USING SEASONAL CLIMATE OUTLOOK TO ADVISE ON SORGHUM PRODUCTION IN THE CENTRAL RIFT VALLEY OF ETHIOPIA

by

Girma Mamo Diga

Thesis submitted in accordance with the requirements for the degree of

Doctor of Philosophy in Agrometeorology

in the Faculty of Natural and Agricultural Sciences,
Department of Soil, Crop and Climate Sciences,
University of the Free State,
Bloemfontein, South Africa

Supervisor: Professor Sue Walker

December 2005

Contents

Abstract

USING SEASONAL CLIMATE OUTLOOK

TO ADVISE ON SORGHUM PRODUCTION

IN THE CENTRAL RIFT VALLEY OF ETHIOPIA

by

Girma Mamo Diga

PhD in Agrometeorology at the University of the Free State

December 2005

Seasonal rainfall is an important source of water for rainfed farming in the semi-arid regions of the world, where rainfall is marginal and variable. However, as rains are unpredictable in terms of onset, amount and distribution, there is a need to understand the variability and other basic rainfall features in order to use the information in agricultural decision making. More specifically, combining the seasonal rainfall prediction with crop water requirement and soil water information is the core component to successful agriculture. The ultimate objective of this study was to characterize and obtain a better understanding of the most important rainfall features that form the basis for classifying the areas into homogenous rainfall zones and then to develop a seasonal rainfall prediction model for the Central Rift Valley (CRV) of Ethiopia.

The source data for the analyses was primarily obtained from the National Meteorological Services Agency (NMSA) and partly from Melkassa Agricultural Research Centre (MARC) and the web site of the International Research Institute for Climate and Society (IRI). Rainfall variability and time series analyses were done using INSTAT 2.51 and coded time method, respectively. Rainfall onset and March-April-May (MAM) rainfall totals are the two most variable features both at Miesso and Abomssa. For both stations, rainfall end date displays the least variability.

Rainfall onset date at Miesso ranges from the lower quartile (25 percentile) of DOY 61 to the upper quartile (75 percentile) of DOY 179 with a 42% coefficient of variation (cv). At Miesso, the main rainy season terminates during the last days of September

(DOY 272 - 274) once in four years and terminates before DOY 293 in three out of four years. At Abomssa, the c.v for the lower quartile (DOY 61) to the upper quartile (DOY 134) was found to be 40.5%. At both locations, planting earlier than 15 March (DOY 75) only proves successful once in every four years. Further, at Miesso this upper quartile statistic can extend up to the DOY 179, whereas at Abomssa planting earlier than 15 April (DOY 134) is possible in three out of four years (75 percentile). At Abomssa, rainfall terminates by DOY 286 and the end of October (DOY 305) for the 25 and 75 percentile points respectively. From the time series analyses, there was no conclusive evidence for the existence of a trend for both Miesso and Abomssa, information which is useful for long-term research and development planning, as well as seasonal rainfall prediction for the study area.

The classification study for the spatial rainfall pattern resulted in four homogenous rainfall zones that form distinct development and research units, using the FORTRAN-90 based NAVORS2 program. The south facing Alem Tena-Langano zone has a better rainfall pattern than drier zones and thus formed zone 1. The southern, southwestern and southeastern area has formed the wet zone (zone 2), the northwestern to northeastern facing part (Debre-Zeit-Nazerth-Dera) that receives a higher rainfall amount than zone 1 has formed zone 3 and finally, the drier northeastern part constituted zone 4. Twenty seven seasonal rainfall prediction models with varied performance skills that can be used for the operational farming were developed for the March-September monthly rainfall using the Climate Predictability Tool (CPT v.4.01) from IRI. It was understood that with increased observing networks and data availability, useful operational climate prediction could be achieved for a smaller spatial unit and with a short lead-time.

The tempo-spatial water requirement satisfaction pattern analyses were conducted using AGROMETSHELL v.1.0 of the FAO. Fourteen concurrent sorghum-growing seasons that give a general picture of crop water requirement satisfaction were mapped. The southern, southwestern and southeastern parts (zone 2) of the CRV constitute the most favourable location for growing a range of sorghum maturity groups. The northwestern and central (zone 3) parts constitute the next most suitable zone. The wide northeastern drylands (zone 4) of the study area, except the pocket area of Miesso-Assebot plain, does not warrant economic farming of sorghum under rainfed conditions.

From the growth stage-based Water Requirement Satisfaction Index (WRSI) analyses, mid-season / flowering stage of the sorghum cultivars was found to be three times more sensitive to changes in sorghum yields for both cultivars and experimental sites as compared to the WRSI from the rest of growth stages. The results from the water production function analyses (WPF) also indicated the potential of WRSI for prediction of the long-term sorghum yields.

The cumulative density function (CDF) and stochastic dominance analyses for the 120-day grain sorghum cultivar grown at Miesso show the June planting to be the most efficient set by first degree stochastic dominance (FSD), while May was found efficient for Melkassa. The CDF for Arsi Negele shows April planting date to be the best set. Therefore, these planting dates are to be preferred by farmers seeking 'more' yield at the respective locations, regardless of their attitude towards risk.

The sensitivity analyses conducted using different levels of the seasonal rainfall related input variable combinations (sorghum planting date, maturity date, number of rainy days and WRSI) for Miesso, Melkassa and Arsi Negele provide useful information. By keeping input variables other than WRSI at the most preferred level (i.e. early planting date, extended maturity date, and greater number of rainy days) and only changing WRSI from 100% to 75% resulted in a 49.7% yield reduction in case of Miesso, 40.8% in case of Melkassa and 24.3% in case of Arsi Negele. Further, when WRSI was reduced down to 50%, there was a total crop failure in the case of Miesso and Melkassa, while the reduction was 48.6% for the Arsi Negele case. Similar results were found when WRSI was varied across other input level combinations.

Visual Basic v.6.0 was used to write the algorithm for the decision support tool (DST) relating sorghum planting dates in CRV, to which the name ABBABOKA 1.0 was given. By using the rainfall prediction information from three different sources (the new prediction model developed in chapter 3, NMSA and ICPAC), ABBABOKA suggests the best possible planting alternatives for a given homogenous rainfall zone and planting season. When decision making under this predictive information alone is not sufficient, soil water parameters need to be consulted for more reliable decision making. This simple and briefly constructed ABBABOKA is expected to provide a suite of guidelines to the users. Certainly, this constitutes a significant departure from the fixed 'best bet' recommendations I learned from research systems in the past.

It is recommended that the time-space classification of agricultural areas into homogeneous zones needs to be extended to the rest of the country together with the tailored rainfall prediction information. Research needs to be geared towards crop water requirements, climate risks and simulation modelling aspects. A network of weather stations and soil database needs to be developed in order to promote the soil-crop-climate research in Ethiopian agriculture. More importantly, the use of decision support tools and the well-established models (like APSIM) need to be included in agricultural research and development efforts.

Uittreksel

DIE GEBRUIK VAN SEISOENALE KLIMAATSVOORUITSIG

BY RAADGEWING VIR SORGUMPRODUKSIE

IN DIE SENTRALE SKEURVALLEI IN ETHIOPIë

deur

Girma Mamo Diga

PhD in Landbouweerkunde by die Universiteit van die Vrystaat

Desember 2005

Seisoenale reënval is 'n belangrike bron van water vir droëlandboerdery in die semi-ariede gebiede van die wêreld waar reënval beide marginaal en veranderlik is. Alhoewel reën minder voorspelbaar is in terme van aanvangstyd, hoeveelheid en verspreiding, is daar nogtans 'n behoefte om die basiese eienskappe van die reënval, en spesifiek die veranderlikheid daarvan, te verstaan ten einde hierdie inligting in landboukundige besluitneming te kan gebruik. Die kombinering van die seisoenale reënvalvoorspelling met gewas-waterbehoefte en grondwaterinligting is 'n belangrike sleutel tot suksevolle landbou. Die uiteindelike doel van hierdie studie was om 'n beter begrip te verkry van die belangrikste reënval-eienskappe wat die basis sou vorm vir die klassifisering van die Sentrale Skeurvallei (SSV) van Ethiopië in homogene reënvalsones, en om dan 'n seisoenale reënvalvoorspellingsmodel vir hierdie gebied te ontwikkel.

Die brondata vir die analise is vanaf die Nasionale Meteorologiese Dienste Agentskap (NMSA) en gedeeltelik vanaf Melkassa Navorsingsentrum (MARC) en die Internasionale Navorsingsinstituut vir Klimaatsvoorspelling (IRI) verkry. Reënval veranderlikheid en tydreeksanalise is respektiewelik deur INSTAT 2.51 en die gekodeerde tydsmetode verkry.
Die begin- en einddatums van die reënval vir Maart-April-Mei (MAM) reënvaltotale is die twee mees veranderlike reënvalkenmerke van beide Miesso en Abomssa. Vir beide stasies toon die einddatum die minste veranderlikheid.

Die begindatum vir die reën by Miesso strek vanaf die onderste kwartiel (25 persentiel) van dag van die jaar (DVJ) 61 tot die boonste kwartiel (75 persentiel) van DVJ 179 met 'n variansiekoëffisiënt (vk) van 42%. By Miesso eindig die hoof reënseisoen gedurende die laaste dae van September (DVJ 272 - 274) een maal elke vier jaar en voor DVJ 293 in drie uit vier jaar. By Abomssa is gevind dat 'n vk van 40.5% die onderste kwartiel (DVJ 61) tot die boonste kwartiel (DVJ 134) beskryf. By albei plekke is gevind dat aanplanting voor 15 Maart (DVJ 75) in slegs een uit vier jaar sukses sal lewer. By Miesso kan hierdie boonste kwartiel statistiek tot by DVJ 179 verleng word, maar by Abomssa is aanplanting voor 15 April (DVJ 134) in drie uit elke vier jaar moontlik. By Abomssa staak die reën respektiewelik teen DVJ 286 en die einde van Oktober (DJV 305) vir die 25 en 75 persentiel punte. Die tydreeksontledings het geen konkrete bewyse gelewer vir die bestaan van enige neigings by òf Miesso òf Abomssa nie – inligting wat nuttig is vir langtermyn navorsing- en ontwikkelingsbeplanning, sowel as die seisoenale reënvalvoorspelling vir die studiegebied.

Die klassifikasie-studie vir die ruimtelike reënvalpatroon het gelei tot die totstandkoming van vier homogene reënvalsones met duidelike ontwikkelings- en navorsingseenhede. Die FORTRAN-90 gebaseerde program NAVORS2 is vir hierdie doel gebruik. So het die Alem Tena-Langano sone met 'n suidelike aansig en beter reënvalpatrone as die droër sones, sone 1 gevorm. Die suidelike, suidwestelike en suidoostelike streek vorm die nat sone (sone 2), terwyl die Debre-Zeit-Nazerth-Dera area met sy noordwestelike tot noordoostelike aansig en 'n hoër reënval as sone 1, sone 3 vorm. Die droër noordoostelike streek vorm sone 4. Sewe-en-twintig seisoenale reënvalvoorspellings-modelle met verskillende prestasievaardighede wat vir operasionele boerdery gebruik kan word, is ontwikkel vir die Maart-September maandelikse reënval met gebruik van die klimaat voorspelligshulpmiddel oftewel Climate Predictability Tool (CPT v.4.01) vanaf IRI. Dit het aan die lig gekom dat met verhoogde waarnemingsnetwerke en data beskikbaarheid dit moontlik is om bruikbare operasionele klimaatvoorspelling te behaal vir kleiner ruimtelike eenhede met 'n korter voorgeetyd.

Die tydelike-ruimtelike waterbehoefte vervullingspatroon-ontledings is met AGROMETSHELL v.1.0 van die FAO uitgevoer. Veertien opeenvolgende sorghum groeiseisoene wat 'n algemene prentjie van gewaswaterbehoefte vervullingskets, is

gekarteer. Die suidelike, suidwestelike en suidoostelike dele (sone 2) van die SSV het die mees gunstige ligging vir die verbouing van 'n reeks volwasse sorghumgroepe. Die noordwestelike en sentrale dele (sone 3) het die naasbeste klimaat. Die uitgestrekte droë lande van die noordooste van die studiegebied (sone 4) is, met die uitsondering van die Miesso-Assebot vlakte, nie gepas vir ekonomiese boerdery met sorghum onder droëlandtoestande nie.

Met die groeistadiumgebaseerde waterbehoefte vervullingsindeks (WBVI) ontledings is gevind dat die middel-seisoen/blomstadium van die sorgum kultivars drie keer meer sensitief is vir veranderings in sorghum opbrengs vir beide kultivars en eksperimentele gebiede vergeleke met die WBVI van die ander groeistadiums. Die uitslae van die waterproduksiefunksie (WPF) ontledings het ook gedui op die potensiaal van WBVI om langtermyn sorghum opbrengs te voorspel.

Die kumulatiewe digtheidsfunksie (KDF) en stogastiese dominansie-analises vir die 120-dag sorgum kultivar wat by Miesso verbou is, toon dat die Junie plantdatum die mees effektiewe stel is wat betref eerstegraad stogastiese dominansie (ESD), terwyl Mei die effektiefste vir Melkassa was. Die KDF vir Arsi Negele wys die April plantdatum as die beste stel aan. Dus word hierde plantdatums verkies deur boere wat 'hoër' opbrengste by die verskeie gebiede verlang, ongeag die houding teenoor risiko.

Die sensitiwiteitsanalises wat uitgevoer is deur gebruik te maak van verskillede vlakke van seisoenale reënval en inset veranderlike kombinases (sorgum plantdatum, datum waarop volwasse stadium bereik word, aantal reëndae en WBVI) vir Miesso, Melkassa en Arsi Negele, verskaf bruikbare inligting. Deur inset veranderlikes, met die uitsondering van WBVI, op die verkieslike vlak te hou (d.w.s. vroeë plantdatum, verlengde volwasse stadium datum en 'n groter aantal reëndae), en slegs WBVI te verander vanaf 100% tot 75%, het gelei tot 'n 49.7% opbrengsverlaging by Miesso, 40.8% by Melkassa en 24.3% by Arsi Negele. Verder is daar gevind dat 'n verlaging van WBVI tot 50% sou lei tot 'n totale gewasmislukking by Miesso en Melkassa, terwyl daar 'n afname van 48.6% in die opbrengs by Arsi Negele sal voorkom. Soortgelyke resultate is verkry waar WBVI toegelaat is om oor ander insetvlak-kombinasies te varieer.

Visual Basic v.6.0 is gebruik om die algoritme vir die besluitneming ondersteuningshulpmiddel (BOH) te skryf wat sorgum plantdatums in die SSV bereken. Dié program is ABBABOKA 1.0 genoem. Deur gebruik te maak van die reënvalvoorspellingsinligting vanaf drie verskillende bronne (die nuwe voorspellingsmodel ontwikkel in hoofstuk 3, NMSA en ICPAC) stel ABBABOKA die beste moontlike plantdatum-alternatiewe vir 'n gegewe homogene reënval sone en plantseisoen voor. Wanneer besluitneming met behulp van hierdie voorspellingsinligting alleen nie genoeg is nie, moet grondwater-eienskappe geraadpleeg word vir meer betroubare besluitneming. Dit word verwag dat die eenvoudige en kort gestruktueerde ABBABOKA 'n hele klompie riglyne aan verbruikers sal verskaf. Dit dui verseker op 'n noemenswaardige afwyking van die vaste "beste raai" aanbevelings wat deur navorsingstelsels tevore verskaf is.

Daar word aanbeveel dat die tydelik-ruimtelike klassifikasie van landboukundige gebiede tot homogene sones tot die res van die land uitgebrei moet word tesame met die aangemete reënvalvoorspellingsinligting. Daar is 'n behoefte vir navorsing wat gemik is op gewas-waterbehoeftes, klimaatrisikos en simulasie modelleringsaspekte. Die waarnemingsnetwerk en klimaat en gronddatabasisse behoort ontwikkel te word om grond-gewas-klimaatnavorsing in Ethiopië se landbou te bevorder. Wat van meer belang is, is dat die gebruik van besluitneming ondersteuningshulpmiddels asook gevestigde modelle (soos APSIM) by landboukundige navorsing en ontwikkelingsprojekte ingesluit behoort te word.

Acknowledgements

List of Figures

List of Tables

List of Abbreviations

APSIM	Agricultural Production System Simulator
BD	bulk density
c.v.	coefficient of variation
CDF	cumulative density function
Cl	clay content
CL	cyclic length (number of degree polynomial)
CPT	Climate Predictability Tool
CRV	Central Rift Valley of Ethiopia
CWR	crop water requirement
D-index	Wilmott agreement index
DUL	drained upper limit
DW	Durbin Watson
EARO	Ethiopian Agricultural Research Organization
ENSIP	Ethiopian National Sorghum Improvement Program
ENSO	El Niňo - Southern Oscillation
Eo	free water surface evaporation
ERF	estimated rainfall for the month preceding the target month
ETc	reference crop evapotranspiration
ETo	potential evapotranspiration
GCM	global circulation model
HS	hit score
HSS	hit skill score
ICPAC	Climate Prediction and Application Centre for Intergovernmental Authority for Development.
IRI	International Research Institute for Climate Prediction and Society
ITCZ	Inter-Tropical Convergence Zone
JJAS	June-July-August-September
Kc	crop coefficient
K-S	Kolmogorov-Smirnov
LL	lower limit of soil water content
LLJ	Low-level Jet
MAM	March-April-May
MAPE	mean absolute percentage error
MARC	Melkassa Agricultural Research Center
MSE	mean square error
NMSA	National Meteorological Services Agency, Ethiopia
OND	October-November-December
PAW	plant available soil water
PAWC	plant available soil water capacity
RMSE	Root mean square error
RMSEs	systematic root mean square error.
RMSEu	unsystematic root mean square error.
Si	silt content
Sa	sand content
SAT	Semi-Arid Tropics
SO	Southern Oscillation
SOI	Southern Oscillation Index
SST	Sea Surface Temperature
SSTA	Sea Surface Temperature Anomaly
SWC	measured soil water content
TEJ	Tropical-easterly jet
WRSI	crop Water Requirement Satisfaction Index
WPF	Water Production Function

Chapter 1

General Introduction

1.1 Background

The annual march of the earth around the sun provides a periodic solar forcing which acts as a strong pacemaker for the general circulation of the terrestrial climate. The resulting seasons are the complex non-linear response of the land-atmosphere-ocean interactions that represent the most important variability of the climate system on a global scale (Pezzulli *et al.,* 2003). Moreover, climate itself is a complex non-linear system having its own internal chaos and instabilities together with the dynamics that modulate the response to the solar forcing.

General circulation model (GCM), which is described as the quasi permanent ocean-atmosphere pattern, represents these giant phenomena, mainly through using the methods of classical physics applied to a continuous fluid on a rotating earth being heated more at the equator than at the poles (Jean *et al.*, 2004; Landman and Goddard, 2002). El Niño and La Niña events are essential components of the ocean-atmosphere interactions and therefore assume a particularly important position in seasonal rainfall prediction. Understanding of the influence of ENSO phases on climate variability and computation of the associated risks in crop production at a particular location and season is a developing aspect of the existing climate forecasting techniques.

The current interest in ocean-atmosphere interactions was preceded by approaches such as response farming (Stewart, 1980), which is based on the empirical relationship between the relative earliness of a rainy season and the length and the amount of rainfall received. Easterling (1999) claimed that the ability to forecast rainfall variability based on ocean-atmosphere interaction is one of the premier advancements in the atmospheric sciences during the 20th century. Currently, climate (mainly rainfall and temperatures) variability is predicted using sea surface temperature and pressure anomalies.

The target of this thesis is to summarize existing seasonal rainfall prediction knowledge and experiences in order to apply them to the farm level tactical decision making. A detailed account of the existing scientific understandings, seasonal rainfall prediction and the underpinning factors is discussed, together with the rainfall and risks associated with sorghum production in Central Rift Valley of Ethiopia.

1.2 Explanation of the terms El Niño, La Niña, SOI and Sea Surface Temperatures (SSTs)

More than 100 years ago, the name El Niño was originally coined by Peruvian fishermen to describe the unusually warm waters that would occasionally form along the coast of Peru and Ecuador (eastern Pacific region), peaking near Christmas (Philander, 1985 & 1990; Trenberth, 1991).

Under normal conditions the frictional effect of the trade winds causes warm surface waters to be pushed towards the western side of the Pacific Ocean, causing cold and nutrient rich waters from the trenches off South America (eastern Pacific) to be drawn up to the surface. In other words, as easterlies near the ocean surface travel from east to west across the Pacific, the warmest water is found in the western pacific (http://iri.columbia.edu/climate/ENSO/index.html).

However, during an El Niño episode, the trade winds weaken and can even reverse (van Loon and Shea, 1985, 1987), resulting in trade winds becoming warmer and covering the wide central and eastern tropical pacific. As a result, the warmer waters of the western Pacific begin to flow back towards the eastern Pacific. This creates a large pool of the anomalously warm water that effectively cuts off the upwelling and water temperature rises (by approximately 0.5 °C) on the eastern side.

The earliest association to be linked with the El Niño phenomena was the large scale atmospheric pressure differences between the eastern and western side of the Pacific, *i.e.* sea level pressure tends to be lower at the eastern Pacific (Tahiti-French Polynesia) and higher in the western Pacific (Darwin-Australia) (Walker and Bliss, 1932 & 1937; Bjerknes, 1969). This sea-saw (standing wave) in the atmospheric pressure between the eastern and western tropical Pacific is called the Southern Oscillation (SO). Sir Gilbert Walker (1923) was the one who made the landmark

studies on teleconnections and described the surface pressure 'sea- saw' in relation to rainfall and temperature fluctuations. Sir Gilbert Walker was also the first to coin the word 'Southern Oscillation' (Rasmusson and Carpenter, 1982). Subsequently, to stress the relationship between El Niño and SO, the term ENSO was coined (Bjerknes, 1969, Trenberth, 1991).

