.1	9.3	13.4	59.5	20.9	9	38.6	60.9	10.3	18.5	16.2	7.4	14.2	101	357.8	214.7	0.6
2000	17	138	83.5	5.3	14.3	13.5	9.6	38.2	31.7	11.8	6.5	73.8	6.7	18.7	2.7	2	45.3	85	363.6	218.2	0.6
1987	19	139	109	193.3	0	0	1.7	33.4	10	28.4	0.8	29.6	52.5	3.1	4	3.8	10.9	91	480.5	288.3	0.9
2005	19	139	198.7	30.3	15.1	33.5	0	16.3	27.6	32	44.5	5.2	17.4	3.4	14.9	8	30.1	77	477	286.2	0.8
1996	21	142	32.4	93.3	19.8	0.1	30.6	23.4	37.5	8.4	20.7	15.2	10	86	41.6	28.4	5	111	452.4	271.4	0.8
2007	27	147	136	124.7	92.8	65.3	17.5	3.5	32	42.5	39.3	39.8	20.8	23	14.2	80.6	14	116	746	447.6	1.3
1984	4	156	23.4	122.9	53.3	32.5	10.2	17.8	21.7	10.3	21.4	3.5	4.1	15.5	25.1	0	10.1	76	371.8	223.1	0.7
2002	8	159	46.9	39.1	21.3	47.2	18.1	10.2	0.3	48.8	6.1	32.6	23.9	18.3	0	0	0	95	312.8	187.7	0.6
1989	8	159	88.5	140.1	58.5	19.1	11.2	6.5	47	13.7	4.7	64	20.7	25.2	17.4	47.5	0.5	112	564.6	338.8	1.0
1999	8	159	44.6	82.9	22.5	47.8	9.5	2.8	22.3	22.7	26.8	32.4	13.6	28.5	19.6	26.4	50.1	120	452.5	271.5	0.8

Appendix 8: Continued

				ETc, mm/dec	1.6	17.1	15.2	17.5	25.3	32.4	36.5	41.2	38.2	38.4	36.4	25.8	12.1			ETc	337.7
	DOS	GERM Date		Intila	Seedling	Rapid vegetative growth				Tasseling/silking/grain forming					Maturation and harvest					0.6*TSW	
Year	D	J	Soil water at GERM	Period 1 (29)	2	3	4	5	6	7	8	9	10	11	12	13	14	DUR	TSW	ETa	WAR
1986	12	163	56.3	97	22	13.6	39.3	5.2	32.6	103.8	4.8	0	28.3	36.5	17.4	18.5	20.9	114	496.3	297.8	0.9
1994	14	165	33	146.7	5.2	29.1	19.9	102	23.4	19.3	13.6	30.7	2.8	80.1	0	0	0	99	505.8	303.5	0.9
1982	14	165	73	67.4	9	59.5	31.7	37.2	38.2	108.9	83.5	39	4.1	0	27.5	63.1	59.4	120	701.5	420.9	1.2
1997	14	165	107.4	101.8	34.4	105.8	0.7	35.4	12.3	13.3	21.7	14.2	10.3	2.2	8.6	0	0.8	72	468.9	281.3	0.8
1978	15	166	78.4	96.2	32.8	15.5	63.8	4	53.2	12	50.5	0	42.1	0	2.2	15.8	3.2	87	469.8	281.9	0.8
1992	21	173	33.6	120.7	62.4	63.7	6.7	59.9	38.6	25.8	0	0	7	0	5.6	53.8	0	69	477.8	286.7	0.8
2004	23	175	100.6	52	21	23	36.3	16.2	3	1.5	15.9	61.5	23.7	0.4	9.7	10.6	0	90	375.4	225.2	0.7
2006	27	178	220.6	197.1	31.7	15	10.5	35.5	10	14.5	18.8	8.5	0	14.5	0	0	0	56	576.7	346.0	1.0
2003	29	180	24.5	129.3	25.8	2.5	32.6	103.8	9.6	8.8	2.8	3.6	0	2.5	1.7	4.4	8.6	55	360.5	216.3	0.6
1991	18	199	59.3	158.1	54.7	23.1	4.9	29.9	1.4	11.5	0	0	0	0	0	0	0	53	342.9	205.7	0.6
1977	4	216	24.6	97	9	39.3	30.8	14.9	11.2	18.6	8.4	7.8	7.7	0	0	0	0	45	269.3	161.6	0.5

Appendix 9: Impacts of water supplies in different growth stage of a post-onset planted 90-day maize variety at Adami Tulu

(1977 - 2008)