On the other hand, La Niña is the counterpart to El Niño and is characterized by cooler than normal temperature across much of the equatorial eastern and central Pacific. During La Niña, the easterly winds are strengthened, cooler than normal water and extend westward to the central Pacific (Trenberth, 1991, Van Loon & Shea, 1985). At the same time, the warmer than normal water in the western Pacific is accompanied by above normal rainfall in areas which normally remain dry during that particular season. In general terms, La Niña follows an El Niño event and vice versa. The time between successive El Niño and La Niña events is irregular, but they typically tend to recur every 3 to 7 years, lasting 12-18 months once developed.

Another measure of the ENSO phenomena (also used in this study) is the Sea Surface Temperature (SST) that more often is described in the form of its departure from the long-term average temperature (anomaly). Being important for monitoring and identifying El Niño and La Niña phenomena, several regions have been named in this context in the tropical Pacific Ocean. The most common ones are Niño 1.2, Niño 3, Niño 3.4 and Niño 4. For a wide spread global climate variability, Niño 3.4 is generally preferred, because the SSTs variability in this region has been shown to have the strongest relationship with the shifting direction of rainfall pattern and this also greatly modifies the location of the heating that drives the majority of the global atmospheric circulation. (http://iri.columbia.edu/climate/ENSO/index.html). Apart from the Pacific Ocean SSTs, the SSTs of the Indian and Atlantic Oceans also occupy a significant position in the simulation of the global climate models.

1.3 Application of ENSO information for food security and at farm level, for climate risk decision analyses

Although a one to one correspondence does not exist, El Niño phenomena are usually followed by the La Niña condition. Generally, the two phenomena result in the great disruption of the usual precipitation pattern resulting in excessively dry or wet conditions. Presently, several research groups are working to develop and

finetune statistical and numerical models to predict ENSO-related SSTs (Barnston, 1994; Landman and Goddard, 2002).

There are different levels of resolution at which ENSO information could be used. These include: food security, national or regional development planning, agronomic/farm level, crop/livestock mix, household economic or business decisions (Jean *et al.*, 2004). At the level of food security and related issues, ENSO information is now recognized as an important tool, particularly in the wake of extreme events (Mjelde *et al.,* 1998; Pfaff *et al.*, 1999; Broad and Aggrawala, 2000; Finan and Nilson, 2001). Dilley (2000) reported on the consequences of the El Niño years like 1991/1992, 1994/95 and 1997/98 in Southern Africa in which effective prediction prior to the arrival of El Niño years diverted the adverse consequences, through early warning information supplied to the relief agencies. Similarly, decision making at regional level could be guided by climate forecasts such as importing and distribution of inputs i.e. fertilizers, seeds, market capacity/crop price setting at planting or pre-harvesting, planning for storage and transportation needs (Bi *et al.*, 1998).

Agronomic decisions guided by rainfall forecasts may involve selection of a long or short season cultivar, adjusting planting density and fertilizer application levels and allocation of area to a given crop. Heavier soils could be preferable if forecast is for dry conditions, or more freely draining soils if forecast is for the wetter condition. In many regions of the world, ENSO based skilful predictive information generated at the lead time from 1 to 12 months provides useful strategic and tactical decision aid to the farmers as well (Hansen, 1998). For example, Hansen classified the ENSO phases as El Niño, Neutral, and La Niña series, which served as a categorical measure of ENSO activity in the management of six economically important crops (tobacco, tomato, peanut, cotton, corn and soybean) in the U.S. The result suggested that SST had a strong influence on yields of the six crops in Florida (r = 0.871) and a weaker influence in South Carolina (r = 0.822).

Studies have also demonstrated ENSO's impact on maize yields in Zimbabwe (Cane *et al.,* 1994; Phillips *et al.*, 1998), rice production in Indonesia (Rosamond *et al.*, 2001), sorghum yields in Australia (Nicholls, 1986), soybean and maize production

in southeastern Australia, field crops production in U.S (Legler *et al.*, 1999) and wheat in Australia (Potgieter *et al.*, 2003).

The use of the SOI phases has also been found to improve risk management and profitability in Australian wheat (Stone *et al.*, 1996; Hammer *et al.*, 1996) and peanuts in Australia (Meinke *et al.*, 1996; Stone and Aulciems, 1992). The tactical responses include selection of cultivar maturity group and N-fertilizer strategy based on seasonal rainfall prediction. In simulation studies Phillps *et al.* (1998) emphasized the relative importance of rainfall prediction of favourable seasons and managing for enhanced maize productivity as compared to forecasting adverse seasons in Zimbabwe. There is also a potential to anticipate the risk associated with some crop pests based on weather forecasting. Maelzer and Zalucki (2000) for instance reported a good correlation of Helicoverpa species infestation with SOI from up to 6 to 15 months in advance.

In crop/livestock systems, decisions may relate to planning for future stocking rates and management of a particular forage crop for grazing. In some instances grain harvest, intensity and timing of grazing on different areas, the need for supplemental feed and to guide purchase, sale or movement of animals based on the anticipated forage/feed availability (Jean et al., 2004) could be related to ENSO phenomena.
.
At the household resolution level, business decisions could include marketing or hedging based on climate forecast in the local area as well as in major global production areas for a particular crop. Forecast of unfavourable seasons might lead to the decision to diversify farm enterprises. In some cases, climate predictions might influence decisions about the need for off-farm income relative to the need for on-farm labour and food security (Jean *et al.,* 2004).

For application at farm level decision making, it is important to know how climate at a given location relates to the prediction product. Interpretation needs to be made relative to the local normal, rather than the regional or national normal climate (Letson *et al.*, 2001). A critical early step in the process is engaging the user community to determine their understanding of climate forecasting and to find out how they want to apply climate prediction to their operational system.

1.4 Linking rainfall prediction to soil water content information

Rainfall prediction provides information about the likely amount of crop water use, which is usually related to large impacts on yield. Due to the variation in amount and distribution of growing season's rainfall, there is a negative relationship between crop yield and soil water content. Since soil water depletion has a major influence on crop water use and is highly variable in many regions, particularly at planting time, opportunities to integrate measurement of soil water content at planting with use of climate prediction need to be investigated (Stewart and Steiner, 1990). Carberry *et al.*, (2002) have worked with Australian farmers who have had some successes in using seasonal rainfall prediction in farm-level decision making. Their system (FARMSCAPE) combined soil water monitoring and simulation with the climate prediction and involved farmers, advisors and researchers working closely together. Their experience indicated that seasonal climate prediction without the other tools provided little benefit.

1.5 Application of seasonal rainfall prediction knowledge to farming decisions

In the Ethiopian context, experiences from the previous droughts and the frequent rainfall anomalies suggest that the return period of drought is 3-5 years in the northern and 6-8 years over the whole country (Haile, 1988). Haile (1988) underlines the fact that the combined effect of El Niño and southern oscillation, along with SSTAs in the southern Atlantic and Indian oceans, are the major causes for the Ethiopian drought. Attia and Abulahoda (1992) reported that El Niño episodes are negatively teleconnected with the floods of the Blue Nile and Atbara River that originated in Ethiopia. Glantz *et al.* (1991) also reports the existence of strong association between droughts in Ethiopia and the atmospheric teleconnections.

In this study, seasonal rainfall prediction using the sea surface temperature anomaly (SSTAs) of the global oceans were conducted with a view to applying the existing seasonal rainfall prediction knowledge into farm level decision making in Central Rift Valley of Ethiopia (more details are given in chapter 3).

1.6 Types of seasonal prediction models

The likelihood of the occurrence El Niño conditions is monitored by measured SOI phases or modelled SSTAs. There are two general types of these models. The first type is a dynamical or numerical model, which consists of a series of mathematical expressions that represent the physical laws underpinning how the ocean-atmosphere system performs. To make a prediction, dynamical models are subjected to the current conditions in the ocean-atmosphere and then the GCM determines what the future conditions (Landman and Goddard, 2002) would be.

The second type of prediction model is the 'statistical' one, to which uses correlations between past conditions to make predictions of the future. The data are of the same kind that would be used as input for dynamical models, but extending back in time by as much as 30 to 50 years. Statistical models are 'trained' on the long history of these precursor events so that, given the current observations, the likelihood of various possible ENSO conditions could be predicted. In contrast to dynamical models, the mechanisms underpinning the ENSO changes remain unknown in statistical models, as the model simply predicts on the basis of a regression equation.

In both kinds of climate forecasting techniques, any of the three equi-probable events i.e. below normal (B / El Niño), near normal (N / neutral condition) or above normal (A / La Niña) rainfall anomalies could occur. Without any forecast clues, the probability that any of the 3 outcomes will occur is equal i.e. 33.3 : 33.3 : 33.3. This is referred to as tercile values or climatological values or simply climatology, which means that if situations could be "re-run" many times, each outcome would occur once out of 3 times. However, given the forecast clues, such as the presence of El Niño or La Niña event, the probabilities of the terciles would no longer be equal, so that the probability of one or (two) of them would be greater than 33.3% and the remaining one or two of them less than 33.3%.

The use of tericle probabilities provides both the direction and dimension of the forecast relative to 'climatology', as well as uncertainty of the forecast. For example, if a forecast states the precipitation probabilities of 20% below normal, 35% near normal and 45% above normal, then since the wet tercile is 'biased' to above normal

and the dry is below 33.3%, this forecast suggests that above normal precipitation is more likely as compared to the climatology. One can visualize, however, that uncertainty present in the forecast (i.e. even though it is in the direction of the above normal precipitation) the probability for the above normal is still less than 50%. And the probability of below normal is 20%, implying that, still in one time out of 5 cases, the below normal precipitation event could occur. In general terms, even though a forecast may show a tilt of the odds towards wetness or dryness relative to the climatology, because of the degree of uncertainty in the outlook, there is a possibility that the other categories in the forecast, which were not anticipated, could occur (http://iri.columbia.edu/climate/ENSO/index.html).

1.7 Description of the study region

1.7.1 Ethiopia

Ethiopia forms part of the Greater Horn of Africa (Fig 1.1). In terms of topography, the country has the largest proportion of elevated landmass in Africa, sometimes appropriately described as the "roof of East Africa" (Addis Ababa University, 2001). Accordingly, seasonal and spatial rainfall variability is so high over short distances and time steps. The basic features of the Ethiopian rainfall are summarized in Table 1.1 (Mamo, 2003).

Geomorphologically, the Horn of Africa has been strongly influenced by two major tectonic episodes in the earth's history: the Arabo-Ethiopian swelling in the Eocene to early Oligocene and the major rift faulting movements through the whole of Africa rift system from the Miocene to the Quaternary, resulting in much of the present day macro-relief (Geological Survey of Ethiopia, 1972; FAO, 1984). These movements include subsidence and/or relative uplifting and tilting of large blocks in reaction to the destabilizing effects of the processes, which led to the formation of the Great Rift System. The Ethiopian Rift is part of the Great Rift System that extends from Palestine-Jordan in the north to Malawi-Mozambique in the south, a distance of about 7200 kms, of which 5600 km is in Africa and 1700 km in the Ethio-Eritrea (United States Geological Survey (USGS), 2005).

On the land, the widest part of the Rift Valley is at the Afar Triangle (200-300 km),

the place where the three rift systems (The Red Sea, Gulf of Aden and the main Ethiopian Rift Valley) meet; also known as a triple junction. This northeast-southwest facing Great Rift System of Africa is an extensive graben, cluttered with
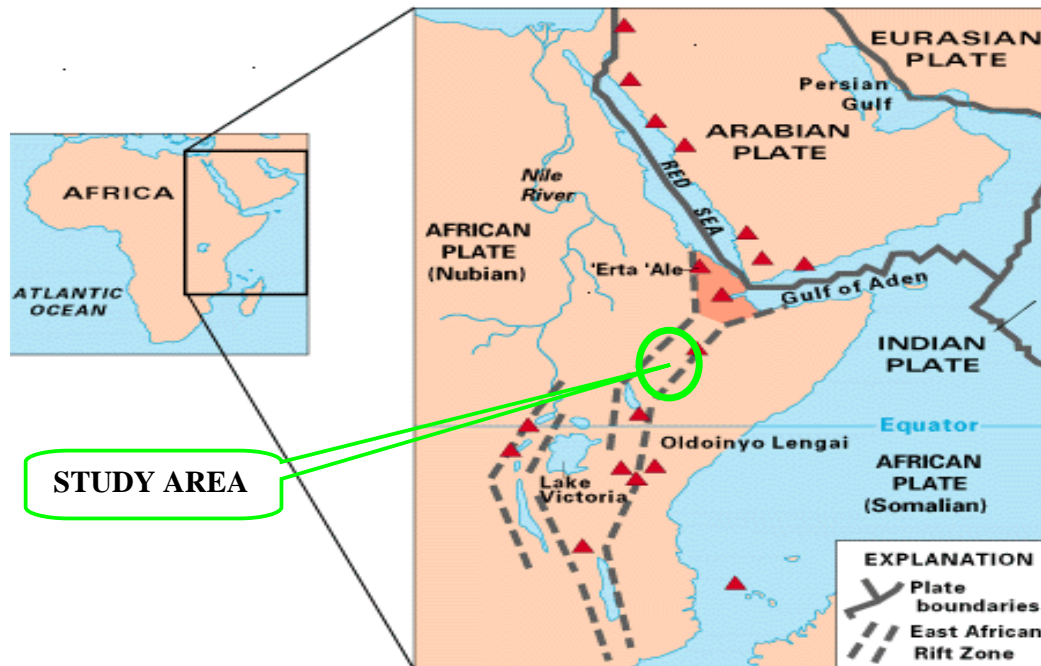
Figure 1.1 Overview of the Great Rift System and the study area (Source: United States Geological Survey (USGS) http://publs.usgs.gov/publications/text/East_Africa.html).

evidence of recent volcanism in the north and bounded by impressive stepped horsts of the plateaux on the west and south east margins, with major escarpments trending north and east respectively beyond the point of separation. The original landmass resulting from the enormous uplifted swell has thus been divided into two extensive plateau units by the Rift System *i.e.*the Ethiopian plateau to the west and the Somalia plateau to the east (FAO, 1984).

1.7.2 Central Rift Valley of Ethiopia

The Ethiopian Central Rift Valley constitutes the heart and corridor of the Ethiopian Rift that extends from the Afar Triangle in the north to the Chew Bahir in southern Ethiopia (FAO, 1984). It is part of the tectonically formed structural depression that has two major and parallel escarpments bounding it and splitting the Ethiopian highlands and lowlands into two (Addis Ababa University, 2001). The floor is dotted with mountains in many places, including Mount Ziquala, Fantale, Boset, Aletu (north of Lake Ziway) and Chebi (north of Lake Awasa). The prominent features

however are the numerous lake basins that are characterized by their alkalinity (Addis Ababa University, 2001).

Physiographyically, Central Rift Valley is characterized by almost level to gently sloping (reaching up to 1800 m.a.s.l) and a benched rift valley without sedimentary surface features. It has also volcanic lacustrine terraces formed in quaternary lacustrine siltstone, sand stone, inter-bedded pumice and stuffs, with fault topography bordering the major lakes plus parallels and low coastal ridges. It also has quaternary alluvial landforms, mostly bordering the main river valley or located at the foot of the higher plateaus, as alluvial colluvial cones (Markin *et al.,* 1975; FAO, 1989).

1.7.2.1 Soil types

The soil types in the study area are related to the parent materials and their degree of weathering. The main parent materials are basalt, ignimbrite (consolidated ash flow), lava, volcanic ash and pumice, riverine and lacustrine alluvium that form the gently undulating plain characteristic of the area. Weathering varies from deeply weathered basalt in sub-humid highland areas to the recent un-weathered alluvial deposits in the drier part (Markin *et al.,* 1975, FAO, 1989).

The soil texture is mainly sandy loam with pH ranging from slightly acidic to very alkaline. Nearly all the soils of the area are exploited and losses by erosion at a rate much exceeding soil formation from the undergoing geological processes is high (Markin *et al.,* 1975). Low organic matter, essential and trace nutrients, low water retention and infiltration capacity are the main characteristics of the soil. Toxic heavy metals are also prevalent in some places (Itanna, 2005). Adverse physical properties such as weak structure, high bulk density, surface crusting and hardpan formation are the obvious symptoms of the land degradation in the study area (Itanna, 2005).

1.7.2.2 Rainfall pattern

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 northeasterly winds and the moist winds of southwesterly origin typify the dry and wet season climate pattern respectively (Markin *et al.,* 1975;

Table 1.1 Rainfall characteristics, challenges and potential farming system strategies in Ethiopia (tropical climate)

	Seasonal rainfall/evapotranspiration features	Challenges/problems	Possible strategies (thematic research areas)
Cyclic	Total absence of rainfall/acute shortage/sub-marginal	<250 mm : Rain-fed farming impossible	Full irrigation, off season tillage and fallowing
	Low amount of rainfall	Cropping possible, rainfall insufficient to meet crop water requirement	Selection of drought tolerant crop/varieties, soil water conservation Reduced seed rate/lower planting density Reduced fertilizer rate Split application of fertilizers Supplemental irrigation, increase length of growing period
	Low predictability of effective onset date/erratic	Difficult to adopt fixed recommendations (date of sowing, cultivars, planting density, fertilizer rates and time of application)	Building prediction capacity Off season tillage to capture early rains Generation of crops and varieties of wider ecological plasticity
	Late onset date, early cessation (short duration)	High yielding long cycle crops and cultivars cannot be grown successfully	Generation of early and extra early crops and varieties In-field water harvesting to double soil water content and extend length of growing period Standardize fertilizer rates Adjust planting density
	Erratic distribution (high variability-intra-season and inter-annual)	Water stress at critical crop growth stages	Generate cultivars with maximum water use efficiency Soil water conservation Split application of fertilizer Water harvesting
	Intermittent drought Early stage (seedling establishment and vegetative stages) Mid season (flowering and fertilization stage)	Reduced stand establishment Slow growth rate Premature switchover from vegetative to reproductive stage Shortened grain filling period, shrivelled grain	Change crop or varieties according to the existing tradition and expected rainfall scenario Thinning down standing plants by certain percentage Soil water conservation, supplemental irrigation Harvesting for animal feed/fodder
	Terminal stress (grain filling/maturity stages)	Reduced yield or total crop failure	Further thinning by certain percentage, weed removal, mulching techniques, repeated inter-cultivation,("hoes have water") Protective irrigation

Table 1.1 continued

	High intensity index/torrential storms over a short period	Rainfall exceeds infiltration capacity of the soil (considerable kinetic energy) Accelerated surface run off Soil erosion and increased sedimentation load Nutrient depletion /leaching/shallow soil depth and low water holding capacity Breakage of soil aggregates (weak structure and compaction of surface soil and sealing)	Techniques to Increase opportunity time for concentration and infiltration Runoff water harvesting (inter row, inter plot, on farm pond)/dam Use sub-soilers/crust breakers Employ appropriate soil water conservation techniques (biological, physical, integrated)
	Evaporative demand exceeds rainfall amounts	Quick soil water depletion, stiff competition for scarce water among crop stands, wilting	Select drought tolerant crops and varieties (improved water use efficiency) Repeated intercultivation (soil mulching, residue and plastic mulches) Soil water conservation practices (biological, physical and integrated)
	Excess moisture/water logging	Nutrient leaching, high erosivity, diseases and pest prevalence (damped environment)	Fallowing, harvesting Growing crops on residual soil water Integrated surface and subsurface drainage (safe water ways) Devise appropriate diseases and pest control technologies
Non-cyclic (trend) -	Climate change	Irreversible shift and decline in rainfall start and end days, reduced rainfall totals, shortened crop growth periods	Adjustment of research strategies (long term planning) according to the rainfall trend, reformulation of objectives, natural resources rehabilitation projects (eg, integrated watershed management) in the short term plan

Adapted from Mamo (2003)

FAO, 1989).   During November to January, when northeasterly winds persist, long periods of dry winds are experienced, with little or no cloud and low relative humidity. Between March and May, the weather becomes unstable and convergence of moist southeasterly winds originating from Indian Ocean with the weakening northeasterly air stream causes rainfall to occur over most parts of this region.

The area receives its first rain during the March-April-May season. This is the time when the high pressure cell (anticyclone) over South west Asia weakens or is in the process of disintegration and when the effect of the north east trade winds is considerably reduced. With the further progress of the season, air mass from the Indian Ocean invades the study area, as well as the western and southwestern plus northeastern parts of the country (NMSA, 1996a & b).

On the other hand, the area receives rainfall during the June-July-August-September (JJAS) period, when the ITCZ migrates towards the northern Ethiopia on the Red Sea coast and Gulf of Aden side. During this season, both the Atlantic and Indian oceans contribute major rainfall to the region. The length of the rainy season varies from place to place, depending on the length and duration of the predominant winds (NMSA, 1996a & b).

Despite the variability in rainfall and the prevalence of the long established spiral of land degradation in the region, there is considerable scope for raising the level of farmers' returns through transfer of improved technologies (material and knowledge). The region consists of the most productive soils, such as the mid Meki-valley, which in combination with the micro irrigation and water harvesting techniques can form a base for an intensive cropping system. Moreover, many research and development institutions work in this region. These include Melkassa Agricultural Research Center (MARC), Debre Zeit Research Center, Adami Tulu Research Center, Awasa Research Center, Werer Research Center, Miesso and Arsi Negele sub-stations, Kulumsa Research Center, Wenji Sugar Estate, Metehara Sugar Estate, Upper Awash Agro Industries, Horticultural Crops Farm at Ziway, Adami Tulu Pest Control Plant, Abernosa Ranch as well as many private investors and processing plants.

1.8 Motivation

It is a fact that agriculture provides a strong backbone to the overall Ethiopian economic welfare, employing over 85% of the population and accounting for 40 % of the GDP (Woldemariam, 1989). While the country has about 3 million hectare of irrigable land plus 110 billion cubic meter of surface water, the cropping system is almost totally carried out under the rainfed condition.

Uses of low and traditional inputs, diversity of cultivated crops, poor yield and very limited use of improved soil water management or irrigation schemes are common features of this subsistence economy. A subsistence economy is one that provides sufficient food to last only from one harvest to the next. Therefore, a failure of one harvest means starvation for the ensuing year, shortage of seed for the next cropping season and loss of animal power to plough the fields (Abate, 1994).

Recurrent droughts like those of 1970s, 1980s and 1990s, whether natural or man made, both exacerbate the adversaries and lead to increase in food price, increased imports of food, rural-urban exodus, and relocation of people to resettlement centres. Social and political strife and famine form part of the problem as well.

Studies pertaining to seasonal rainfall prediction have been started in semi-arid subtropics, where there is a strong 'signal to noise' ratio and high coefficient of variation in the rainfall series. Accordingly, this has been successfully achieved at global and regional scales over the last two decades (Glantz, 1993; Dilley, 1997; Landman and Goddard, 2002). This has been possible, using global circulation models in which SSTs and SOI constitute the most important indices for seasonal climate outlook in combination with spatial and optimal mix of statistical analyses.

Today, rainfall predictive information is available to farmers in many developed countries, while similar services are only in the beginning stage in developing nations. In view of the recurring impacts of drought and famine, seasonal rainfall prediction assumes a key position to maximise economic gains for the commercial farmers and is a matter of survival for the poor farmers.

Moreover, since the balance between rainfall and evapotranspiration is a particularly useful indicator of the agricultural and hydrological potential of a given location,

proper understanding of the cropping system's water requirement, climate risk and decision analyses assume priority position. It is this basic issue that justifies the unified study of the seasonal climate outlook, sorghum water requirement satisfaction, climate risk and decision analyses. The target users include the Ethiopian rainfed farmers, researchers and extension workers in general and the Central Rift Valley farmers in particular.

Sorghum was used in this study with the aim of indicating the dimensions of crop yield variability in relation to climate variability in the study area. Sorghum is a C4 plant and efficient user of soil water and adapted to the unreliable rainfall pattern, as well as to a range of soil types. Moreover, the reasonable performance of the crop under higher temperature ranges (30-35ºC) makes it a suitable crop for such studies, as well.

The benefit from such an approach is expected to be high in the light of the exchange of improved material technologies (seeds) and decision aids (ideas) among the key actors, based on the seasonal rainfall prediction and soil water information.

1.9 General objectives of this study

To statistically characterize the seasonal rainfall variability in Central Rift Valley of Ethiopia;

To develop homogenous rainfall zones using March- September monthly rainfall indices;

To develop SSTs based seasonal rainfall predictive models for the Central Rift Valley of Ethiopia;

To determine crop water requirement satisfaction index and risks associated with crop water needs under different planting windows;

To develop a simple decision support tool to be used together with the seasonal and spatial rainfall predictive information in the study area.

1.10 Organization of the chapters

Overall, the study has addressed 12 specific objectives that are organized into the above 5 general objectives. The research chapters start from Chapter 2, which deals with a variability contained in the seasonal rainfall features (onset date, end date, duration, dry spell length and seasonal rainfall amounts) and very important for

operational farming. INSTAT [Interactive Statistical Processing Package (version 2.51, Stern and Coe, 2002) was used for these calculations. Chapter 3 deals with dividing the Central Rift Valley into homogeneous rainfall zones and developing seasonal rainfall prediction models for each zone using NAVORS2 and Climate Predictability Tool (CPT) of the International Research Institute for Climate and Society (IRI) respectively (http://iri.clolumbia.edu). This chapter forms the centrepiece of the study.

Chapter 4 deals with the seasonal crop water requirement satisfaction patterns for 14 possible and concurrent crop growing seasons (March-September) using the FAO crop water requirement satisfaction index model (WRSI) in AGROMETSHELL (Mukhala and Hoefsloot, 2004) and Ref-ET (Allen *et al.,* 1998). From this, spatial and temporal sorghum suitability maps were drawn and water production function analyses were conducted. Chapter 5 analysed climatic risks related to sorghum planting windows in the study area. A stochastic dominance analysis (SDA) was done using SIMETAR software (SIMETAR Inc., 2004). Sensitivity analysis was done using Microsoft Excel 2000, while APSIM (version 4.0) of the Agricultural Production Systems Research Unit (APSRU, 2005) was used for the crop simulation study.

Chapter 6 deals with the climatic decision analysis for on-farm level decision making, which could be useful for smallholders and commercial farming alike. In this chapter, a short and simple tactical decision support tool (DST) that uses a wealth of information extracted from chapters 2 through chapter 5 was developed. Chapter 6 is therefore a binder of all the information generated in the preceding chapters and paves the way for the future more targeted research and development efforts in the study area. Chapter 7 comprises the summary, conclusion and recommendation of the whole document.

Chapter 2

Statistical Analysis of Seasonal Variability and Prediction of Monthly Rainfall Amount Using Time Series Modelling

2.1 Introduction

Ethiopia has one of the most variable rainfall patterns that forms a natural part of farming in the world. A number of professionals and organizations have documented scientifically interesting reports on Ethiopian rainfall variability through classifying the country into various and a wider temporal and spatial rainfall categories (NMSA, 1996a & b; FAO, 1984; FAO, 1989; Degefu, 1987; Gemechu, 1977; Ethiopian Delegation, 1984; Gonfa, 1996; NRRD/MOA, 2000) and many others. According to Haile (1986) drought occurs every 3-4 years in the northern and 6-8 years in other parts of Ethiopia. According to Kidson (1977) a steady downward trend of rainfall since the peaks of the 1950s has expanded more in 1980s covering almost the whole of Africa. In the Ethiopian context, opinions are also divergent regarding the arrival of the rainy season, which used to occur in March but is now gradually shifting to April through to July and, therefore, there is a progressive shortening of the growing periods and the corresponding seasonal rainfall totals.

Owing to such a pronounced inter-annual and seasonal rainfall variability as well as extreme events, production risks and stresses to which the farming systems are exposed can arise from a wide variety of sources. Evidences indicate that daily records of the past rainfall episodes can be examined and combined effectively so as to eventually reveal certain useful pattern pertaining to farm level strategic and tactical decision making (Landberg, 1960). Therefore, determining the possible ranges of rainfall onset date, end date, duration, seasonal totals and dry spell length, which together make up the overall rainfall features, can provide deep insight into translation of the 'rainfall variability' into the field level management options through proactive responses (Meinke, 2003).

Substantial mechanisms exist to analyse variability in the above listed rainfall features, including probabilistic and deterministic ways applied over different spatial and seasonal scales. The cumulative rainfall departure (Xu and Tonder, 2001) and

time series analyses (Makridakis *et al.,* 1983; Hoshmand, 1998; Sincich, 1993; Fleming, 2000) are a few among a variety of rainfall pattern expressions. Particularly the time series analysis technique serves two main purposes. Firstly, to decompose the series into the components (trend, cyclical, seasonal and random) that helps to examine whether there is a change in rainfall pattern over time and space. Secondly, in many practical applications, time series analyses is used to predict future values of the series, with the assumption that naturally the past and the future atmospheric phenomena are interrelated stochastically. Accordingly, the future values have a probability distribution which is conditioned by an intimate knowledge of the past rainfall behaviour (Green, 1966).

While Ethiopia has more than 2000 manual ground weather observatory stations with limited records, the scientific advances in making use of this resource in agricultural research and the development arena is rather limited. Only few individuals (Mersha, 2003; Simane and Struik, 1993; Reddy and Georgis, 1994, Tesfaye, 2004) reported general or crop specific climatic analyses and none of this information has been used in operational farm management decisions. Generally, the analyses of sensitivity thresholds that, if exceeded, could lead to a catastrophic effect have not been done in any detail and/or for any specific location. The impact is apparent; viz. whenever drought occurs, it is inevitably followed by an immediate famine and economic crisis, culminating in chronic reactive appeals for humanitarian assistance at government level. Meagre harvests, total crop failures and rapid decline in productivity, particularly in drought prone areas like the Central Rift Valley, are common characteristics.

However, for the rainfed-based farming to be *productive* and *profitable*, the relationship between the two has to be decisively subjected to detail examination. For this, two prominent questions need an urgent reply. The first concerns the necessity of the study of the variability in various rainfall properties, including onset date, duration, end of the season and dry spell length. Secondly, the accuracy with which these various rainfall properties can be predicted to allow advance decision on the possible proactive adaptation of specific categories of technologies to be used over a given temporal and spatial resolutions (Green, 1966). The latter can be answered through time series prediction model fitting. If these questions can receive appropriate

answers and if used together with the seasonal climate outlook guidance, this would mean a boon for Ethiopian agriculture.

In Ethiopian agriculture it is this basic knowledge that is deficient and the weather-based research has yet to receive sufficient attention. This could replace the current trial and error experimentation, which in the past has often been performed at high cost. In short, in rainfall climatology, water requirement of various crops and agriculturally significant rainfall patterns must be studied jointly. The recent statistical report of Tilahun (2005) on a monthly and annual rainfall and evapotranspiration variability basis at nine arid and semi-arid areas of Ethiopia is a useful example. Such detail analyses enable a proper understanding of the underpinning factors of drought and the associated famine that could develop and appropriate measures to be taken to mitigate the impact of the drought and famine syndrome.

Therefore, this chapter presents a detail account of the rainfall variability statistics and time series model-based rainfall prediction results with a view to achieving the following three specific objectives for possible application to cropping system management in the Central Rift Valley of Ethiopia.

a) To examine the unique rainfall features and inter-station variability using daily rainfall data of two weather stations
b) To examine the trend, seasonal and cyclical components of the rainfall series
c) To fit time series prediction models to the March-October rainfall of Miesso and Abomssa weather stations.

This point statistics-based attempt, despite being far from adequate in addressing the agriculturally useful rainfall variability and prediction in the complex Ethiopian agriculture, can at least form a firm footing for drought related investigations at a specific spatial and temporal level.

2.2 Materials and Methods

Daily rainfall data from two weather stations having varied time series were used for these analyses. Abomssa, representing the adequate moisture situation and Miesso,

representing the inadequate rainfall farming zones were chosen, as they also represent the classic sorghum growing environments in the study area.

2.2.1 Data acquisition and extraction

The majority of daily rainfall data were obtained by courtesy of the National Meteorological Services Agency (NMSA) of Ethiopia, and partly from the archive of Melkassa Agricultural Research Center (MARC). Data were captured into Microsoft Excel 2000 spreadsheet following the days of year (DOY) entry format. In order to make the series amenable to further analyses, the missing values were patched using Markov chain simulation model of INSTAT (Stern *et al.,* 2002). This statistical package fits a model to the past data and then generates similar time series for any number of desired years. The type of distribution/shape parameter used at this step was a gamma probability density function (Stern and Coe, 1984; Wilks, 1989).

$$f(x) = \frac{x^{\alpha-1}}{\beta^{\alpha} \Gamma(\alpha)} \exp\left[\frac{-x}{\beta}\right] \qquad (2.1)$$

Where: α = shape parameter

β = scale parameter

Γ = gamma function evaluated at α level

x = amount of rainfall.

Data quality was checked using the single mass curve technique (Abate, 1994) in which a given station's rainfall record is assigned in a cumulative way to the y-axis and years assigned to the x-axis. Since rainfall series show significant variations, the homogeneity test was done prior to performing the analyses. Data may lack homogeneity, because of many external factors like station relocation, change of observers, change in time of observation and recalibration of the instruments (Green, 1966).

2.2.2 Analytical methodology

After patching and quality checking, daily rainfall datasets were subjected to detail analyses using sequences of statistical packages. At the outset, the box and whiskers plotting technique was used to illustrate the inter-seasonal spread of the series with respect to onset date, end date, duration, MAM and JJAS rainfall seasons. In a box and whiskers plotting, the box represents the middle 50% of the whole dataset, while

whiskers represent the magnitude of the spread of the rest of the dataset about the median or mean. Most of the rest of statistical analyses were done using INSTAT package version 2.51 (Stern *et al.,* 2002). The results are tabulated and plotted graphically.

Owing to the very broad perception that rainfall pattern in the study area exhibits a bimodal nature (short rain during MAM and long rains during JJAS), March 1st was picked as a potential planting date. Therefore, any rainfall amount occurring before the last day of February was excluded from the ensuing rainy season with the assumption that this season is dry, which is the basic rainfall characteristic of the study area. Then, the definition of effective onset date was employed in order to evaluate the historical rainfall series and to identify successful planting dates from the past records. In setting an onset date of the past records, many different criteria exist for different crops exhibiting different maturity plus drought tolerance levels and soil types. Here, the one with 20 mm of total rainfall received over three consecutive days that were not followed by greater than 10 days of dry spell length within 30 days from planting was adopted (Raman, 1974). Sivakumar (1988) also used similar criteria, except that he used 7 day dryspell length. These criteria are useful particularly in mitigating the seedling establishment related rainfall risk. The Ethiopian National Sorghum Improvement Program (ENSIP) also uses this, especially the first part of the onset definition.

On the other hand, the end of the growing season is mainly dictated by the stored soil water and its availability to the crop after the rain stops. In this study, the end of the rainy season was defined as any day after the first of September, when the soil water balance reaches zero (Stern *et. al,* 1982). In determining the end date, a fixed 5 mm of evapotranspiration per day and 100 mm/meter of the plant available soil water were considered. In addition to the above onset date criteria, the probability of dry spells length exceeding 5, 7, 10 and 15 days within the next 30 days after planting was also calculated for every month with potential for planting (March-September).

2.2.3 Time series analysis

In a time series decomposition analysis, the critical task is to separate patterns (trend, seasonal and cycle-random components) and use the resulting information in planning for long term/future changes and for the current business decisions. 'Trend' represents a smooth and relatively slowly changing feature of the time series (Green,

1966, Shiskin *et al.*, 1967; Makridakis *et al.*, 1983; Pezzulli, *et al.*, 2003), implying that the observations are not randomly distributed. This non-randomness could be the characteristics of any record in which the rainfall of consecutive years show a certain degree of persistence.

As such, information on trend is of high significance in operational agriculture, because not only does it imply the constantly changing levels in the potential rainfall supply, but also, if it dominates the pattern, it might render the seasonal rainfall distribution and totals to be seriously deficient. In fact, owing to the large sampling errors and insufficiently long series, questions involving rainfall trend analyses have frequently been inconclusive (Landberg, 1960) and this is necessarily true for Ethiopia, where weather stations are sparse and have a very short recording history.

The choice of which method to use in time series analyses depends on the theoretical considerations and historical patterns the data may have followed. In time series analyses, one can use different methods that make different underlying assumptions and reveal different aspects of seasonality, but the primary goal of all of them is to achieve the highest possible accuracy in predicting a given series value (Pezzulli, *et al.,* 2003). In this study, the monthly rainfall series was analysed for fractionation into the major components using a least square method of coded time (Hoshmand, 1998). It follows that if there is no rainfall trend and if the seasonal rainfall variation completes regularly in a cycle of one year, then the series could have optimal seasonal predictive utility (Hoshmand, 1998). Therefore, such a breakdown of the observations into the components could facilitate improved accuracy in predicting and aid better understanding of the behaviour of the series

Using the coded time concept in the least square helps one not to deal with large numbers such as 1995, 1996, and so on. Furthermore, it simplifies the equations that are used in computing the intercept (a) and the slope of the trend line (b). To code the time, the mean of the series was subtracted from the value of each of the sample times. In this computation, the additive model was adopted as follows.

$$X_t = T_t + S_t + CI_t \tag{2.2}$$

Where:
X_t = observed monthly rainfall series (mm)
T_t = trend component
S_t = seasonal component
CI_t = cyclic-irregular component

In order to compute the trend, one needs the coefficients (a and b).

$$a = \frac{\sum X_t}{n} \qquad (2.3)$$

Where:
a = average value (intercept)
n = total number of observations (series)
X_t = observed monthly rainfall series as given in Eq. 2.2

$$b = \frac{\sum x X_t}{\sum x^2} \qquad (2.4)$$

Where:
b = slope of the trend line
x = time code for the series.

Thus the least square equation for the trend line is:

$$T_t = a + bx \qquad (2.5)$$

Likewise, the equation for the seasonal (S) component is:

$$S_t = X_t - T_t - CI_t \qquad (2.6)$$

Where:
CI_t = Cyclic-irregular component

Finally, the cyclic-irregular component (CI) was computed by eliminating the seasonal component, as follows:

$$CI_t = X_t - T_t - S_t \qquad (2.7)$$

Where:
X_t, T_t and S_t are as defined above.

The objective of this part of the analyses is therefore to examine whether the monthly rainfall series is in a declining or increasing direction as well as to determine the drought cycle.

2.2.4 Time series prediction model fitting

Following the decomposition analysis and finding that the data does not show a significant trend, harmonic regression models (7 models for Miesso and 8 models for Abomssa) were fitted to the monthly rainfall total. Owing to the fact that the amplitude of each month's rainfall values (the magnitude of the peaks and the valleys) appears to vary with years (forming a wave-like pattern), a harmonic regression that combines time and trigonometric functions was found suitable for these analyses.

Harmonic regression is one of the commonest methods of describing periodic phenomena whose values are repeated at equal intervals of the independent variable (in this case, time) requiring the sine-cosine statistics (Makridakis, *et al.*, 1983; SIMETAR Inc., 2004).

In fitting the model, reducing the error component or increasing goodness of fit (how well the prediction model is able to reproduce the observed series) was the main target and therefore calibration (setting parameters that reduce the prediction error) was done for each model. Accordingly, in this time-dependent deterministic model fitting, a varying degree of polynomial regressions with the highest r^2 values as well as, reasonable levels of error quantifier statistics including Durbin-Watson (DW), root mean squared error (RMSE) and mean absolute percentage error (MAPE) were used. The DW statistic is a significance test of a first order (lag = 1) autocorrelation (Eq. 2.11). Since r_1 ranges between –1 and 1, the DW statistics ranges between 0 and 4 (Makridakis, *el al.,* 1983). If after fitting the model, DW statistic is close to 2, then r1 is close to 0; an indication of small autocorrelation among the random values, while the DW values of below 2 and above 2 indicate the existence of definite autocorrelation among the random series. Further, for better results, the RMSE and MAPE values should also be as low as possible. These measures of prediction errors are available as outputs in SIMETAR.

In these prediction models, the first-degree components were restricted/excluded from the resulting model, as the monthly series lacks linearity. Furthermore, each autoregressive model predicts the future values of the series with lag 1, which means, last year's March rainfall (X_{t-1}) for instance is used to predict the value for the same month this year (X_{t+1}). For Miesso 23 years data (1975-2003) were used to develop the model and the remaining 6 years data were used for cross validation. For Abomssa, 17 years data (1982-2003) were used to develop the model, while the remaining 5 years data were used for cross-validation. The model parameters development involve the following generic equation:

$$X_{t+1} = b1X_{t-1} \pm b2T \pm b3T^3 \pm bnT^n \pm (2PiT/CL) \pm Sin(2PiT/CL) \pm Cos(2PiT/CL) \qquad (2.8)$$

Where:

X_{t+1} = one step ahead predicted value
X_{t-1} = previous value in the series (1 lag)
b1, b2 ....bn = model parameters
T = Time (year 1, 2, 3............year n)

$$CL = \text{number of polynomial degrees} \quad CL \geq 1$$

$$RMSE = \sqrt{\left(\sum_{T=1}^{N} e_T^2 \right) / n} \tag{2.9}$$

Where: RMSE = root mean squared error
T = time (year 1, 2, 3........year n)
N = number of observations
e = error (observed minus predicted).

$$MAPE = 100* \left(\sum_{T=1}^{N} \left| \frac{e_t}{X_t} \right| \right) \tag{2.10}$$

Where: $MAPE$ = Mean absolute percentage error
e_t = Residual value at time t
X_t = Observed value at time t

$$DW = 2(1 - r_1) \tag{2.11}$$

Where: DW = Durbin Watson statistics
r_1 = first order (lag =1) autocorrelation.

2.3 Results and Discussion

The distribution of the operationally useful rainfall features listed above formed a good starting point for examination of the series. The lower (25 percentile), median (50 percentile) and upper quartile (75 percentile) caps of the whiskers in Fig 2.1a and Fig 2.1b provide a complete and useful explanation of the existing variability in the rainfall features. In Fig 2.1a, the variability in onset date for the two weather stations is high as compared to the rest of the rainfall features. For instance, for the onset date at Miesso, the respective lower and upper quartiles fall between 61 and 179 DOY (four months) with 42.0% c.v and between 61 and 134 DOY (two and a half months) with the 40.5% c.v for Abomssa. Therefore, at both locations planting earlier than 15 March (75 DOY) is possible only once in every four years time (see Table 2.1 also). Further, at Miesso this upper quartile (75 percentile) statistic extends up to the 179 DOY (last days of June) at Miesso and 15 April (134 DOY) at Abomssa.

At Miesso, the main rainy season terminates during the last days of September (272 DOY) once in four years time and terminates earlier than 293rd DOY (2nd week of October) in three out of four years. The same statistic for Abomssa was found to be 286th DOY (12th October) and the end of October (305th DOY). Accordingly, the main

growing season would not extend beyond the second week of October in the case of Miesso and beyond the end of October for Abomssa. The lowest (4-6%) c.v and the much smaller box for the rainfall end date in Fig 2.1a indicate that the ending dates vary over a short time span at both places. Therefore, as less variability implies that patterns could be more understood, decisions pertaining to harvesting and storage could be made more easily than the decisions pertaining to planting at both locations.

A further note could also be made from Table 2.1 and Fig 2.1a that rainfall duration is dependent mainly on the onset date. At Miesso, rainfall duration is lower than 102 days in only 25 % of the years, while it is lower than 204 days in 75% of the years. Similarly, the lower quartile for rainfall duration at Abomssa is below 161 and below 222 days in 75% of the years. The early onset date suggests that crop cultivars of the longer maturity type could do better with the late onset date (Stewart, 1988). The issue of rainfall duration deserves further attention, in that one needs to know the type and level of risks of yield loss associated with cultivars of different maturity categories, requiring different amounts of water during a sequence of growth stages. It is only then that one can confidently pinpoint the most suitable maturity cultivars to be planted in seasons with different onset date scenarios (Stewart, 1988). According to Borrell *et al. (*2003), such weather information guided farming help in combining the genetic solutions into the management aspects, providing farmers with a range of viable options to combat drought.