			ETc	mm/dec			8.5	13.6	19	32.6	37.9	38.9	43.8	36.6	25.8	3.8				ETc	261
	DOS	GERM Date	Soil water at GERM	Initila	Seedling	Rapid vegetative growth				Tasseling/silking/grain forming					Maturation and harvest					0.6TSW	
Year	J	J	mm	Period 1 (25)	2	3	4	5	6	7	8	9	10	11	12	13	14	DUR	TSW	ETa	WAR
2007	171	174	169	176	3.5	3.7	70.8	0	39.3	29.3	18.5	12.8	0	23	14.2	80.6	14	89	654	327.0	1.5
1994	171	174	69.6	87.7	4.5	39.7	5.9	61	64.4	0	19.3	0	14.8	11.5	20.7	4.7	75.5	90	479	239.5	1.1
1982	171	174	69.3	39.2	65	2	13.5	21.3	34.9	37.4	87.8	88.7	18.5	36.4	1.6	2.5	0	75	514	257.0	1.2
2008	172	175	51.9	190	45.5	19.5	69.6	9	23.5	33.5	14	62	16	0	54.5	5	13	81	594	297.0	1.4
1998	171	175	211	101	68.4	0	0	54.1	19.7	6.3	17.7	55.8	4.8	9.5	0	0	4.6	61	534	267.0	1.2
1996	172	176	47.5	72.1	27.5	8.4	2.2	18.5	15.2	0	43.1	52.9	38.4	10.4	26.2	0	7.3	77	357	178.5	0.8
1992	174	177	33.6	103	62.4	37.2	26.5	6.7	16.8	44.4	37.3	24.8	1	0	0	7	0	65	393	196.5	0.9
2004	172	177	88	50	2	21	23	36.3	0	16.2	1.5	1.5	1.5	15.9	2.2	61.5	21.5	88	342	171.0	0.8
2006	171	178	221	158	39.3	11.7	35	0	10.5	15.5	23	7	14.5	5	18.9	3.4	0	56	510	255.0	1.2
1989	171	179	111	141	10	5.5	1.1	46.9	13.6	3.3	22.1	43.4	20.7	2	23.2	5	52.3	90	501	250.5	1.2
2005	171	181	218	72.5	3.4	44.5	0	5.2	17.4	0	7.7	10.6	8	4.6	35.9	2	41.3	90	472	236.0	1.1
1984	177	181	50.2	96	7.8	29	2.7	0	10.3	21.4	3.5	0	7.9	11.7	22.9	2.2	10.1	51	216	108.0	0.5
2001	171	182	118	95.5	53.1	4.1	8.6	5.5	33.2	22.5	40.3	5.9	20.2	49	17.3	0	0	77	473	236.5	1.1
1993	171	183	141	127	5.8	18.7	14.2	4.7	23.4	6	16.7	0.1	0	13.8	0	2.9	0	46	327	163.5	0.8
1986	171	184	65.7	71.1	37.6	0	9.6	25.5	104	4.8	0	0	28.3	34.8	9.1	10	9.4	74	379	189.5	0.9
2003	180	185	56.2	77.6	25.8	0	9.6	25.5	104	7.1	2.5	8.8	2.8	0	3.6	0	0	50	299	149.5	0.7
1997	171	186	135	155	7.4	28.7	6	19.6	0	21.7	3.2	11	9.2	2.1	1.2	8.6	0	51	370	185.0	0.9
1990	171	187	95.1	158	14.3	2.6	31.8	54.6	1.7	49.7	7.4	17.6	1.9	120	22.2	34.3	0	81	603	301.5	1.4