It is noted in Table 2.1 and Fig 2.1b, MAM season rainfall at Miesso is 0 and 125.5 mm, while the same term is 0 mm in one out of four years with upper quartile value of 147.7 mm in case of Abomssa. During MAM season, Miesso records a maximum value of 280.6 mm rainfall and Abomssa records 323.8mm.The least box in Figure 2.1b reflects how the MAM rainfall total is lower for the two stations. From the same table, it is noted that the median rainfall during MAM is much less than the corresponding averages for both the stations (for Miesso, the median is 19.8 mm and the average is 67.7 mm). For Abomssa, the median is 17.0 mm and average is 74.9 mm. The MAM rainfall exhibits the highest variability for the two stations, with the standard deviation (s. d) of 86.3 mm for Miesso and 97 mm for Abomssa. The c.v. is 127.5% and 129.9% for Miesso and Abomssa respectively.

Similarly, the bottom and upper quartiles of JJAS rainfall total for Miesso are 200.3 mm and 688.9mm respectively and 418.7- 875.5 mm for Abomssa. Table 2.1 further elaborates that the median rainfall total of JJAS for Miesso is less than the average (551.9 mm vs 584.7 mm). For Abomssa these values are larger than the average of the season (median = 768. 0 mm; average = 712.3 mm). The c.v of the JJAS rainfall for the two stations ranges from 29.1 to 37% for both stations.

Overall, except for the magnitude, the two weather stations have similar patterns with respect to the rainfall variation. Given such a wide variation particularly in onset date, it is noticeable how planting decisions in rainfed farming would be critical to these farmers. It is this fundamental point that justifies the need for seasonal climate outlook information and various field level alternatives under semi arid conditions (Stewart and Hash, 1982; Jean *et al.*, 2004).

According to the traditional wisdom of farming in these zones, longer duration cultivars are preferred to the shorter maturity ones and therefore more desirable. This is in agreement with the scientific understanding that longer duration cultivars yield more biomass. However, the delay in onset date is frequent particularly at Miesso, hindering planting of long duration cultivars. Hence, farmers have no choice but to opt for growing the lower yielding short duration cultivars with late arrival of rainfall. For these farmers, growing longer maturity cultivars could be rewarding, if supported by seasonal outlook information pertaining to rainfall distribution and appropriate soil water management techniques, as a means of knowing which level of input (intensive or low cost and low yield targeted cropping) to adopt in a given season.

2.3.1 Rainfall bimodality

As stated, the available body of literature and popular perceptions support the persistence of bimodal type of rainfall (NMSA, 1996a, b) in the study area. Given 1st of March to be the potential planting date, a search was made for a successful planting date from the past records that helped to ascertain whether there exists a true bimodal nature of the rainfall pattern in production terms. Fig 2.2 elaborates how the early onset date is associated with the increased rainfall totals at both Miesso and Abomssa. Early onset dates in this case imply the start of rainfall some time before June or before the end of MAM season. From the linear regression line, onset date explained 59% of the

variability in longer rain totals for Miesso and 45% for Abomssa. According to this linear regression, Miesso receives a maximum of 975 mm of rainfall and Abomssa

Table 2.1 Descriptive statistics of important rainfall features for Miesso and Abomssa weather stations

Seasonal Rainfall features	Minimum	Quartile 1 (25%ile)	Quartile 2 (Median)	Quartile 3 75%ile)	Maximum	Average	S.D ($\pm$)	C.V (%)
				Miesso				
Onset date (DOY)	61	75	104	179	200	119	51	42
End date (DOY)	245	272	282	293	345	283	18	6
Duration (no. of days)	55	102	178	204	268	164	57	35
MAM total (mm)	0	8.0	19.8	125.5	280.6	67.7	86.3	127.5
JJAS total (mm)	200.3	424.3	551.9	688.9	1069.2	584.7	216.3	37.0
				Abomssa				
Onset date (DOY)	61	74	90	134	192	108	44	40.5
End date (DOY)	274	286	294	307	331	297	15	5.1
Duration (no. of days)	99	161	211	222	244	189	49	25.9
MAM total (mm)	0	9.2	17	147.7	323.6	74.9	97	129.9
JJAS total (mm)	418.7	506.6	768.1	875.5	111.7	712.3	207.5	29.1
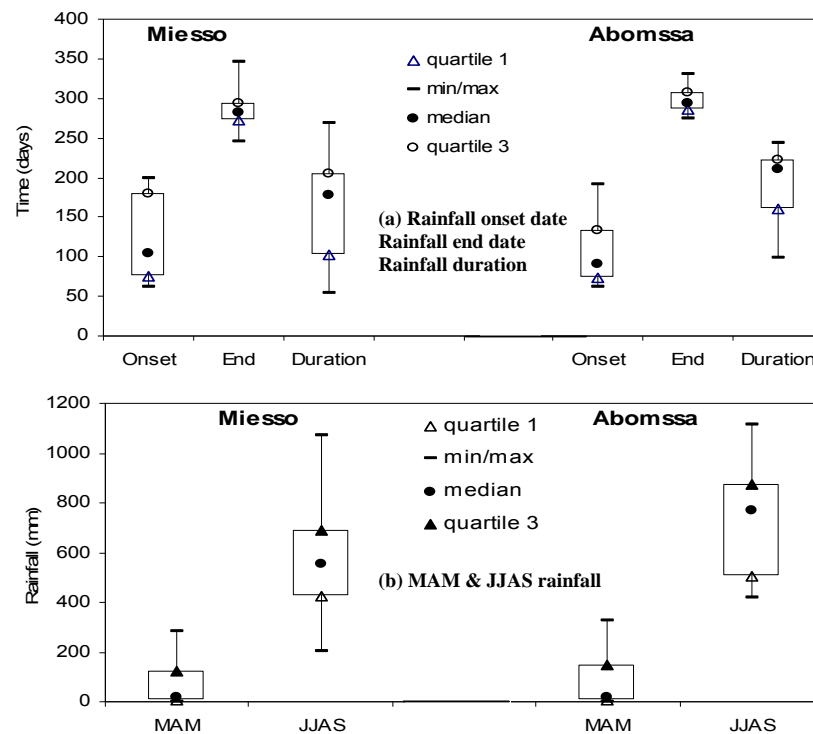
Figure 2.1 Five agriculturally important seasonal rainfall features at Miesso (1974 - 2003) and Abomssa (1981- 2003), CRV of Ethiopia (a) rainfall onset date, end date and duration; (b) MAM and JJAS rainfall totals.

reaching a maximum of 1063 mm, both of which reduce by the order of 3.2 mm for every day delay in rainfall onset.
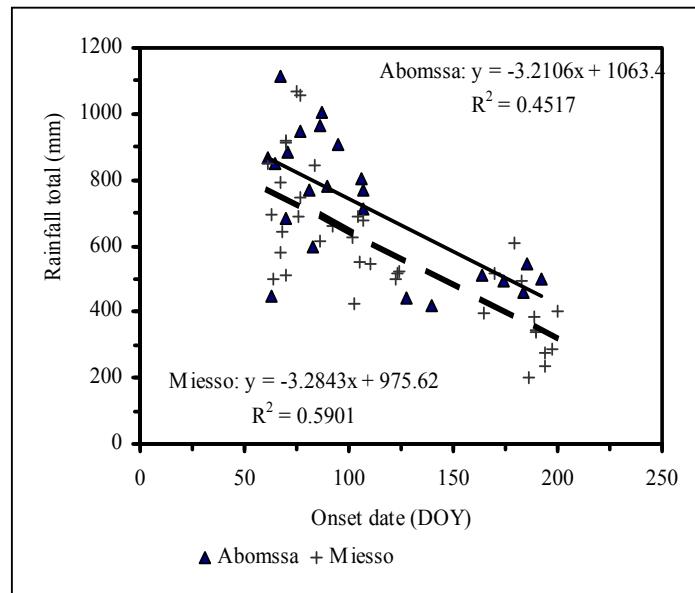
Figure 2.2: Rainfall onset date versus MAMJJAS rainfall total at Miesso (+) and Abomssa (▲) (the broken line represents Miesso and the solid trend line represents Abomssa).

The start of the main rain before June implies the merge of MAM and JJAS seasons that corresponds to the reduction in MAM rainfall totals. Particularly during such a merge of the two seasons, MAM rains cannot meet the amount of water required to sustain crop or cultivar of any shorter duration to reach maturity within the confines of the same season. Indications are, and particularly from the economic farming perspective, that the seasonal rainfall pattern in the study area does not have distinct bimodality and because of these characteristics, it could be concluded that there is an overlap between the two seasons (Fig 2.2). Gissila (2001) also reports that the break period between the two rainy seasons is brief over the central parts of Ethiopia, while it increases from southwest to the northward and eastward directions.

2.3.2 Probability of dry spell length

In rainfed farming, the intermittent dry spell becomes critical, particularly for the seedling establishment during the first 30 days or so after planting. In fact, a dry spell of any length could occur at any stage of crop growth; however, it is potentially damaging if it coincides with the most sensitive stages such as flowering and grain filling (Stern and Coe, 1984).

To provide a viable decision aid to various practitioners, different dry spell lengths were examined. Accordingly, given a condition that 1st of March is a potential planting date, the probability of dry spells longer than 5, 7, 10 and 15 days were analysed (Figure 2.3). This sheds insight into the risks related to a range of dry spell lengths during the entire rainy season. Also, the reason behind including the 'dry spell length' conditions into the later months of the growing season is to provide a complete picture of how the dry spell length of various magnitudes are distributed during the entire growing season and to examine the associated risk at each location.

The 'parabolic-type' curves in Fig 2.3 explain, for instance, the probability of dry spells longer than 15 days within the 30 days after planting on the first day of any month that forms part of the rainy season (March-September). For both Miesso and Abomssa stations, the probability of dry spells longer than 15 days in March is less than 10%, whereas it shows a certain degree of upward slope in April and May (note the mini peaks on the left arm of the curves) and descends down to 0 from the middle to end of June. The same Figure also demonstrates how the probability of 5 and 7 days of dry spell curves stays at the value of 1.0 during the earlier months. All the dry spell length probability curves converge to their minimum only during the peak rain period (July and August or DOY 180-244) for both stations and turn upward again around September (244-274 DOY), signalling the end of the growing season.

Information on the probability of such a range of dry spell lengths is useful for different groups of farmers who work under different capability or resource endowments. For instance, farmer 'A' (a risk taker) who may have access to irrigation water or have a crop adapted to suspend its growth under a longer dry spell could decide to plant during the earliest /risky months of the growing season. In this way, one can maximize outputs by taking risks associated with such a long dry spell. On the other hand, a resource poor farmer 'B' (a risk averse) lacking water resources or other soil water management techniques or decision tools to manage any risk of dry spell longer than 5 or 7 days has to wait until the sufficient soil water accumulates. Since the two farmer groups do not utilize resources at the same level (time of planting, crop cultivars and other inputs), the expected yield level would not be similar for the two farmer categories. In any case, late onset is the least preferred situation, obviously because it shortens the available length of the crop growing period and the potential to satisfy the crop water requirement (Green, 1966).
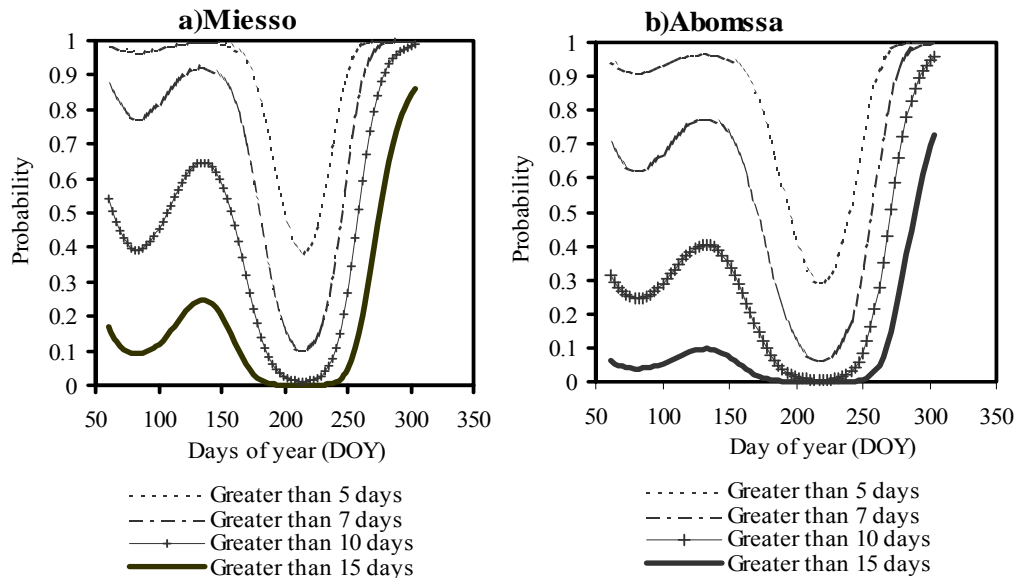
Figure 2.3 Probability of dry spell longer than 5, 7, 10 and 15 days, given 1st of March as potential planting date at (a) Miesso and (b) Abomssa, Central Rift Valley of Ethiopia

Overall, this information serves different farming groups working under different practical settings to help make tactical decisions and take appropriate actions within their own 'real life' farming circumstances and to combat or avoid drought conditions.

2.3.3 Time series analysis output

Fig 2.4a shows the monthly historical, trend, cyclic-irregular and seasonal components of the rainfall series of Miesso for the years 1970-2003 (n = 30). Miesso, located at the northeastern flank of the study area is characterized by a variable rainfall pattern, receiving a long-term annual average of (730) mm. The linear trend line fitted reveals that, though the observed rainfall values oscillate along time, the corresponding monthly rainfall trend constantly varies about the mean monthly value of 62.6 mm.

On the other hand, it can be noted from the curve that during 1974-1976 (3 years) the positive contribution of the cycle to the rainfall series was evident, while during 1977-1983 (7 years) the contribution of the cyclic component to the system was positive. Further, the curve had also captured the 1984-1986 drought period, followed by the 1987 wet and 1988 dry year. The next drought episode was in 1992, followed by the 1996-97 wet year. In the recent years drought has taken place in 1998-99 and in the year 2002. Generally, the cyclic-irregular component of the monthly rainfall series at Miesso shows the irregular pattern that doesn't show the clear-cut return period of

drought. However, as a first approximation it could be generalized that the drought cycle at Miesso ranges between 2 and 3 years and this result is consistent with the frequent crop failure experienced in the area.

Among many others, the frequent crop failure could be attributed to the very high evaporative demand and the corresponding high crop water requirement, which could also be true for many regions situated close to the equator. For the research system to help with this complex problem and to arrive at the conclusive statements, detail studies including other local factors (soil and topography) are required.

Similarly, the seasonal component with the wavy pattern (bottom curve in Fig 2.4) shows the periodicity of rainfall peaks and troughs (*i.e.* the peaks represent the positive contribution of the months to the rainfall producing system, while the troughs indicate the normally dry, as well as drought, months). In comparison, July and August months make highest contribution to the season's rainfall total. However, with the possible high evaporative demand considered for the same time period, the contribution of July and August rainfall to the water balance is lower and therefore this could be one reason for the frequent crop failures at Miesso. This information could be used in seasonal rainfall prediction and soil water related research and development efforts.

Fig 2.4b on the other hand examines the same time series components for Abomssa for the years 1981-2003 (n = 23). Abomssa, situated at the southeastern part of the study area and receiving an average annual rainfall of 895 mm is the major sorghum growing zone in the region. From Fig 2.4b and the linear regression fit, the monthly trend oscillates with almost constant monthly rainfall values of 75 mm and without a distinct decline or increase in direction. This implies that the rainfall of the area does not show any significant trend. Unlike the Miesso case, the cyclic-irregular component in the Abomssa series depicts both below and above average rainfall patterns. For instance, 1983- 1987 was a period of below average rainfall, while the 1988-1990 period was above average. Therefore, as the sample size is not sufficient, a clear return period of drought could not be easily drawn.
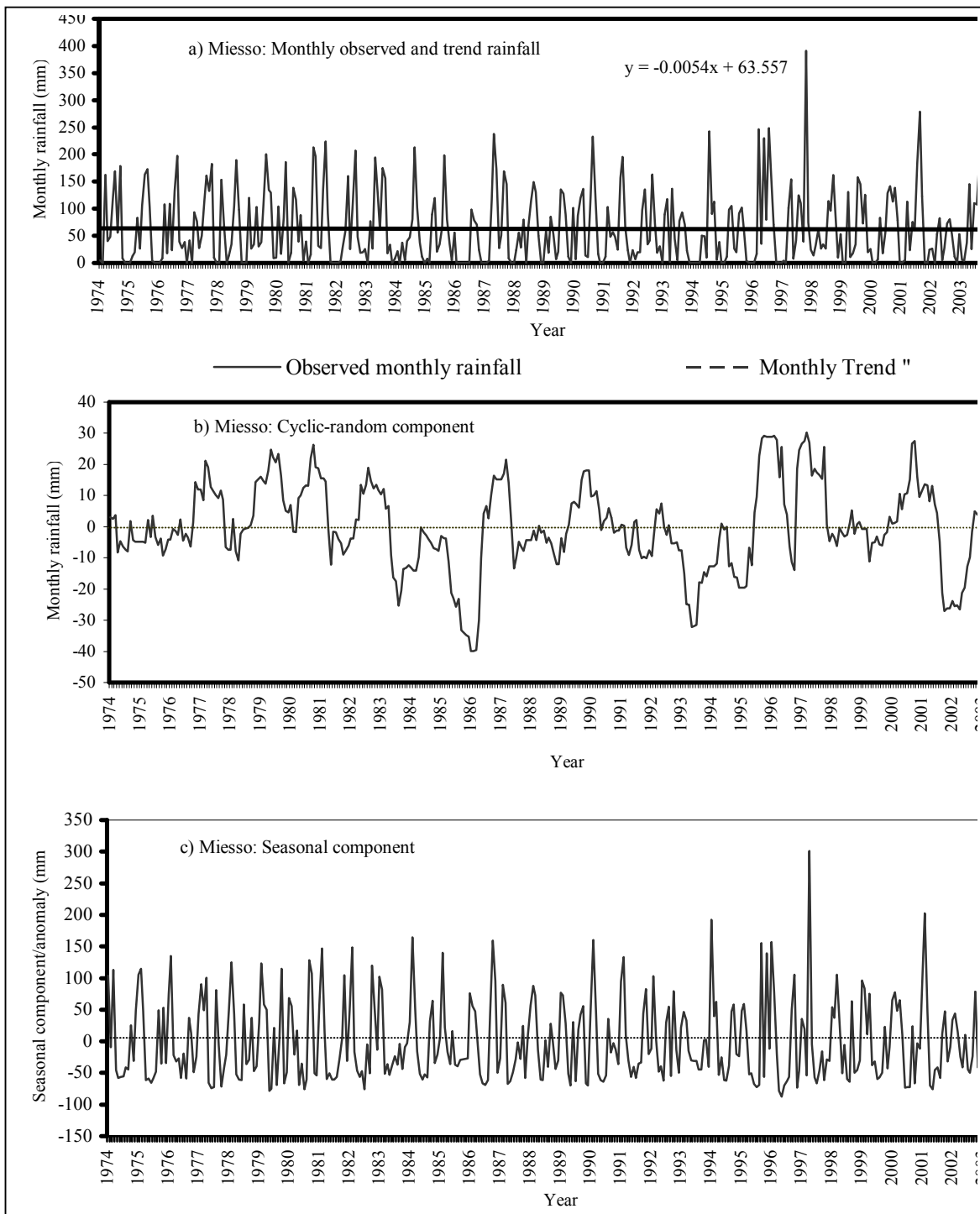
Figure 2.4 Monthly observed/trend, cyclic-random and seasonal components of the rainfall (a) monthly observed and trend; (b) monthly cyclical-random component and (c) monthly seasonal component from the Miesso weather station
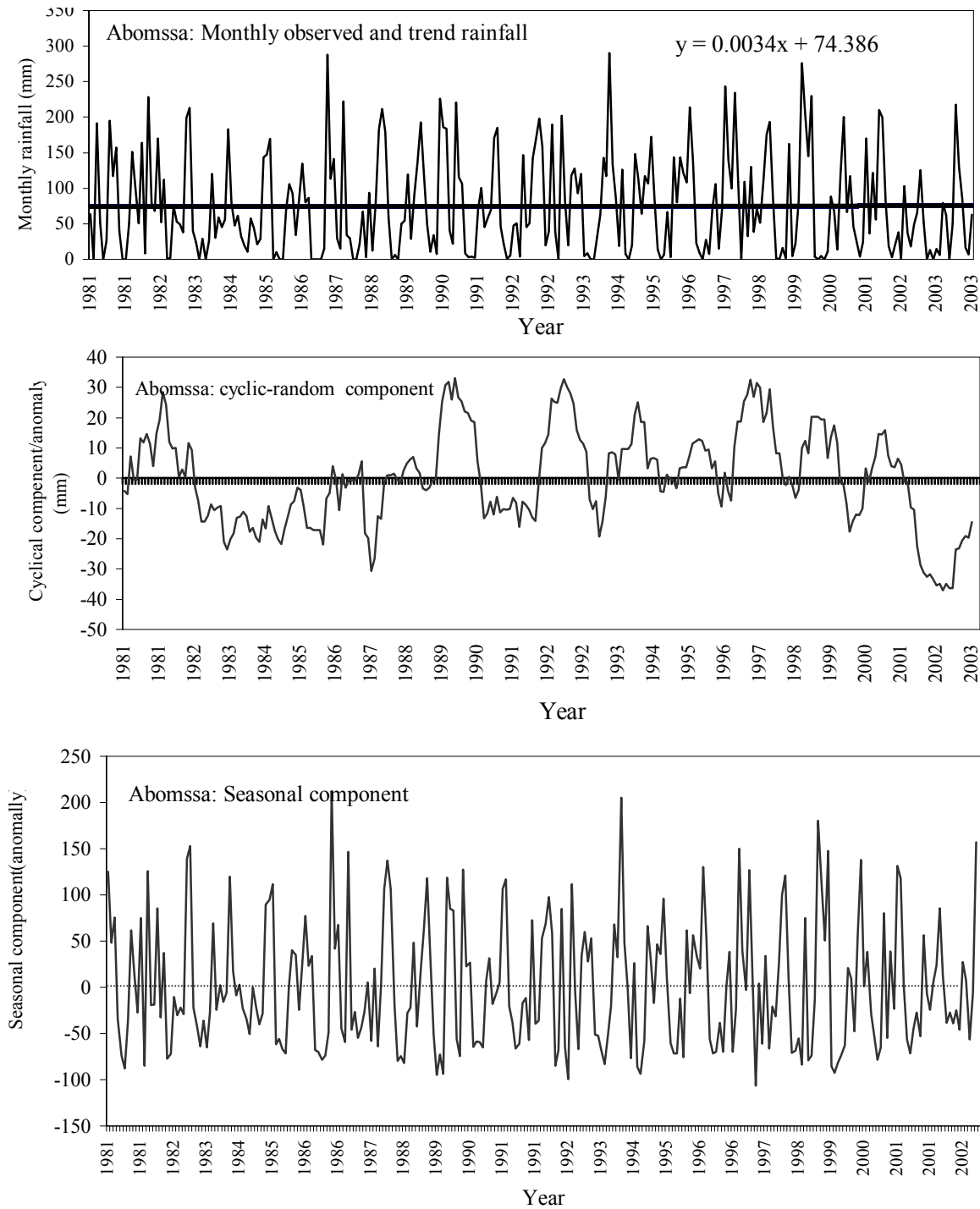
Figure 2.5 Monthly observed/trend, cyclic-random and seasonal components of the rainfall (a) monthly observed and trend component; (b) monthly cyclic-random component and (c) monthly seasonal component from the Abomssa weather station

The seasonal component of the rainfall series at Abomssa also contributes positively to the season's rainfall, with July and August contributing the most. The June to

September component of the rainfall series of the year 2002 reveals above average contribution (43.3% to total of 291.9 mm rainfall that took place during these months). Generally, the seasonal component shows alternating patterns; peaks during the rainy months and troughs during the dry periods that make it predictable for use in the operational farming. However, as the data series is too short, more meaningful results have to be worked out in the future, as and when the dataset has accumulated sufficiently.

In comparison with Abomssa, the observed and the trend line for Miesso is lower (Fig 2.4a and Fig2.4b). As the series is too short, trend could not be detected, implying that rainfall variability is the natural part of the agroecosystem in these zones. In other words, this study did not find that drought is becoming a frequent phenomenon in the area. Therefore, time series prediction models could be fitted to both stations series. There is a need for the revision of the analyses with further accumulation of the necessary dataset.

2.3.4 Time series prediction model fitting

An examination of Table 2.2, Table 2.3, Fig 2.6 and Fig 2.7 underlines how the prediction models fitted to the seasonal series, behave. Table 2.2 and Fig 2.6 explain the time series-model relationship for rainfall at Miesso, the r2 value for March being 0.845 (Eq. 2.12 in Table 2.3). For the rest of the growing season reasonable relationships were observed for all months under consideration, except May (r2 = 0.620, see Eq. 2.14 in Table 2.2). Better relationships were noted particularly for July and August with r2 = 0.924 for July and 0.937 for August (Fig 2.6e and Fig 2.6f and Eq. 2.16 and Eq.2.17 in Table 2.2). The relationships for April, June and September are also quite acceptable (Fig 2.6 b, d, g and Table 2.2) with r2 values ranging from 0.818 to 0.86, indicating the models' agreement with the monthly series of Miesso.

From Fig 2.7a and equation 2.19 in Table 2.3 the model was able to capture the-non-linear or wavy pattern of March rainfall series at Abomssa (r^2 = 0.886; RMSE = 43.3; DW = 1.99 and MAPE = 105.8). Equation 2.20 in Table 2.3 shows a better fit of the April prediction model with r^2 value of 0.918 with the other error quantifier statistics performing reasonably as well. On the other hand, with a closer look at the 1991,

Table 2.2 Time series prediction models for March to October rainy season for Miesso

Month	Prediction Model	Equation No.	R^2	RMSE	Durbin-Watson	MAPE (%)	CL
March	$Y = -0.367X_{t-1} - 1.349T^2 - 0.221T^3 + 0.018T^4 +$ $35.888(2PiT/CL) + 52.893(Sin2PiT/CL) - 6.438(Cos2PiT/CL)$	2.12	0.845	38.8	2.24	82.0	7
April	$Y = -0.391X_{t-1} - 12.907T^2 + 1.067T^3 - 0.041T^4 + 0.001T^5 +$ $89.874(2PiT/CL) - 23.169(Sin2PiT/CL) + 27.479(Cos2PiT/CL)$	2.13	0.818	50.0	2.12	72.3	8
May	$Y = -0.185X_{t-1} - 6.403T^2 + 0.507T^3 - 0.017T^4 + 27.329(2PiT/CL) -$ $9.974(Sin2PiT/CL) - 31.329(Cos2PiT/CL)$	2.14	0.620	49.7	1.79	229.6	5
June	$Y = 0.321X_{t-1} - 3.51T^2 + 0.287T^3 - 0.01T^4 + 11.009(2PiT/CL) +$ $10.464(Sin2PiT/CL) - 13.181(Cos2PiT/CL)$	2.15	0.837	21.9	2.57	44.9	4
July	$Y = -0.324X_{t-1} - 17.445T^2 + 1.175T^3 - 0.003T^4 +$ $111.67(2PiT/CL) + 3.6893(Sin2PiT/CL) + 21.65(Cos2PiT/CL)$	2.16	0.924	42.2	22.05	25.2	7
August	$Y = -0.352X_{t-1} - 23.635T^2 + 1.765T^3 - 0.061T^4 + 0.001T^5 +$ $173..31(2PiT/CL) + 36.353(Sin2PiT/CL) + 24.925(Cos2PiT/CL)$	2.17	0.937	49.3	2.09	23.1	8
September	$Y = 0.03X_{t-1} - 10.502T^2 + 0.865T^3 - 0.031T^4 +$ $42.691(2PiT/CL) + 0.859(Sin2PiT/CL) + 13.152(Cos2PiT/CL)$	2.18	0.867	40.7	2.30	43.7	5

Table 2.3 Time series prediction models for March to October rainy season for Abomssa

Month	Prediction Model	Equation No.	r^2	RMSE	Durbin-Watson	MAPE	CL
March	$Y = -0.094X_{t-1} - 9.031T^2 + 0.087T^3 - 0.045T^4 - 0.002T^5 +$ $37.627(2PiT/SL) - 18.843(Sin2PiT/CL) - 33.958(Cos2PiT/CL)$	2.19	0.886	43.3	1.99	105.8	5
April	$Y = 0.167X_{t-1} + 2.55T^2 - 0.404T^3 + 0.012T^4 +$ $11.82(2PiT/CL) - 6.615(Sin2PiT/CL) - 3.223(Cos2PiT/CL)$	2.20	0.913	35.94	2.98	61.9	5
May	$Y = -0.559X_{t-1} - 36.331T + 4.11T^3 - 0.194T^4 + 0.003T^5 +$ $134.98(2PiT/CL) - 10.441(Sin2PiT/CL) + 46.97(Cos2PiT/CL)$	2.21	0.824	41.6	1.70	66.6	7
June	$Y = -0.488X_{t-1} - 14.130T^2 + 1.606T^3 - 0.0.77T^4 + 0.001T^5 +$ $69.390(2PiT/CL) - 24.434(Sin2PiT/CL) + 15.967(Cos2PiT/CL)$	2.22	0.928	22.8	2.50	39.1	8
July	$Y = -0.504X_{t-1} - 72.603T^2 + 8.385T^3 - 0.411T + 0.007T^5 +$ $350.374(2PiT/CL) + 13.719(Sin2PiT/CL) + 77.439(Cos2PiT/CL)$	2.23	0.896	57.3	2.19	52.5	9
August	$Y = -0.207X_{t-1} - 22.791T^2 + 1.763T^3 - 0.058T^4 + 0.001T^5 +$ $154..888(2PiT/CL) + 14.13(Sin2PiT/CL) + 13.211(Cos2PiT/CL)$	2.24	0.956	44.5	1.98	20.2	8
September	$Y = -0.169X_{t-1} - 15.767T + 1.521T^3 - 0.066T^4 - 0.001T^5 +$ $46.779(2PiT/CL) - 4.816(Sin2PiT/CL) + 19.376(Cos2PiT/CL)$	2.25	0.871	50.9	2.30	42.3	4
October	$Y = 0.03X_{t-1} - 14.187T + 1.529T^3 - 0.067T^4 + 0.001T^5 +$ $65.726(2PiT/CL) + 45.818(Sin2PiT/CL) + 30.978(Cos2PiT/CL)$	2.26	0.767	64.4	1.97	116.9	8
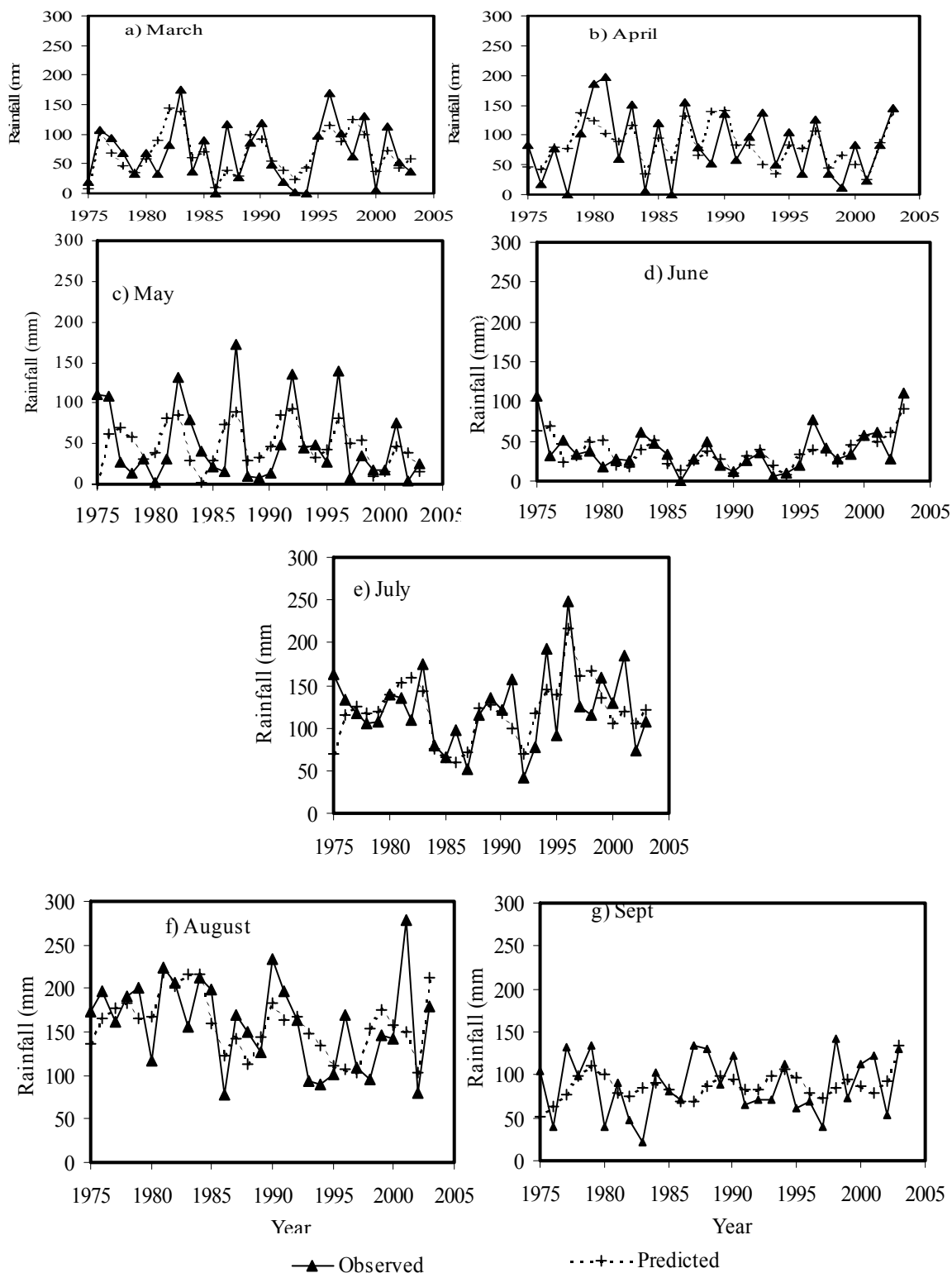
Figure 2.6 Observed and predicted March-September monthly rainfall totals at Miesso, CRV of Ethiopia
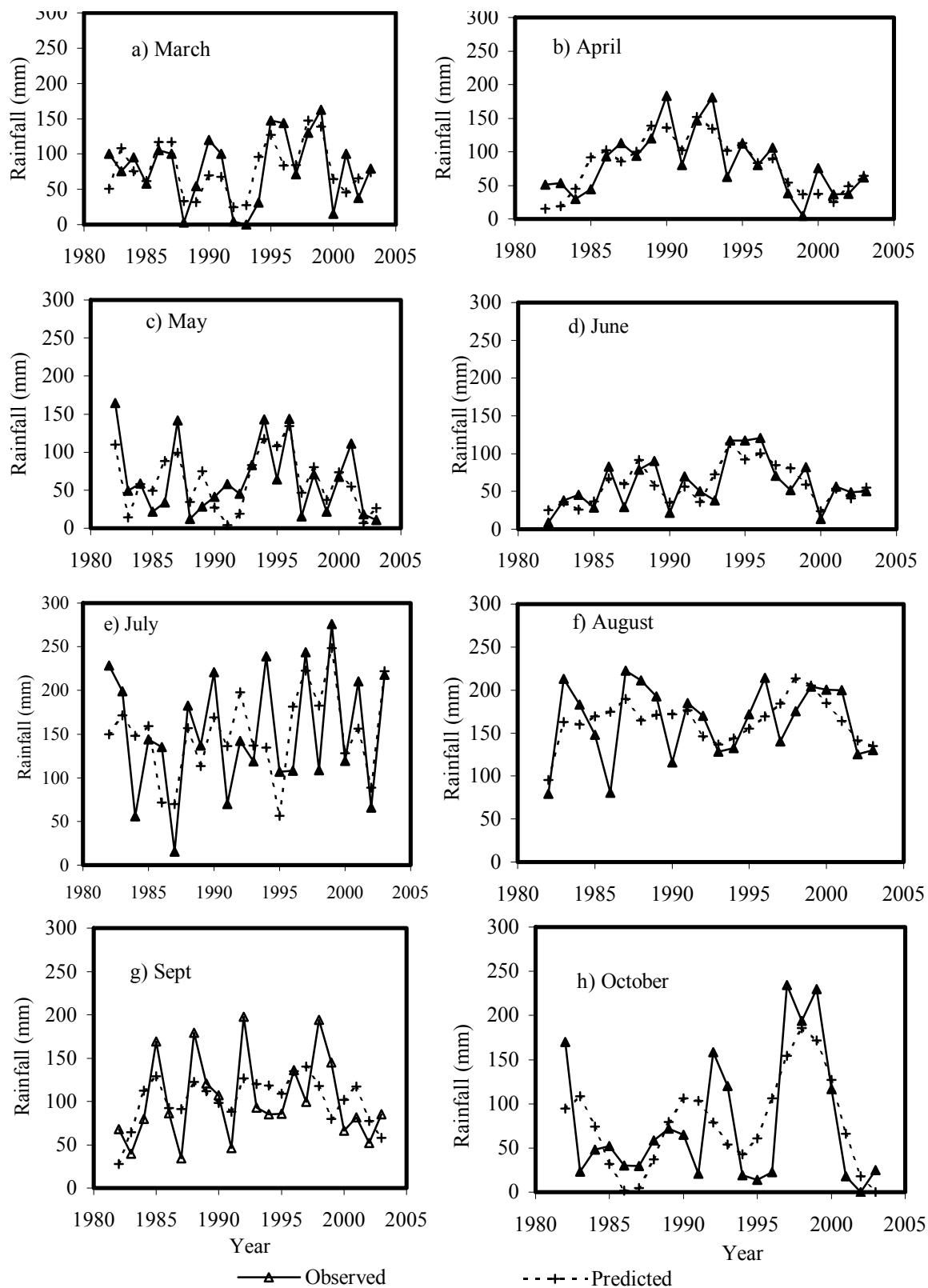
Figure 2.7 Observed and predicted March-October monthly rainfall totals at Abomssa, CRV of Ethiopia

1994, and 1995 October series, the corresponding model values at Abomssa could be judged differently. Fig 2.7h underlines how the two curves diverged, rendering the October series-model relationship relatively poor. The error quantifier statistics in Table 2.3 (Equ. 2. 26) also give a similar explanation (r^2= 0.767, RMSE = 64.4 and MAPE = 116.9%). Similar insight could be obtained for the 1991 May series-model relationship (r^2 = 0.824; RMSE = 41.6; DW = 1.70 and MAPE = 66.6). For the case of August (Eq. 2.24), the model performs well with r^2 = 0.956; RMSE = 44.5; DW = 1.98 and MAPE = 20.2%) indicating the higher degree of agreement between the series and the model output. A similar useful trend holds for July and September as well (Fig 2.7g, equation 2.23 and 2.25 respectively in Table 2.3). One of the problems with time series prediction model is that it does not provide the factors underpinning future values. Moreover, because of the high possibility of a change in model structure, mainly due to climate change, the risk associated with predicting outside the observed range of the independent variable could be high (Sincich, 1993). Despite this difficulty, an overall evaluation shows that the models could provide a reasonable predictive utility for farm level decision making, particularly in conjunction with the other prediction tools.

2.4 Conclusions

The statistical analyses have collated essential numerical evidences for the existence of variability in important seasonal rainfall features in the study area, giving possibilities for monthly rainfall prediction using time series models. The first section of the chapter focused on capturing the variability in onset date, end date, duration and the seasonal rainfall totals. Of all the features, onset date and the MAM rainfall totals were found to vary considerably for both the two weather stations (c.v. for onset date and MAM rainfall total is 42 % and 127.7% respectively at Miesso; 40% and 129.9% for Abomssa).

The bimodality of rainfall pattern in the study area was also studied in relation to the onset date. The result shows that early onset (the start of rainfall any time between March and end of May) is associated with the overlap of the short and long rainfall seasons, as explained by the linear regression line for season total rainfall versus onset date at Miesso (r^2 = 59% for Miesso and 45% for Abomssa). Therefore, the MAM rainfall totals, particularly during such a merge, cannot support the successful growth and development of any short

duration sorghum cultivars within the confines of the MAM period. Indications are, and particularly from the economic farming perspective, that no clear evidence exists for bimodal pattern of the rainfall, at least at the studied weather stations.

Further, once the rainy season has commenced and planting actions have taken place, the risks related to the intermittent dry spell length comes into the picture. Probabilities pertaining to a range of dry spell lengths were also discussed in which values for longer than 15 days is less than 10% during the entire March-September period. This could be compared with the probabilities of 5, 7 and 10 days longer or any other intervals that carry useful information for both risk averse and risk taking farmers.

The second part of the chapter dealt with the time series analyses and prediction model fitting to the monthly rainfall series. Important findings include the non-existence of trend for the stations. The trend lines fitted indicate the irregularity of the series with mean monthly values of 62 mm for Miesso and 74 mm for Abomssa. This is also useful information for long-term development planning, as well as attaching seasonal time series prediction models that could be used in reducing uncertainty and risks associated with rainfall and, therefore, sorghum planting dates in the study area. The seasonal components for the weather stations also reveal a certain degree of periodicity in which August and July contribute most to the system. The models developed for the two stations were able to capture the past and recent drought years, including that of year 2002, justifying the usefulness of the rainfall series in estimating its own future values. Accordingly, a total of 15 time series prediction models (7 for Miesso and 8 for Abomssa) were fitted to the months with potential for cropping in the region. March to September/ October season was considered for this purpose.

Generally, the detail knowledge and understanding of such basic rainfall features and model fitting can lead to further improvements in risk management practices. It places the influences of current climate variability on the farming system in perspective. In order to identify the real cause of frequent crop failure at Miesso, focus should also be on detailed soil water balance studies that consider the evapotranspiration component, rather than dealing only with rainfall per se. When complemented with the other rigorously analyses done, the technique could be a useful decision support tool for farming in the study area.

Chapter 3

Homogeneous Rainfall Zones and Seasonal Rainfall Prediction

3.1 Introduction

At the world scale, seasonal rainfall bearing weather features range from the local land-sea breeze and thundercloud to the large-scale wave patterns that circumscribe the globe, all of which are part of the coupled ocean-atmospheric process of transport of energy and water vapor. This giant pattern, covering the entire planet earth, is appropriately explained by global circulation models (GCMs) that compactly represent the fact that the solar energy absorbed in the equatorial-tropical region is greater than the outgoing infrared radiation, while the opposite operates in Polar Regions (Seleshi, 1996).

The increasing concern about the socio-economic impacts of climate risks, both due to natural and anthropogenic reasons has led to a rapid model development and the increased urgency for climate prediction at the global scale (Kassahun, 1990). GCMs outputs are being used extensively in seasonal forecasting globally (Palmer and Anderson, 1994; Ji *et al.,* 1994; Hunt, 1997; Mason *et al.*, 1999; Landman and Mason, 1999; Goddard *et al.,* 2001; Landman and Goddard, 2002).

Two approaches are currently used to determine the future behaviour of the ocean-atmosphere system; namely a purely empirical statistical and a dynamical one. The advantages of the classical statistical forecasting models over the dynamical ones involve their capacity to converrt uncertainty values into probabilistic terms. This is in the sense that a particular set of predictors will always produce the same forecast for the predictand, once the forecast equation has been developed (Landman *et. al.*, 2001). The use of probability elements in the forecast framework is advantageous, because it provides a large solution space (from 0 to 1) for the expression of the inherent uncertainty or state of knowledge about the future behavior of the predictand (Murphy, 1977; Krzysztofowicz, 1983).