Appendix 9: Continued

			ETc	mm/dec			8.5	13.6	19	32.6	37.9	38.9	43.8	36.6	25.8	3.8				ETc	261
	DOS	GERM Date	Soil water at GERM	Initila	Seedling	Rapid vegetative growth				Tasseling/silking/grain forming					Maturation and harvest					0.6TSW	
Year	J	J	mm	Period 1 (25)	2	3	4	5	6	7	8	9	10	11	12	13	14	DUR	TSW	ETa	WAR
1999	182	188	65.4	82.6	0	22.3	22.7	0	40.4	17.6	14.8	0	28.5	19.6	9.6	16.8	38.4	86	374	187.0	0.9
1991	183	188	57.3	114	39.3	34	13.9	15.3	53.7	8.8	4.9	29.9	0	1.4	11.5	0	0	50	327	163.5	0.8
1995	171	190	67.1	51.2	12.2	17	0.2	41.6	21.4	0.7	28.9	12.8	3.8	0	0	0	0	49	209	104.5	0.5
1985	171	190	93.7	85	45.8	24.1	1.3	18.5	16.2	5.5	1.9	13.2	5.7	35.5	0	0	1.1	54	288	144.0	0.7
2000	172	190	82.6	65	26.4	53.4	5.2	17.5	2.6	1.3	2	6.5	40.9	34	31.2	2.9	0	80	369	184.5	0.8
1978	171	193	92.1	141	4	52.4	0.9	12	50.5	0	33.1	9	0	0	18	0	3.2	60	386	193.0	0.9
1987	171	195	216	39.2	36.2	45.3	3.5	0.5	3.7	3.8	0.5	10.4	13.9	2	0	9.9	0	35	336	168.0	0.8
1983	171	195	222	125	9.5	12.6	53.1	5.7	10.6	21.7	40	0	12.1	3.8	0	0	0	56	494	247.0	1.1
1988	191	195	34.1	79	30.1	18.8	15.9	16.3	18.7	0	31.8	7.8	34.4	24.1	1.4	1.3	0	71	311	155.5	0.7
1981	171	197	110	102	57.3	19.1	28.1	28.6	57.2	66.3	7.8	40.3	30.8	0	0	0	0	70	547	273.5	1.3
1979	193	197	60.9	67.9	22.6	15.6	29	0	27	0	0	10.5	0	11.4	1.3	0	0	47	223	111.5	0.5
2002	172	198	63.3	28.6	35.4	17.4	6.9	27.8	6.3	17.6	18.3	0	0	0	0	0	0	56	222	111.0	0.5

Appendix 10: Continued

	Date of onset	Germ date		1	2	3	4	5	6	7	8	9	10	11	12	13	14	
Year	Julian	Julian	Soil water at GERM	Period 1	30	40	50	60	70	80	90	100	110	120	130	140	150	TSW
1981	128	142	17.7	17.7	36.4	46.1	67.2	94.9	181	258	294	403	430	436	445	493	513	513
2006	93	145	69.8	78.1	97.4	132	234	291	352	447	533	556	640	689	694	694	696	696
1982	138	158	156	156	177	227	295	335	359	504	535	643	653	653	653	664	664	664
1990	159	168	29.2	86	129	207	248	273	398	460	500	543	545	590	590	590	590	590
1994	165	178	45.3	151	251	326	357	429	449	498	502	503	510	610	643	645	655	655
1999	166	178	53	187	228	306	385	393	475	515	524	554	635	677	677	677	677	677
1996	166	178	20.1	168	249	325	404	412	501	541	553	582	663	705	705	705	705	705
1987	164	181	33.7	157	181	220	319	431	474	496	515	521	522	530	530	530	530	530
1995	133	189	15.8	192	336	521	575	610	639	674	704	806	806	806	806	806	806	806
1988	118	200	37	147	264	313	367	382	420	441	443	443	443	443	443	443	443	443
1986	185	203	103	217	293	324	398	425	456	457	470	470	470	470	470	470	475	475

Appendix 10: Cumulative early season rainfall (mm) used in developing prediction models for thinning time and mid-season rainfall at Melkassa (1977 - 2008)

	Date of onset	Germ date		1	2	3	4	5	6	7	8	9	10	11	12	13	14	
Year	Julian	Julian	Soil water at GERM	Period 1	30	40	50	60	70	80	90	100	110	120	130	140	150	TSW
1993	91	99	69.3	125	140	163	197	249	281	291	317	378	399	454	494	527	603	603
2003	91	99	54.1	125	125	129	129	133	135	177	207	269	359	400	432	519	597	597
2000	92	100	63.1	134	134	138	138	142	144	186	216	278	368	409	441	528	606	606
1989	91	100	45.5	53.1	53.1	66.3	66.3	66.3	76.9	125	196	240	329	420	475	577	624	624
1980	92	103	47	83.5	83.5	84.7	84.7	85	85	87.5	123	201	318	359	435	468	511	511
1978	91	104	77.1	93.4	94.7	97	97	99.6	139	150	196	199	214	263	357	379	404	404
1977	91	104	135	206	222	238	243	310	382	462	507	561	619	649	676	740	789	789
1992	99	107	51	102	102	105	113	113	149	191	303	350	353	464	502	560	603	603
1985	96	108	37	49	74.6	177	186	189	189	225	272	288	314	430	518	539	548	548
2004	92	109	51.1	55.6	55.6	55.7	55.8	63.1	101	141	236	246	343	412	443	458	535	535
2007	91	109	130	130	160	221	245	260	293	308	352	434	544	598	639	776	887	887
2008	100	111	26.3	71.7	98.6	134	144	155	183	235	381	518	540	707	803	826	880	880
1991	107	117	29.6	169	206	238	243	243	308	446	502	535	583	637	647	660	692	692
2002	102	123	31.4	47.6	47.6	59.7	61.9	67.8	85.3	99.3	143	209	256	296	307	337	337	337
2001	119	134	62.4	111	145	212	240	324	387	441	500	543	598	627	646	647	647	647
1998	119	134	63.2	112	146	213	241	324	388	442	501	544	599	627	647	648	648	648
1979	125	136	32.1	85	142	188	254	339	416	483	503	549	591	617	649	675	675	675
1997	119	136	51.8	51.8	66.2	69.6	130	260	365	389	522	627	651	686	693	741	760	760
2005	109	137	89.1	119	129	151	202	219	270	373	409	509	539	626	644	663	667	667
1984	101	140	31.9	46.7	66	113	202	208	282	293	348	356	379	438	449	459	459	459
1983	125	140	43.5	47.3	69.2	73.4	131	178	300	439	504	594	647	678	691	691	691	691