In order to attain maximum predictive utility in economic farming, however, there is a need to study spatial and temporal rainfall variability as well as its persistence that arise at a particular location due to external forcing. Sea surface temperatures (SSTs) are among such external forcing factors. The value of prediction lies in its ability to explain the unique pattern of drought at a specific location and season. In other words, the value of the forecast information, whether of good quality or not, can only be assessed if someone makes a decision and takes action based on that forecast information. This notably holds for agriculture, which is highly sensitive to the influence of weather and climate. Along this line, the study report of Jury *et al.* (1997) to the South African Water Research Commission emphasizes the potential possibility of downscaling seasonal rainfall prediction from the global to regional, national and district level. It is implied that there are possibilities of regionalizing the areas into further homogeneous rainfall zones, based on which specific rainfall prediction could possibly be practiced for each zone.

The striking correspondence of the positive sea surface temperature anomalies (SSTAs) with the drought incidences in the 1960s, 1970s, 1980s and 1990s in the Sahel region is evident. Accordingly, there have been several recent studies (Kassahun, 1990) examining connections between GCMs outputs and Ethiopian rainfall variability, notably through SSTAs of the global oceans. This involves either warming or cooling of the ocean surface, mainly the eastern Pacific, Atlantic and Indian that have a substantial influence on the tropical climate system.

For Ethiopia, the increasing central and equatorial Pacific SST (ENSO warm phase) results in a drought condition during the June-July-August-September (JJAS) rainfall season. In contrast to this event, the relative cooling of the central and equatorial Pacific "La Niña", the cold ENSO phase, results in 'below normal' rainfall during the March-April-May (MAM) season but in 'above normal' rainfall during the JJAS season (Bethke 1976; Henricksen and Durkin, 1986; Ogallo *et al.,* 1988; Ininda *et al.,* 1987; Haile, 1986 & 1988; Kassahun, 1990; Babu, 1991; Glantz *et al.*, 1991; Beltrando and Camberlin, 1993; Abate, 1994; Seleshi, 1996; Attia and Abulahoda, 1992; Koricha, 1999, 2002a &b; Camberlin and Philipon, 2001; Lemma, 2003).

According to Folland *et al.* (1986) GCM experiments have shown a reduction of about 30% in rainfall over the Sahel, as a function of the anomalies in the Global SSTAs pattern, showing it to be an important cause of drought in the region. Folland *et al.* (1986) maintained that the anomalous SST features of the north Indian Ocean have greater impact on the rainfall variation in Sudan and Ethiopia. Also, the SSTAs pattern over the South Atlantic shows their clear influence on the recurrence of drought in Ethiopia (Folland *et al.*1986).

The subsequent studies by Palmer (1986) reflect that the Atlantic and Pacific Ocean SSTAs have a comparable effect in reducing the rainfall of the Sahel, while the Indian Ocean SSTAs bring an enhancement in rainfall, except over the north-eastern part of Africa where drought was simulated. The study made by Lamb (1978a & b) and Hastenrath (1985) show that the inter-annual climatic variability in the Sahelo-Ethiopian zone is strongly affected by the global anomalies. A detailed account of ENSO related phenomena can be obtained from Rasmusson and Carpenter (1982), Philander (1990) and Glantz (2001).

3.1.1 Seasonal climate prediction: Status in Ethiopia

In its seasonal rainfall prediction and early warning information, the National Meteorological Services Agency (NMSA) of Ethiopia has been using ENSO phases since 1987 (Taddese, 2000; Walker *et al.,* 2003). Moreover, many reports have divided Ethiopia into different climatic, agroclimatic and agro-ecological zones, providing information that could form a solid foundation for rational planning of agricultural research and development (Bethke, 1976; Gemechu, 1977; FAO, 1984; Henricksen and Durkin, 1986; Tuker and Goward 1987; Haile 1988; FAO, 1989; Abate, 1994; Gonfa, 1996; NMSA, 1996a & b; NNRD/MOA, 2000; Yeshanew, 2003).

At present, NMSA issues seasonal rainfall outlook information for MAM, JJAS and October–November–December (OND) seasons. During the JJAS (long rainy season), most parts of the country receive substantial rains, except the southern and Southeastern lowlands, where MAM constitutes the main rainy season and OND forms the short rain season (Koricha, 1999). Accordingly, NMSA classifies Ethiopia in terms of seven homogeneous rainfall zones for JJAS (Koricha, 1999), eight zones for MAM

(Amedie, 2000; Koricha, 2002a) and eight for the OND seasons (Koricha, 2002b). During JJAS, the major rainfall producing systems are the northward progression and establishment of the Inter Tropical Convergence Zone (ITCZ), the formation of low level jet (LLJ), the strengthening of the Mascarene High pressure, the strengthening of St. Helena High pressure, the strengthening and frequent emergence of the Tropical Easterly Jet (TEJ) and the associated monsoon systems (NMSA, 1996a & b).

During the MAM season, the rain producing mechanism is associated with the formation of a high-pressure centre over the Arabian Sea, as well as the formation of easterly/southeasterly moist winds towards the eastern and central parts from the north Indian Ocean, generated by the Arabian High (NMSA, 1996a). Moreover, the displacement of the extension of the Siberian ridge over Arabia by the eastward moving mid-latitude depression crossing the Mediterranean Sea is the major cause for the establishment of the high pressure centre over the Arabian sea (NMSA, 1996a & b).

3.1.2 Seasonal climate prediction: Service provision, use and users in Ethiopia

In Ethiopia, despite the availability of extensive climatic information, few advances have been made in view of promoting 'tailored' predictive information and utility at national, regional and small spatial level. Firstly, there is a lack of a drought policy and strategy that provides full inertia to including meteorological information into the national agricultural development agenda that can help farmers become self reliant, regardless of drought episodes of any magnitude. Secondly, a significant amount of climatic information is scattered among various agencies and therefore is difficult to access, constituting a major reason for the fragmented discontinuity and insufficient detail in analyses and experience in this field. Thirdly, the inadequacy of a client oriented meteorological information dissemination mechanism is another weakness. Such a targeted forecast service provision is essential, especially for the farming community with the aim of helping them make better decisions regarding input purchases and choosing the planting date according to the anticipated rainfall scenario. The best example could be the pilot forecast project undertaken for the power industry (Babu *et al.,* 2004) that gives clear indications of the greater need for such a targeted seasonal prediction information service for the farming community as well. Fourthly, some of the findings are concerned with the complex scientific understanding, which implies that

the extraction and translation of the implications of the prediction information from such studies into a usable farm level product is an issue that has not been handled yet. These are critical at times, especially when the information communicated is important despite its complexity. Particularly those information aspects pertaining to the start of rainy season and therefore the choice of a cropping strategy at a specific location are very important.

At the other end of the scale, the lack of preparedness from the user community to respond to the tailored forecast information is another shortcoming. For instance, agricultural research has been a scientific endeavour since the 1950s. However, the existing climate prediction knowledge has never been used in cropping decisions. This is a lost opportunity, as the knowledge has been available for the last 80 years (Walker, 1923). Thus far, agricultural technology generation and transfer efforts for rainfed cropping have been conducted within the confines of trial and error experimentation with no quantitative account of the risks associated with a variable climate.

The collective consequence is insufficient capacity to proactively respond to drought years (e.g. year 2002) and as a result all groups who have a stake in agriculture, ranging from the government down to the farming community, would be challenged whenever drought of any magnitude occurs. In principle, the term drought has no universal definition and its meaning varies for various societal groups. For instance, the 1976 rainfall shortage in Great Britain was a severe drought in respect of urban water supply, whereas, Britain's agriculture was hardly affected (cereal yield in 1976 was higher than that of 1950s); hence that year was not a drought year for these farmers (Sandford, 1978).

3.1.3 Seasonal rainfall prediction: State of the art at the world and regional scale

Throughout recorded history, fluctuation of weather has played a major role in human life (Seleshi, 1996) and attempts have always been made to predict how the future weather will behave. The earliest prediction is the biblical reference to Joseph's interpretation of the Pharaoh's dream: "Behold, there come seven years of great plenty throughout the land of Egypt and there shall arise after them seven years of famine" (Genesis 41: 29-30 King James Version). In fact, what Joseph forecast was the

fluctuation of the flow of the Nile River that comes from the Ethiopian highlands and is dependent on the rainfall of this area.

Today, after a passage of over 4000 years since Joseph's forecast, the issue of having a valuable rainfall forecast is still a challenge. However, with the advent of reliable instrumentation, monitoring of the oceans, space and the atmosphere, more information on basic characteristics of climate is becoming available. Particularly, in the second half of the 20th century, the spatial and temporal coverage of such information has expanded (Seleshi, 1996).

Brunt (1968) stated that it is hardly necessary to comment on the validity to agriculture of a significant improvement in the reliability of the seasonal forecasting. John Von Neumann in the 1950s described the quantitative machinery of climate as "the most difficult and unsolved" problem that still confronts the scientific intellect of mankind (in Russel, 1991). Over a century ago, Todd (1893) stated that the importance to the farmer, the horticulturalist and pasturalists of knowing beforehand the probability of having a dry or wet season, and whether the rain will be early or late or both, has naturally led to a desire for seasonal prediction. According to Clements (1991), managers of agricultural systems in semi-arid regions have aspired to long-term rainfall predictors for more than 100 years. He claimed that it was only in the previous 10 years that the goal had appeared within reach. Clements' observation of the century old aspiration to predict seasonal rainfall ahead is certainly still true today.

One useful physical explanation for the possibility of seasonal rainfall prediction, particularly in the tropics, involves the fact that the oceanic field (e.g. SSTs) evolves more slowly (steadily) than the atmospheric perturbations themselves (Palmer and Anderson, 1994). The oceans serve as the source of moisture and, with an enormous heat capacity, they drive the whole atmospheric system (Landman *et al.*, 2001; Indeje, 2004). This asynchronous coupling makes the response of the atmosphere to this boundary/external forcing to be tractable and detectable well in advance, compared to the internal and seemingly random or chaotic variability in the atmosphere, which inherently depends on its initial state (Rowell, 1998; Indeje, 2004; Dilley, 1997). This detection is possible mainly through monitoring of the SSTs fields. Therefore, statistical

estimation of the evolution of SST anomalies potentially provides a means of generating prediction of seasonal average weather (Graham *et al.,* 1987a & b).

Presently, the scientific community is exerting all possible efforts to make climate prediction a routine part of the climate information system and efforts are made to downscale the information to farm level decision making. Accordingly, a widely used forecast of global and regional climate is made by the International Research Institute for Climate and Society (IRI) and the National Climate Prediction Centre (NCEP) of the National Oceanic and Atmospheric Administration (NOAA).

There are also regional rainfall and drought monitoring centres, each of them providing the seasonal climate outlook for their respective regions. These include the IGAD Climate Prediction and Application Centre (ICPAC) in Nairobi, Kenya), Drought Monitoring Centre for the Southern African Development Countries (SADC-DMC), Harare, Zimbabwe European Center for Medium Range Weather Forecasting (ECMWF), the Long Range Forecasting Group of the South African Weather Service and the Research Group for Statistical Climate studies (RGSCS) in Pretoria. The Australian Commonwealth Scientific and Industrial Research Organization (CSIRO) releases seasonal climate forecasts for the Australian continent and for the rest of the world. Australian Bureau of Meteorology Research Centre (BOMRC) and CSIRO Marine Research (CMR) have also developed a state of the art coupled ocean-atmosphere seasonal prediction model known as POAMA (Predictive Ocean Atmosphere Model for Australia). This model has the capacity to represent the Madden-Julian Oscillation (MJO) and has a subroutine to produce forecasts for the intra-seasonal variability of rainfall (Alves *et al.,* 2003).

All of the above listed stakeholders invariably use the spatial and temporal analyses and provide a probability statement of a range of possible outcomes across a season, relative to the normal distribution of the climate for that particular region and season. Regardless of whether the prediction is 'above or below normal'; any outcome within the probability distribution may be realized. Additionally, because of the high variability within a season, wet seasons may exhibit short term dry period or vice versa. Because

of the inherent uncertainty, economic values of prediction vary depending on what applications are made with the forecasts (Gadgil *et al.*, 1995).

When coupled with the predictive information from the national meteorological/hydrological institutions, this translates into more accurate information that could be channelled into the farming community. As such, without even going much beyond the present state of the art Glantz *(*1993) concluded that seasonal rainfall prediction is the science's legacy to the 21st century. According to Dilley (1997), had it not been for the earthquakes, climate prediction could have been the last frontier in disaster early warning.

This chapter therefore argues on the possibilities of statistical prediction of the rainfall anomalies using global SSTs information for the smaller spatial and short temporal units for monitoring of the rainfall performances. According to Jury *et al.* (1997) the one-month lead period of the seasonal rainfall prediction would be useful in such efforts, because, given enough time for decision making, alternative strategies can be implemented realistically. They reported that, sub-seasonal forecasts (*e.g.* early and late summer independently over a district of some 300km x 300km) are preferred and scientifically viable, despite the effects of local factors like ranges of mountains and land-sea breezes etc. Similarly Mutai and Ward (2000) concluded that a set of SST predictors in the light of the circulation anomalies associated with the East African rainfall give greater confidence in the potentials of the MAM season SST patterns to be connected to the East African rainfall.

3.1.4 Seasonal rainfall prediction for Central Rift Valley of Ethiopia

The current study focuses on a small geographical unit that constitutes the central part of Ethiopia- traditionally known as Central Rift Valley (CRV). This area has unique advantages and faces complex challenges in terms of agricultural production and the associated climate risks. According to previous studies, CRV falls into various ecological zones. For instance, according to NMSA's prediction for JJAS, the region is defined into zone IV. According to Abate (1994) the Lakes Region of the CRV, though generally of a lower altitude, is elevated enough to share similar rainfall patterns with most of the Shewa plateau, while FAO (1984) defined both the Rift Valley Lakes, Shewan plateau

and the Afar Triangle under region E, where short rains in spring (MAM) merge with the long rains (JJAS). Similarly, Degefu (1987) grouped the study area with the Shewa plateau that receives 400-900 mm of annual rainfall. Bethke (1976) classified the area into group III (escarpment-rift) that consists of the eastern and western escarpments of the rift valley receiving summer rain and small rains with about 25% of its annual rainfall from MAM.

In essence, every zone has its own distinct development opportunities and limitations, which should guide the determination of its future development priorities and strategies. In this regard, none of the above mentioned studies succeeded in properly drawing a map that can comfortably match each ecological sub-unit's operational development need, particularly for farming purposes. This is partly because the studies were conducted on a larger spatial unit, in which the inherent sharp relief contrasts with small distances pose complex challenges in extending this information to farm level decision making.

This study therefore is essentially a build on previous findings, but with a major focus on drawing detail information down to the specific location, an approach that has received little attention in the past. The first part of the study involves dividing the region into homogenous rainfall zones, while the second part deals with seasonal rainfall prediction for each month (March-September) as a function of the one-month-lead from the Pacific, Indian and Atlantic oceans SSTs. The overall aim of this regionalization is to identify areas having similar rainfall patterns for the purpose of fine tuning the agricultural research and development efforts. Since previous findings show that the SST variability is the most important component that relates to the Ethiopian rainfall pattern, the focus is only on the SSTs. The objectives are:-

a) To categorize the Central Rift Valley of Ethiopia into homogeneous rainfall zones and generate monthly rainfall indices for use in the months March-September rainfall prediction in each homogeneous zone.

b) To determine whether the rainfall pattern in the study area depends both spatially and temporally on selected global and regional SSTs (predictors).

c) To develop a 1-month lead rainfall prediction model for period March-September for each homogeneous rainfall zone.

Hypothesis:-

The seasonal rainfall variability in the study area is strongly related to the global SSTs predictors that have teleconnection with the Ethiopian rainfall, so that rainfall prediction a month in advance using statistical techniques is possible.

3.2 Materials and Methods

3.2.1 Dataset used

In order to perform a series of temporal and spatial analyses, 16 years (1988 to 2003) and concurrent monthly rainfall records of 25 weather stations situated in the CRV were used. As the requirement was for all the stations to have the same length of dataset, this short (n= 16 years) had to be selected. The weather stations provide a reasonable spatial coverage across the study area. The problem of missing data was overcome by using the INSTAT first order Markov-chain simulation model to patch the data. All the monthly rainfall data were derived from the daily series and contained less than 10% of the total as missing records.

3.2.2 Development of rainfall indices

Firstly, the structured monthly rainfall series was used as input to a FORTRAN 90 based program (NAVORS2) for clustering the stations into homogeneous rainfall regions (Mason, 1998). An attempt was made to cluster the zones on the basis of the analytical results, as well as taking cognizance of local experience of topographic features in the area. A combination of the number of principal components (PCs) and zones were examined: 4 PCs for 2 zones, 4 PCs for 3 zones, 4 PCs for 4 zones, 6 PCs for 2 zones, 6 PCs for 3 zones, 6 PCs for 4 zones, 10 PCs for 2 zones, 10 PCs for 3 zones and 10 PCs for 4 zones. Finally, the case with the closest relation to local rainfall features and with least noise was selected for the prediction study. This suggests that the delineation was not done on a pure correlation between monthly rainfall and predictors alone. The map was drawn using a 1: 25000 scale.

In sequence, monthly rainfall indices were computed in a manner similar to that of Mason (1998) for the chosen case of homogeneous rainfall zones. The indices were computed from the time series of the rainfall-standardized departure for the months March to September for each station within the prescribed climatically homogeneous area.

3.3 Seasonal Rainfall Prediction using Canonical Correlation Analysis(CCA)

A one month-lead statistical prediction model that relates the monthly SSTs values to the rainfall anomaly prediction was developed using the canonical correlation analysis (CCA) technique, a subroutine that is embedded in Climate Predictability Tool (CPT) of the International Research Institute for Climate Prediction and Society (IRI) (Mason and Tippet, 2005). One-month lead prediction implies the prediction would be made for the target month that begins 1 month after the end of the predictor's month, for instance using January SSTs to predict rainfall of March and so on. CCA is an extension of a multiple regression technique to the case of the vector-valued predictor-predictand relationship (Landman and Goddard, 2002).

The CCA approach identifies a sequence of pairs of patterns in two multivariate data sets and constructs sets of transformed variables by projecting the original data onto these canonical variates. In CCA, the patterns are chosen such that the new variables defined by projection of the two data sets onto these patterns exhibit maximum correlation, but are uncorrelated with the projections of the data onto any of the other identified patterns. This condition is known as empirical orthogonal function (EOF) (Barnston, 1994). In other words, CCA identifies new variables that correlate optimally such that the interrelationship between the two datasets could be maximized.

Canonical correlation analysis may be defined using the singular value decomposition of a matrix *C* where:

$$C= R_{yy}^{-1}R_{yx} R_{xx}^{-1}R_{xy}$$ (3.1)

Where: C = matrix of singular value decomposition

R_{yy} = Correlations between Y variables

R_{yx} = Correlations between Y and X variables

R_{xx} = Correlations between X variables

R_{xy} = Corrleations between X and Y variables

$$C = U'U'\Lambda B \qquad (3.2)$$

Where: $\qquad\qquad \Lambda$ = diagonal matrix of C, is made up of eigenvalues (λ) of C.

$$\lambda_i \text{ of matrix of } C = r_i^2 \qquad (3.3)$$

Therefore, $\qquad r_i = \sqrt{\lambda_i} \qquad\qquad (3.4)$

The number of retained predictor (X) and predictand (Y) EOF modes of the fields or combination of fields, as well as CCA mode that produced the highest average cross-validated correlation for March-September, was identified by feeding the maximum value into the CPT input window. Then, the CPT itself identified the optimum number of EOFs modes by using the chi-square goodness of index. The EOF and CCA modes combinations with the highest goodness of fit index were taken as the optimum number for both predictor and predictand variables. More details about CCA is found in Barnett and Preisendorfer (1987), Graham *et al.* (1987a & b), Barnston and Ropelewsky (1992) and Barnston (1994).

3.3.1 SSTs data extraction

The SSTs data were extracted from the IRI web site using a 2° x 2° grid resolution, whose measured values are known prior to the forecast time. Climlab2000 of IRI (Tanco and Berri, 2000) was used for identifying those oceanic areas having a strong relationship with the respective rainfall zones for a target month, in which a threshold correlation (r) value of $\lvert \geq 0.3 \rvert$ was taken into account, which amounts to a minimum 10% of the variance being explained.

3.3.2 Cross validation technique

The cross validation technique is used as it helps to evaluate model performance when it is applied to data that was not used to develop its parameters (Efron, 1982, Efron and Gong, 1983, Michaelsen, 1987, Wilks, 1995). In this, the nth predictor and the corresponding predictand fields would be removed one at a time, while the remaining n-1 partition is used to train or develop the model. This is known as a one-year-out-cross validation. This technique was employed for each of the 16 years (1988 to 2003) climate

period. In other words, 16 similar prediction models were developed, each computed without one of the observations of the predictand.

Such a cross validation procedure is appropriate, especially to avoid the artificial forecast skill that could result from short records. Artificial prediction skill is the skill apparent in testing an empirical prediction technique on historical data, which does not survive in operational implementation because the apparent skill has arisen through capturing chance relationships amongst the historical data, and this could affect model stability (Wilks, 1995). Here the assumption is that once a sound forecast model has been developed and cross-validated, then it can be operationally used in forecasting future values of the predictand based on the future observations of the predictor variable.

3.3.3 Prediction verification / Model performance evaluation

Since our ultimate aim is to support better decision-making using the prediction model as a support tool, the developed model was subjected to skill verification/performance evaluation. Prediction skill evaluation is the process of determining the quality of forecasts. Any prediction evaluation method involves comparison between matched pairs of predicted and the observations to which they pertain.

There are many different ways to evaluate the forecast skill or its accuracy. 'Accuracy' implies the degree of correspondence between individual forecasts and the events they predict. In such a skill evaluation scheme, 3 very basic prediction error quantifiers have been used. The first and the continuous forecast measure is the cross- validated correlation coefficient or the Pearson product-moment correlation coefficient (r). This shows the magnitude of the strength of the relationship between the observed and the forecast values. The second, but categorical forecast measure used is the hit score (*HS*) or the 'proportion correct' and is the most direct measure of the accuracy of categorical forecasts. *HS* is simply a fraction of the *n* forecasting occasions when the categorical forecast correctly anticipated the subsequent event or non-event (Wilks, 1995, http://iri.columbia.edu/software/). Table 3.1 demonstrates how *HS* can be calculated.

$$HS = \frac{a+e+i}{p} *100 \qquad\qquad (3.5)$$

Where :
       a = # of correct forecast of below normal rainfall (B)

        e = # of correct forecast of near normal rainfall (N)

        i = # of correct forecast of above normal rainfall (A)

        b = # of observed 'near normal', when forecast 'below normal'

        c= # of observed 'above normal', when forecast 'below normal'

        d = # of observed 'below normal', when forecast 'near normal'

        f = # of observed 'above normal', when forecast 'near normal'

        g= # of observed 'below normal', when forecast 'above normal'

        h= # of observed ' near normal', when forecast 'above normal'

        p = total count of forecasting occasions.

HS receives the score of one for perfect prediction, while the forecasts equivalent to the reference forecast receives a zero score (Wilks, 1995).

The third categorical forecast measure used is the hit skill score (*HSS*). *HSS* refers to how many more times the forecast was correct, compared to the reference forecast strategy, or it defines the percentage of times (beyond that expected by chance) the forecast categories correspond with the observed category (Oludhe, 2004). The generic formula for *HSS* is written as:

HSS= <u>Number of correct forecasts – Number of forecast expected correct</u>   (3.6)
    Total number of forecasts - Number of forecasts expected correct

$$\text{HSS} = \frac{(a+e+i) - \dfrac{mj+nk+lo}{p}}{p - \dfrac{mj+nk+lo}{p}} \hspace{3cm} (3.6)$$

Where:
      j = total all forecasts but observed was 'below normal'
      k = total all forecasts but observed was 'near normal'
      l = total all forecasts but observed was 'above normal'.
      m = total all observed when forecast was 'below normal'.
      n = total all observed when forecast was 'near normal'.
      o = total all observed when forecast was 'above normal'.

Finally, based on the established skill evaluation values (r, HS and HSS) a separate attempt was made to predict rainfall pattern and classify it in terms of 'below normal', 'near normal' and 'above normal', for months March-September and for each zone.

Table 3.1 Illustration of hit score (HS) and hit skill score (HSS) statistical computations for skill performance evaluation

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

3.4 Result and Discussion

The following sections provide detail accounts of classifying the study area into homogeneous rainfall zones and then the March-September season rainfall prediction. It is important to note that except for some disturbances, the study area shares the influence that SSTs pose on Ethiopian rainfall patterns and therefore any explanation emanating from the prediction study would be the ones valid for Ethiopia.

3.4.1 Homogenous rainfall zones

From the global oceans coarse scale of influence and particularly from the rainfall climatology point of view, it is often difficult to define such small areas into further homogeneous zones, without taking account of the interaction between the atmospheric circulation and detailed topography (Olsen *et al.,* 1995; Dent *et al.,* 1990). However, given the complexity of the climatic patterns in East Africa in general and Ethiopia in particular, it is not surprising to find large spatial variations in rainfall patterns in the study area.

Fig. 3.1 effectively condenses an enormous amount of information that reflects a physically consistent pattern with the atmospheric processes within the study domain. This map was generated with close scrutiny of the various combinations of the principal components and zones. Out of nine such combinations, the 10 PCs for four zones case were selected, as the least noise involved in it. The stations whose monthly precipitation pattern is well correlated and in close proximity to each other tended to be clustered together forming 4 homogeneous rainfall zones. The help of Anna Bartman of the South African Weather Service in working out the map is fully acknowledged.

Accordingly, the central to south sloping part of the study area constituted zone 1. Zone 1 encompasses a relatively low lying area that stretches from Alem Tena (middle) down to Langano in the south. In this area, there is a well-defined wet season between June and September, but with unreliable and longer dry spells being common. The annual rainfall is about 730-780 mm. The eastern part of this zone is dominated by the central section of the Meki valley which comprises a wide gently undulating plain and is drained to the north by the River Meki. Mareko ridges occupy the central part of the zone, while the extreme southwest is occupied by the northern part of Kolito plain (Markin *et al.,* 1975).

Zone 2 (Fig. 3.1) includes the southern flank of the study area: Arsi Negele, Shashamene and Awasa in the extreme south. Moreover, the extended Kela-Butajira-Alaba Kolito-Shone -Bilate caldera in the extreme western side also forms part of this zone. On the other hand, the rifts bordering the highlands in the southeast including Kulumsa-Iteya-Gonde-Huruta plain northwards to Abomssa are also part of this zone. The zone receives quite a substantial amount of rainfall (800-1400 mm annually) that makes it different from the rest of the zones. Lake Awasa as well as River Bilate and Guder are also part of this zone. The western part of the zone comprises an extensive piedmont at the foot of the Guragie mountains, on which is situated the town of Butajira. Moreover, a belt of volcanic cones occupies the central part of the area immediately east of Butajira, including Koshe and Inseno. Much of the land is extensively cultivated to maize, peppers, haricot beans, peas, wheat, barley, sorghum and tef.

Zone 3 (Fig. 3.1) includes the northwest to northeast stretching part, starting from Dukem / Debre Zeit through to Mojo, Koka, Nazreth, Wenji, Melkassa, Dera and Bofa. This zone receives annual rainfall ranging between 600-800 mm. In comparison to Zone 1, this area is characterized by a wet condition, as 75% of the years can be expected to have larger amounts of annual rainfall (Abate, 1994) and seasonal drought severity in this zone is very high during the spring season (MAM). The fairly extensively used River Awash, as well as River Mojo form part of this zone.

The eastern arm of the study area constitutes zone 4. Zone 4 represents the plains, including the extensive Borchata-Kereyu land, Merti-Jeju, Nura Era, Awash-Fantale, Werer, Melka-Sedi until Asebot-Miesso plain that skirts the Chercher highland at the easternmost.edge of the CRV. The zone remains very hot, and dry conditions persist during most parts of the year. This could be explained by the fact that the normal rain triggers from the expected sources for the whole country perform poorly over this zone. Abate (1994) reported similar findings for this zone, with fairly dependable rainfall prevailing only during July-August. The areal average annual rainfall in the zone ranges from 500 to 600 mm.

3.4.2 Seasonal rainfall prediction

As stated, the March to September period marks the particularly relevant season for farmers in the study area. Accordingly, the following section focuses on monthly rainfall prediction, using a one-month lead correlation of the global SSTs datasets. In the prediction, a comparison between matched pairs of observed rainfall anomaly and the cross-validated anomaly prediction values were used. It is assumed that, once sound a prediction model has been developed and cross-validated giving high forecast skill, then the candidate model can be operationally used in forecasting future values of the predictand, based on the future observations of the predictor variable (Wilks, 1995). As can be noted in Table 3.2, different oceans are responsible for the SSTs related to the rainfall patterns of the different months, as well as different zones. Pacific Ocean covers the largest share (75%), while Atlantic and Indian Oceans cover the remaining portion. For clarity, the prediction results would be discussed zone wise as follows

3.4.2.1 Zone 1 (Alem Tena-Langano)

The cross-validated correlation (r = 0.44) between the observed and forecast values of the March rainfall anomaly (Table 3.2 and Fig. 3.2a) was significant at 95% probability level. This provides evidence of a useful relationship and the possibility to predict March rainfall to a certain extent from Pacific Ocean's January SSTs (14ºN-26ºN and 160ºW-178ºW) for this zone. However, the other prediction model skill evaluators, viz. hit score (*HS* = 46.7%) and hit skill score (*HSS* = 20%) are lower and did not show significance at 95% level of probability. With reference to the February SSTs-April rainfall relationship (14∘S-34∘S and 80∘W-112∘W) in Fig. 3.2b, the correlation between

the observed and the predicted rainfall anomalies increased (r = 0.51). In the case of March SSTs (42ºN- 52ºN and 28ºW-46ºW) used to predict May rainfall (Fig. 3.2c), r was 0.48, both of which are significant at 95% probability level. For April rainfall, *HS* and *HSS* remained at the same level as for March rainfall anomaly, while showing slight reduction for May rainfall (*HS* = 40% and *HSS* = 20%).
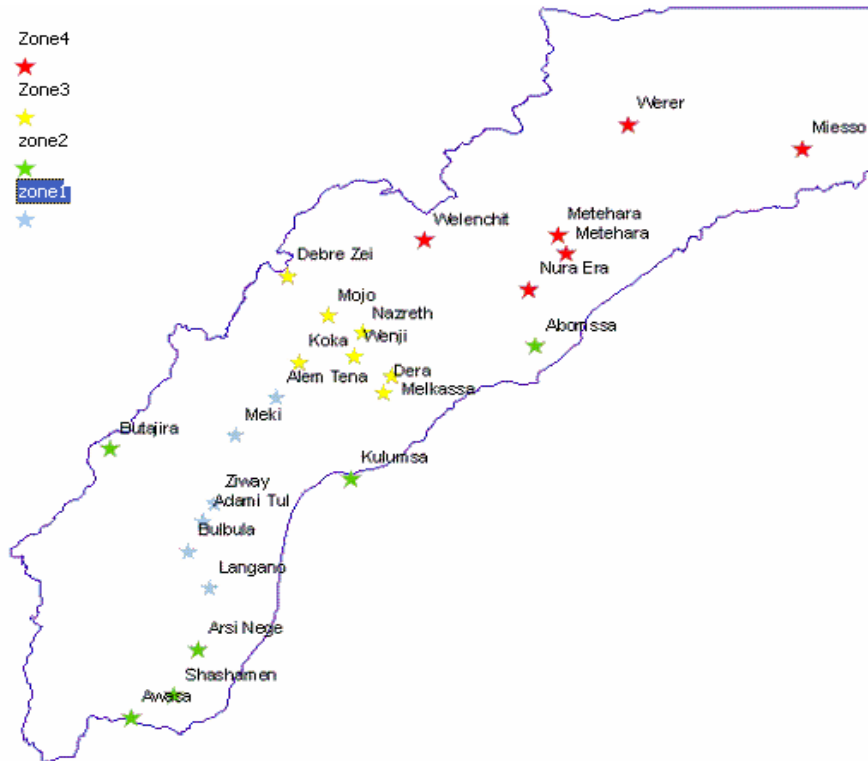
Figure 3.1 Four homogeneous rainfall zones in Central Rift Valley of Ethiopia as defined by the principal component analyses (Zone 1 = Alem Tena-Langano; Zone 2 = Butajira-Awasa-Abomssa; Zone 3 = Debrezeit-Bofa; Zone 4 = Welenchiti-Miesso).

With the progress of the season and particularly for the two next months (June and July) the prediction skill improved further (Table 3.2, Fig. 3.2d and Fig. 3.2e respectively) as reflected by the highly significant correlation of 0.73, as well as both *HS* and *HSS* ranging between 60-73.3%. In this correlation, Pacific Ocean's April SSTs (14ºS-22ºS and 116ºW-144ºW) account for the June rainfall anomaly, while Atlantic Ocean's May SSTs (4ºS-14ºS and 8ºW-10ºE) for July rainfall. Overall, such a high correlation is the manifestation of the effect that teleconnections could have on the

rainfall of the zone and is evidence that the SSTs forcing is a reasonable choice as a predictor in particular for these two months.

For the remaining two months rainfall (August and September), the cross-validated correlation, HS and HSS showed a reduced range with the corresponding *r* values of 0.49 and 0.57 (Table 3.2, Fig. 3.2f and Fig. 3.2g) respectively. Together with the respective HS and HSS values of 53.3% and 30% for both months it indicates that the influence of June and July SSTs on August-September rainfall performance in Zone 1 is much more than a random occurrence. Indian Ocean's June SST (0°-8°S and 86°E-102°E) is found to influence August rainfall, whereas Pacific Ocean's July SST (8°N-22°S and 104°W-178°W) is found to be related to September rainfall anomaly.

3.4.2.2 Zone 2 (Southwestern, southern and southeastern highlands)

In terms of mean annual rainfall, the higher rainfall penetrates from the mid-eastern side, predominantly along Kulumsa's latitude, where the Arsi highlands receive high rainfall totals (Koricha, 2005, personal communication). In terms of the weather systems, the southern sector of the study area (zone 2) has distinct weather producing systems (strong low-level confluence, which establish across Arsi and Sidama mountainous channels). The cross-validated *r* for observed and forecast March rainfall anomaly using Indian Ocean's January SSTs (10°N-20°N and 150°E-178°E) does not carry operationally useful predictive information (*r* = 0.25 and *HS* of only 33.3%). This could be attributed to the disturbing weather activities that take place frequently due to local factors like the Chilalo mountain range that could possibly weaken the SSTs-rainfall relationship (Table 3.2 and Fig. 3.3a). This in turn renders the skill performance to be poor. The predictability improves however with the progress of the season; for instance, the *r* values for the observed versus predicted rainfall anomaly for April was 0.49, which is significant at 95% probability level. Pacific Ocean SSTs (16°S-36°S and 78°W-112°W) account for this relationship (Table 3.2 and Fig. 3.3b). It is also indicated in Table 3.2 and Fig. 3.3c that for May rainfall (from March Atlantic Ocean's SSTs at 42°N-52°N and 28°W-46°W) all the prediction model performance indicators are in the higher order and significant at 95% probability limit (*r* = 0.70, *HS* = 73.3% and *HSS* = 60%). Except for July, where a meaningful relationship could not be established from May SSTs at all, June, August

Table 3.2 Summary of the skill evaluators used in monthly rainfall predictions for each of the four homogenous rainfall zones, CRV of Ethiopia

Oceans SSTs	Oceanic area		Months and zones			Prediction error quantifiers		
	Latitude	Longitude	Predictor	Predicted	Zone	Correlation Coefficient (r)	Hit Score (HS %)	Hit skill score (HSS %)
Pacific	14°N-26°N	160°W-178°W	January	March	1	0.44*	46.7 [NS]	20 [NS]
Indian	10°N-20°N	150°E-178°E	"	"	2	0.25 [NS]	33.3	-
Pacific	16°N-42°N	134°W-158°W	"	"	3	0.59	60	40
Pacific	14°N-26°N	160°W-178°W	"	"	4	0.60	53.3	30
Pacific	14°S-34°S	80°W-112°W	February	April	1	0.51*	46.7 NS	20 [NS]
Pacific	16oS-36oS	78°W-112°W	"	"	2	0.49*	53.3*	30 NS
Pacific	16°S-36°S	78°W-112°W	"	"	3	0.79	73.3	60
Pacific	16°S-36°S	78°W-112°W	"	"	4	0.72	66.7	50
Atlantic	42°N-52°N	28°W-46°W	March	May	1	0.48*	40 [NS]	20 [NS]
Atlantic	42°N-52°N	28°W-46°W	"	"	2	0.70	73.3	60
Atlantic	42°N-52°N	28°W-46°W	"	"	3	0.49	53.3	30
Atlantic	42°N-52°N	28°W-46°W	"	"	4	0.38	53.3	30
Pacific	14°S-22°S	116°W-144°W	April	June	1	0.73*	66.7*	50*
Pacific	22°S-34°S	132°W-164°W	"	"	2	0.54	53.3	30
Pacific	22°S-34°S	132°W-164°W	"	"	3	0.46	53.3	30
Pacific	14°S-22°S	116°W-144°W	"	"	4	0.65	73.3	60
Atlantic	4°S-14°S	8°W-10°E	May	July	1	0.73*	73.3*	60*
	-	-	"	"	2	-	-	-
Atlantic	42°N-52°N	18°W-42°W	"	"	3	0.40	66.7	50
Atlantic	20°S-32°S	62°E-88°E	"	"	4	0.19	33.3	-
Atlantic	0-8°S	86°E-102°E	June	August	1	0.49	60	40
Atlantic	0-8°S	86°E-102°E	"	"	2	0.60	46.7	20
Pacific	2°S-6°N	112°W-178°W	"	"	3	0.57	53.3	30
Pacific	4°S-4°N	98°W-158°W	"	"	4	0.51	73.3	60
Pacific	8°N-22°S	104°W-178°W	July	September	1	0.57	53.3	30
Pacific Nino 3.4	5°N-5°S	120°E- 170°W	"	"	2	0.77	66.7	50
Pacific	10°N-34°N	124°W-148°W	"	"	3	0.47	66.7	50
Pacific Nino 3.4	5°N-5°S	120°E- 170°W	"	"	4	0.63	73.3	50

and September predictions carry some useful information pertaining to this zone (Table 3.2; Fig. 3.3 d, e, f). For June rainfall anomaly (from Pacific Ocean's 22°S-34°S and 132°W-164°W April SSTs), r (0.54) is significant at 95% probability level, with the corresponding 53.3% & 30% for HS and HSS values. The associated correlation skill reaches significantly higher values of 0.60 for August (from 0°S-8°S and 86°E-102°E Indian Ocean) and for September; r is 0.77 at 95% probability respectively. Both are significant at 95% probability limit. It is important to note that Niño 3.4 region (5°N-5°S and 120°E-170°W) is found to associate with September rainfall performance in this zone (Table 3.2), a relationship that can be monitored and used in a decision support tool for operational farming (chapter 6).

Figure 3.2: Observed and predicted March-September rainfall anomalies for zone 1 (a) March; (b) April; (c) May; (d) June; (e) July; (f) August and (g) September
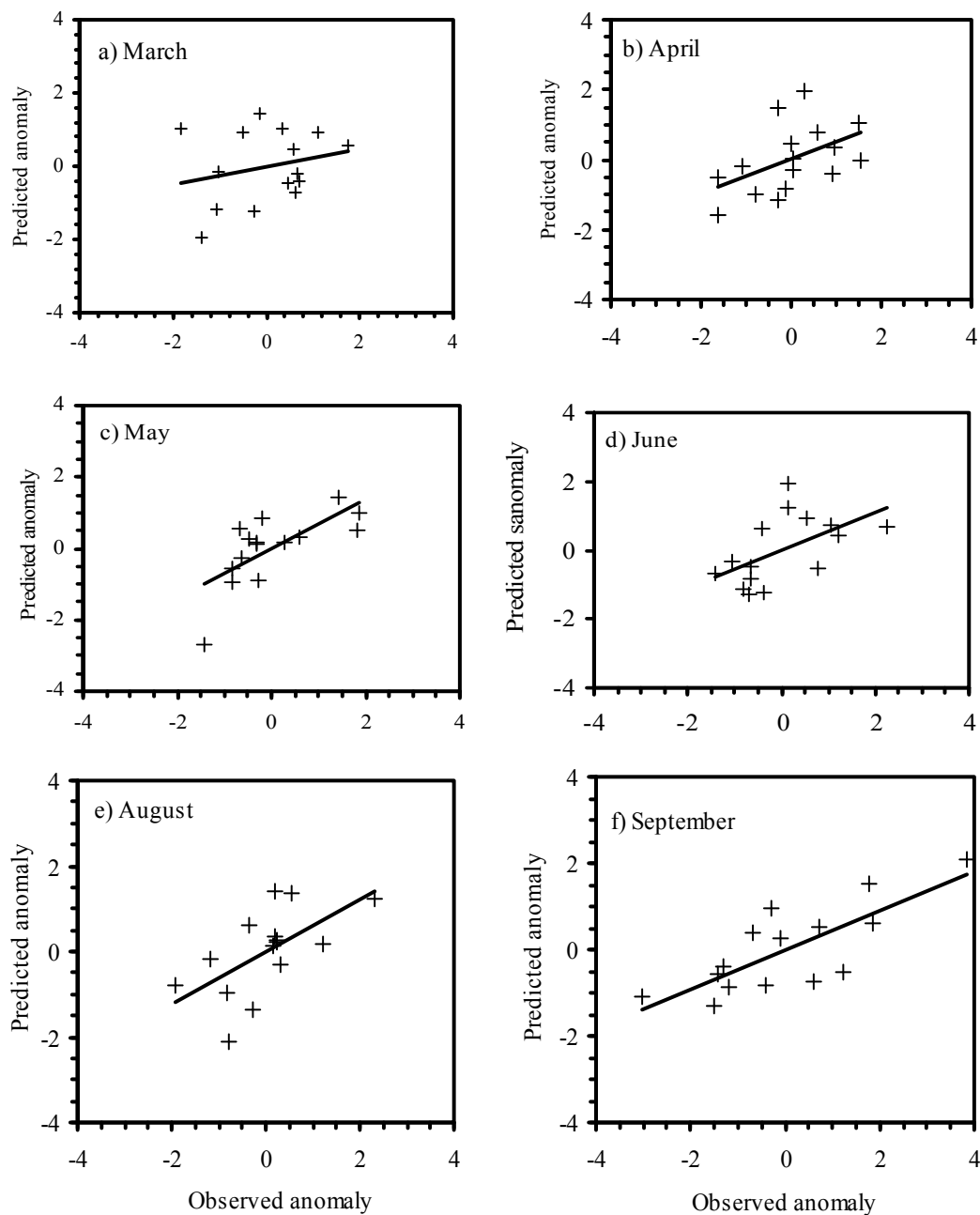
Figure 3.3 Observed and predicted March-September rainfall anomalies in zone 2, CRV of Ethiopia (a) March; (b) April; (c) May; (d) June; (e) August and (f) Septmber. No model for July was obtained

3.4.2.3 Zone 3 (Northwestern)

In terms of weather systems, this middle sector usually receives good rains whenever squall lines develop across Hararghie highlands that propagate westward late in the evening (Koricha, 2005, personal communication). Areas closer to Debre Zeit, Mojo,

Alem Tena and Nazreth are influenced by westerly systems as well as by the presence of surrounding mountains like Mount Ziquala, Mount Boset and Cheffe Donsa.