Appendix 11: Cumulative early season rainfall (mm) used for developing prediction models for mid- to late-season rainfall at Adami Tulu during (1977 - 2008)

Year	Date of onset, J	GERM Date	Soil water at GERM	Period I	30	40	50	60	70	80	90	100	110	120	130	140	150	TSW
1993	91	99	69.3	125.2	139.7	162.5	196.5	249.3	280.8	291.3	316.8	378.2	399.2	453.9	494.4	526.9	603	603
2003	91	99	54.1	124.9	124.9	128.9	128.9	133.1	135.4	176.8	207.1	269.3	358.7	400.1	432.2	519	596.8	596.8
2000	92	100	63.1	133.9	133.9	137.9	137.9	142.1	144.4	185.8	216.1	278.3	367.7	409.1	441.2	528	605.8	605.8
1989	91	100	45.5	53.1	53.1	66.3	66.3	66.3	76.9	125.4	196.3	239.6	329.1	419.8	475	576.8	623.8	623.8
1980	92	103	47	83.5	83.5	84.7	84.7	85	85	87.5	122.5	200.9	318.4	359	434.7	468.2	511.2	511.2
1978	91	104	77.1	93.4	94.7	97	97	99.6	139.4	150.2	195.8	199.3	214.3	262.9	357.4	378.9	403.9	403.9
1977	91	104	134.8	206	221.8	238.4	242.9	310.3	382.1	461.6	507.4	561.1	618.6	649.1	676.4	740.1	788.5	788.5
1992	99	107	51	101.9	101.9	105.3	112.5	112.5	148.7	191.2	303.1	350	353.2	464.1	501.5	560	603	603
1985	96	108	37	49	74.6	176.6	185.6	188.8	188.8	225.2	271.8	287.8	314.2	429.5	518.3	539.1	548.3	548.3
2004	92	109	51.1	55.6	55.6	55.7	55.8	63.1	101.2	141.4	235.6	246	343	412	443	458.4	534.8	534.8
2007	91	109	129.9	130	159.8	221.2	245.3	260.2	292.8	307.5	351.6	434.4	543.9	598.3	638.6	776.3	887.4	887.4
2008	100	111	26.3	71.7	98.6	133.9	143.9	154.6	182.8	235	380.6	518.4	539.9	707.2	802.7	825.9	879.5	879.5
1991	107	117	29.6	168.8	206.4	237.6	242.8	242.8	308.2	446.2	502.4	534.8	583.1	637.1	647.1	660.1	692.1	692.1
2002	102	123	31.4	47.6	47.6	59.7	61.9	67.8	85.3	99.3	142.5	208.6	256.1	296.2	306.7	336.8	336.8	336.8
2001	119	134	62.4	111.4	144.9	211.8	240.1	323.5	387.2	441.3	500.2	543.1	597.8	626.5	646	647.4	647.4	647.4
1998	119	134	63.2	112.2	145.7	212.6	240.9	324.3	388	442.1	501	543.9	598.6	627.3	646.8	648.2	648.2	648.2
1979	125	136	32.1	85	141.8	187.6	253.9	339.2	416.4	483	502.5	549.2	591	617.4	648.6	674.9	674.9	674.9
1997	119	136	51.8	51.8	66.2	69.6	129.7	259.8	364.5	388.7	522.3	627	651.2	686.1	693.1	740.7	760.2	760.2
2005	109	137	89.1	119.1	128.7	151.3	201.8	218.5	270.3	373	409.4	508.5	538.5	626.2	643.5	663.2	667.1	667.1
1984	101	140	31.9	46.7	66	112.6	201.9	207.6	281.8	292.7	347.5	356.2	378.6	438	448.8	458.6	458.6	458.6
1983	125	140	43.5	47.3	69.2	73.4	130.8	178	300.4	438.6	503.7	593.6	646.5	677.7	690.7	691.3	691.3	691.3

Appendix 11: Continued

Year	Date of onset, J	GERM Date	Soil water at GERM	Period I	30	40	50	60	70	80	90	100	110	120	130	140	150	TSW
1981	128	142	17.7	17.7	36.4	46.1	67.2	94.9	181.3	258.1	294.4	402.8	430.4	436.1	445	492.7	512.8	512.8
2006	93	145	69.8	78.1	97.4	132.4	234	291.3	351.6	447.4	533.2	555.5	639.5	689	694.1	694.1	696	696
1982	138	158	156.1	156.1	177.4	226.8	294.9	335.3	358.5	503.5	534.7	643.2	653.3	653.3	653.3	663.6	663.6	663.6
1990	159	168	29.2	86	129.3	207.1	248.1	272.7	398.2	460.2	500.1	542.8	545	590	590	590	590	590
1994	165	178	45.3	151.2	250.6	325.8	356.5	429	448.6	498	502	503.3	509.6	610.2	643.3	644.8	655	655
1999	166	178	53	186.7	228.3	306.4	385.4	393.4	474.6	514.5	524.2	553.8	635.4	677.2	677.2	677.2	677.2	677.2
1996	166	178	20.1	168.2	248.9	324.5	403.5	411.5	501.4	541.3	552.6	581.8	663.4	705.2	705.2	705.2	705.2	705.2
1987	164	181	33.7	156.6	181	220.2	318.7	430.6	474.3	495.5	515	520.7	522	530.2	530.2	530.2	530.2	530.2
1995	133	189	15.8	191.9	336.3	521.1	575.3	610	638.8	673.8	703.6	805.9	805.9	805.9	805.9	805.9	805.9	805.9
1988	118	200	37	146.7	264	312.5	366.6	381.6	419.6	440.8	442.7	442.7	442.7	442.7	442.7	442.7	442.7	442.7
1986	185	203	103.2	217.2	293	324.1	398.4	425.3	456.2	457.2	470.2	470.2	470.2	470.2	470.2	470.2	474.7	474.7

Appendix 12: ANOVA Table for grain yield of maize from three production strategies tested at four sites in the vicinity of Adami Tulu during 2010 crop season

Source	**DF**	**SS**	**MS**	**F-value**	**Probability**
Strategy	2	1461	731	117	0.0000
Site	3	130	43	7	0.0223
Error	6	38	6		
Non-additivity	1	24	24		
Residual	5	13	3		
Total	11	1629			

GM =20.13 GS = 336 N = 12 C.V = 9%

Appendix 13: ANOVA Table for grain yield of maize from three production strategies tested at 14 sites at Dibibissa during 2010 crop season

Source	DF	SS	MS	F-value	Probability
Strategy	2	9951	4975	451	0.000
Site	13	1609	124	11	0.000
Error	26	287	11	-	
Non-additivity	1	114	114	16.44	
Residual	25	173	7	-	
Total	26				

GM =40 GS = 1700 N = 42 C.V = 8.2%

Appendix 14: ANOVA Table for grain yield of maize three production strategies tested at 17 sites for Dibibissa during 2011 crop season

Source	DF	SS	MS	F-value	Probability
Strategy	2	12815	6407	396	0.000
Site	16	1416	88	5	0.000
Error	32	518	16	0.8	
Non-additivity	1	12.4	12		
Residual	31	506	16		
Total	50	14749	-		

GM =42 GS = 2117 N = 51 C.V = 9.7%

Appendix 15: ANOVA Table for grain yield of maize from three production strategies tested at nine sites at Marmarssa in 2010 crop season

Source	DF	SS	MS	F-value	Probability
Strategy	2	6042	3021	49	0.000
Site	8	1811	226	4	0.013
Error	16	989	62	-	
Non-additivity	1	607	607	24	
Residual	5	382	25		
Total	26	8841	-		
GM =30	GS = 803		N = 27	C.V = 26%	

Appendix 16: ANOVA Table for grain yield of maize from three production strategies tested at 11 sites Marmarssa during 2011 crop season

Source	DF	SS	MS	F-value	Probability
Strategy	2	6963	3482	82	0.000
Site	10	2100	210	5	0.0011
Error	20	845	42	-	
Non-additivity	1	0.16	0.155	0.00	
Residual	19	845	44		
Total	32	9909	-		
GM =33	GS = 1073		N = 33	C.V = 20%	