For zone 3 (Table 3.2 and Fig 3.4a), the prediction skill of the model for the observed and forecast March rainfall anomaly (from Pacific Ocean's 16°N-42°N and 134°W-158°W January SSTs) performance is 0.59 (significant at 95% probability limit) with *HS* of 60% and *HSS* of 40%. In case of April rainfall (from Pacific Ocean's SSTs 16°S-36°S and 78°W-112°W, the same performance indicators are 0.79 for *r*, 73.3% for *HS* and 60% for *HSS*, all of which are highly significant at the 95% confidence limit (Table 3.2 and Fig. 3.4b).

With further advance of the growing season and with the exception of August (*r* = 0.57, *HS* = 53.3, and *HSS* = 30%), declining relationships were observed for the remaining 4 months (May, June, July and September) with the respective *r* values of 0.49, 0.46, 0.40 and 0.47 (Table 3.2 and Fig 3.4c, d, e, f). In fact, the *r* values are significant, except for May, while none of the months revealed significant *HS* and *HSS*. Pacific Ocean SSTs account for the June, August September, while Atlantic Ocean SSTs account for the May and July rainfall performance (Table 3.2). Overall, although the sample sizes were small it was noted that most of the models could provide useful information and contribute in enhancing the local level predictive utility in operational farming.

3.4.2.4 Zone 4 (Welenchiti-Miesso)

The cross-validated correlation for predicted March and April rainfall is in the higher range (*r*=0.60 for March and *r* = 0.72 for April) with the respective *HS* and *HSS* of 53.3-66.7% and 30-40% Table 3.2, Fig. 3.5a and Fig. 3.5b). For this dry zone, the least predictive potential was observed for two months (May and July) with the respective predictive skill (*r* values of 0.38 and 0.19) as indicated in Table 3.2, Fig. 3.5c and Fig. 3.5d. May is the time when the atmospheric circulation rapidly brings rainfall events, while July is the peak period for the same event for most parts of Ethiopia. This low skill may occur because the larger portion of the variability in climate of the zone is caused by synoptic scale disturbances and local factors rather than the influence of teleconnections from the SSTs.
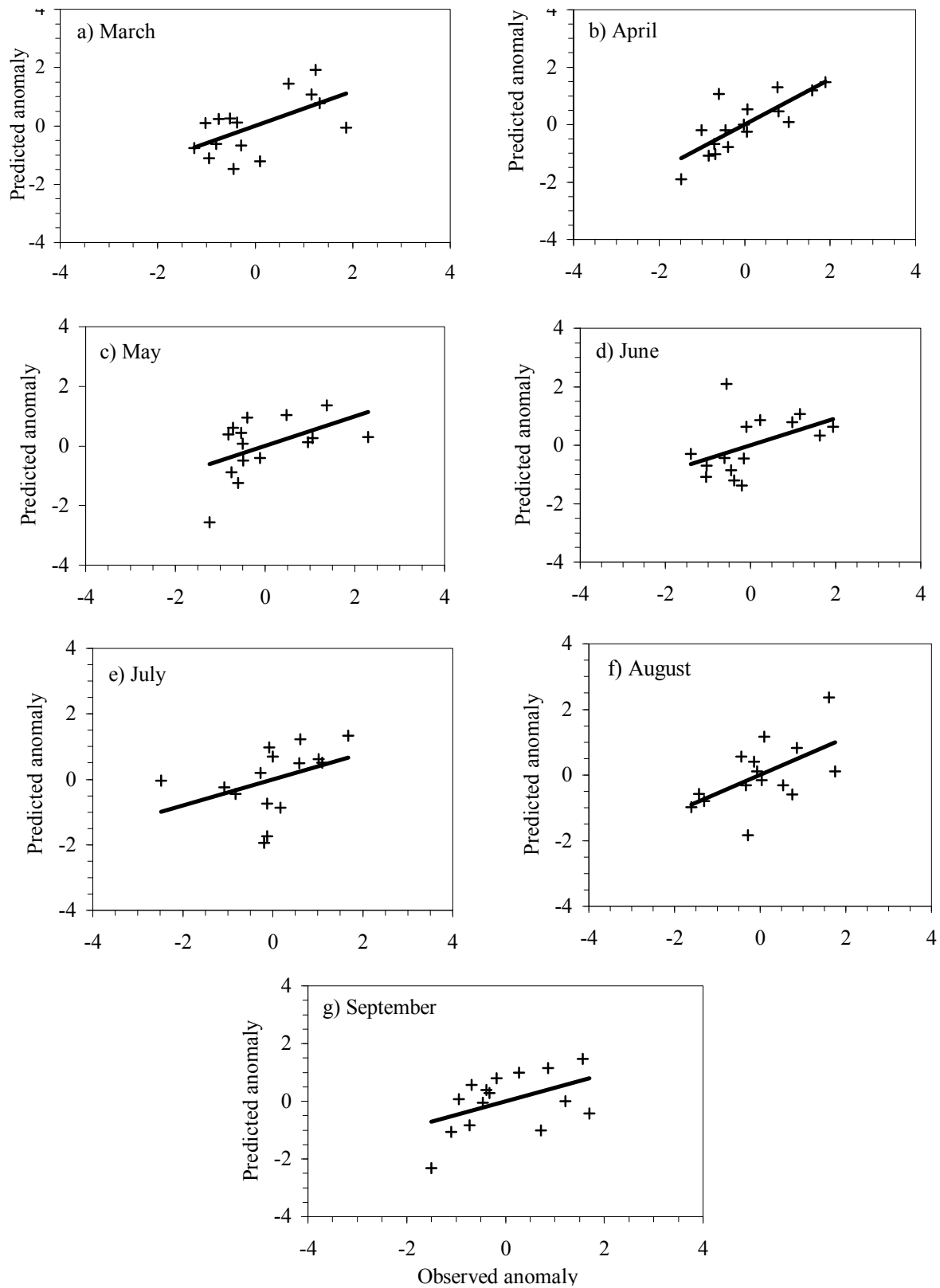
Figure 3.4 Observed and predicted March-September rainfall anomalies in zone 3, CRV of Ethiopia (a) March; (b) April; (c) May; (d) June; (e) August and (f) September. No model for July was obtained

For June (Fig. 3.5d), August (Fig. 3.5f) and September (Fig. 3.5g) rainfall, a reliable skill estimate of the relationship was made. In both cases, the performance indicators were found significantly higher at 95% probability level (*r* ranges 0.51 to 0.65, *HS* is 73.3%, while *HSS* is 60%). Such a relatively better prediction skill implies the usefulness of the models for forecasting rainfall or drought of the respective months in the zone (Table 3.2). It is also important to note that Niño 3.4 (5ºN-5ºS and 120ºE-170ºW) has a strong association (*r* = 0.63) with the September rainfall anomaly in the zone.

In comparison, rainfall of most months and zones are related to the common Pacific Ocean SSTs: for instance, March rainfall anomalies of zone 1 and 4 is related to the 14ºN-26ºN and 160ºW-178ºW SSTs of the Pacific region. April rainfall of all the zones is associated with the SSTs of the 14ºS to 36ºS and 78ºW to 112ºW of the same ocean, whereas May rainfall of all zones is associated with the 42ºN-52ºN and 28ºW-46ºW SSTs of the Atlantic Ocean. August rainfall of zone 1 and 2 is more related to the 0º-8ºS and 86ºE to 102ºE SSTs of the same Ocean. On the other hand, June rainfall anomalies of all the zones are related to Pacific Ocean's SSTs, while September rainfall of zone 2 and 4 is related to Nino3.4. The rest of the months and zones are related individually either to the Pacific, Atlantic or Indian Ocean SSTs. This information helps for monitoring and use of the SSTs information in seasonal rainfall prediction.

3.5 Conclusion

Given the persistence of high rainfall variability, an attempt was made to cluster the stations into four homogenous rainfall zones. Temporally, March rainfall is the least predictable (*r* = 0.25) for zone 2. Moreover, a model that can capture July rainfall pattern was not obtained at all for the same. Zone 2 is the one with a relatively early onset date (Chapter 2) and rainfed sorghum water requirement (chapter 4) could be reasonably satisfied even under a March planting date. Except for zone 1, where *r* was 0.73, July rainfall prediction skill is poor for the rest of the zones, particularly for zone 4 (r = 0.19), followed by May for the same zone (*r* = 0.38). The time series rainfall prediction model constructed for May at Miesso (the station representing zone 4) in chapter 2 (see Table 2.2, equation 2.14) revealed similar weak performance (r^2 = 0.62) as compared to the other months. On the other hand, June and July rainfall patterns are
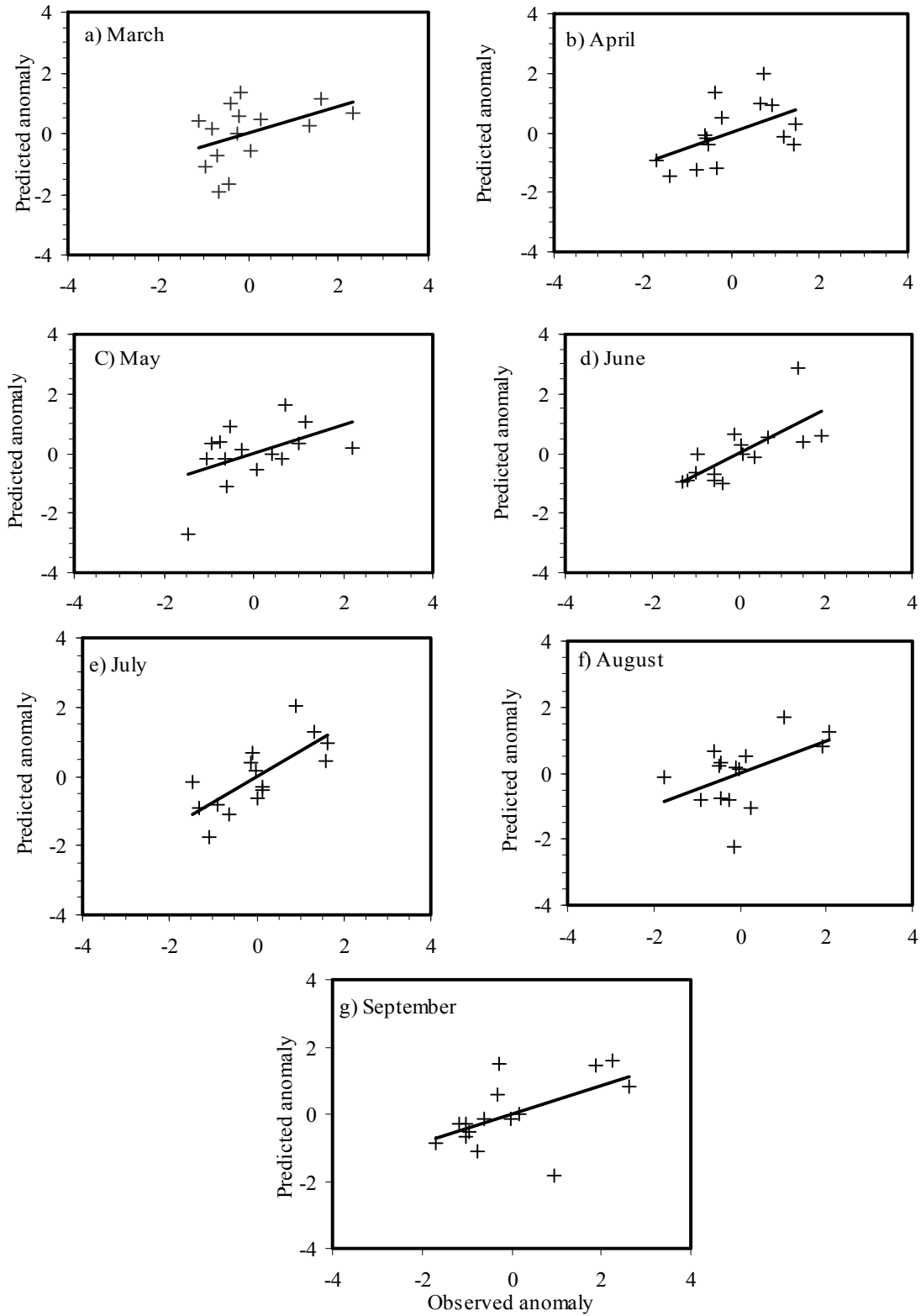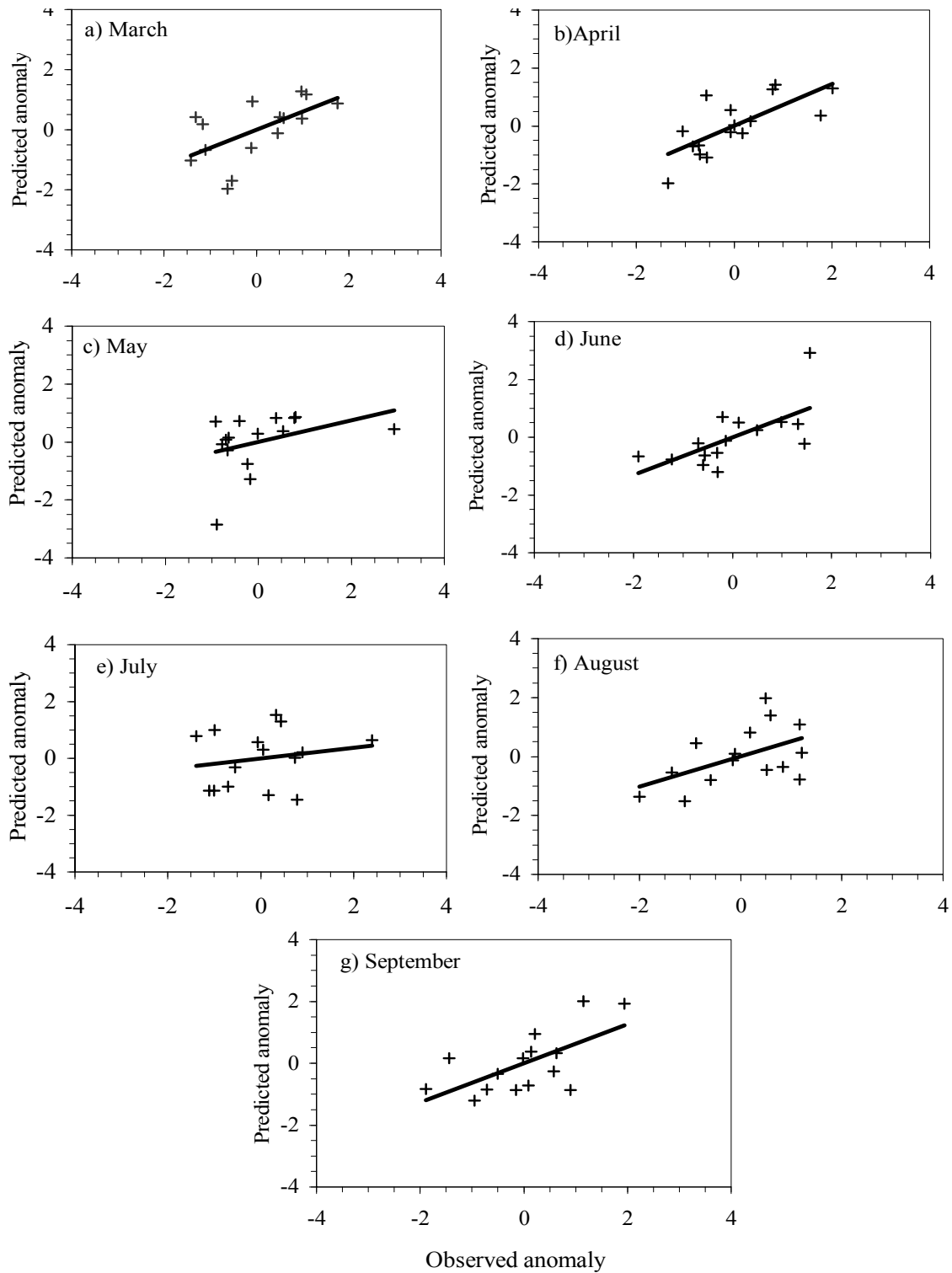
Figure 3.5 Observed and predicted March-September rainfall anomalies in zone 4, CRV of Ethiopia (a) March; (b) April; (c) May; (d) June; (e) July; (f) August and (g) September

.

the most predictable for zone 1($r = 0.73$). In case of zone 2, months including May ($r = 0.70$), August ($r = 0.54$) and September ($r = 0.77$) have highly predictable rainfall anomaly patterns, while for zone 3 and zone 4 the April rainfall anomaly is highly predictable ($r= 0.79$ for zone 3 and 0.72 for zone 4).

Forecasting rainfall in a terrain of complex topography poses serious difficulties particularly over tropical regions (Tapp and McNamara, 1989). A major impediment to predictive skill is derived from the primarily convective nature of tropical rainfall. The difficulties increase during the wet season when extreme rainfall events regularly occur on a localized basis (e.g. dry spell in middle of wet season). It is also recognized that rainfall prediction involving smaller scale convective processes presents a far greater prediction problem than those explained on a synoptic scale (Olsen *et al.,* 1995).

Therefore, a perfect model that can fully capture variability in the midst of such chaos cannot be easily achieved. Accordingly, most of the skill measures produced using CPT hindcast technique are inevitably not in the high range. These lower hindcast indicators can also be explained by the fact that the ocean observing systems have undergone fundamental improvements with time, such that the discrepancy can be wide when explaining observed values under different time scales (Barnston and Smith, 1996). Local factors like the windward or leeward facing mountains including Chilalo and Chercher highlands, Mount Fantale, Mount Boset and Mount Ziquala also pose significant influence on regional atmospheric circulation pattern.

Apart from the above difficulties, a substantial understanding of climatic determinants of CRV's March-September rainfall has resulted from this analysis. This study used historical rainfall records from 25 weather stations, with a concentration in the center of the area (Fig 3.1). The study suggests that, with an increased observing network and data availability, useful and operational rainfall prediction could be achieved for such a smaller spatial unit and with a shorter lead prediction time. To begin with, areas around Miesso, Abomssa and Arsi Negele, which currently produce sorghum on a significant scale, could be a communication target of the prediction information. Other areas could be targeted in a medium term plan to help them establish actual sorghum production systems.

Generally, the statistical relationships established here are intended as a good starting point towards the long-term goal of integrating the underlying ocean-atmosphere interaction into the Ethiopian agricultural research and development arena. Getting acquainted with the notion of bringing the prediction information into a common usage, together with the further assumption that the trend does not exist much, at least within a prediction period, has helped in addressing this problem. It is believed that, despite the above listed time-space difficulties, most of the models carry useful information that could be translated into farm level decision making and therefore can form part of a regional prediction formula to strengthen localized technology transfer and information exchange efforts.

Since such seasonal forecasts are relatively new products and released to a new user group outside the traditional meteorology community, the differential effects to be brought by this approach are expected to be higher at least in the long-term. However, these models need to be verified and improved when a wider dataset becomes available in order to strengthen the knowledge base in this field. Further investigation for evidence of the relationships between the CRV seasonal rainfall and other predictor variables, like Southern Oscillation Index (SOI), outgoing long wave radiation (OLR), Geo-potential height (GPh) Quasi Biennial Oscillation (QBO) and Madden Julian Oscillation (MJO), which are supposed to have strong physical correlation with the tropical rainfall systems, should be pursued.

Studies pertaining to the local factors affecting the region's rainfall pattern, mainly topographical features and climate change aspects, should also receive due attention. This can increase the effort to enhance the economic value of weather forecasts together with the improvement in both the predictive products and user oriented services. The use of the newly emerging technologies such as satellite images for rainfall and resources estimation should also receive attention. In the medium term, this should involve monitoring the economic value of the seasonal rainfall forecast in relation to operational farming in the study area.

Chapter 4

Water Requirement Satisfaction for Grain Sorghum Production

4.1 Introduction

4.1.1 Climate variability and cropping

Climate variability is an unavoidable aspect of rainfed farming all over the world. However, it is not a unique problem that cannot be managed at least partially or may even be tuned to ones advantage, while at the same time being difficult to solve completely (Hayman, 2001). In terms of crop production therefore, it is not rainfall variability per se that poses a risk, but the adverse consequences. Presently, agriculture is in acute competition for water with the other economic sectors. Accordingly, agricultural scientists have been focusing on a variety of problems and prospects associated with the role of water in crop production, especially over the past century (Stewart and Hash, 1982).

One of the outcomes of the earliest crop-water related investigations was the term "transpiration ratio" which was defined as the quotient of the amount of water transpired during crop growth and the dry mass of plants at maturity (De Wit, 1958). The classical works on this aspect are to Briggs and Shantz (1917), Kisselebach (1916) and Dilman (1931) who concluded that water requirement of plants is proportional to a water loss from the free water surface or reference evaporation (Eo). DeWit (1958) analyzed the findings of the early investigations and further identified factors that determine transpiration and yield under field conditions and concluded that the relationship between mass of yield (dry matter, Y) and transpiration (T) for arid and semi-arid regions of the world is as follows:

$$Y = m \, (T/Eo)$$

where m = coefficient accounting for integration of factors such as type of crops (and cultivars), availability of water and weather conditions not accounted for by Eo.

Recently, research aimed at illuminating the relationship between yield and water use has often been guided implicitly by various notions of what constitutes a "required level" of water use. Three general definitions can be identified. Firstly, the work of agronomists and other production oriented scientists frequently focuses on the goal of establishing the level of water that is "optimum" to achieve maximum yield per unit area (Bidinger, 1978) which assumes that water does not become a production-limiting factor. The second view concerns maximum water use efficiency. Maximum water use efficiency (WUE) exists when the crop yield per unit of water input is maximized, which at plant level is a transpiration efficiency (dry weight change/ transpiration), at crop field level (yield/water use) and at farm level (production/rainfall plus irrigation) (Hayman, 2001). The third definition is advanced by economists who argue that for water to be used efficiently, it should be applied up to the point where the price of the last unit of water applied (marginal cost) is equal to the marginal revenue obtained because of its application (Botha *et al.*, 2000).

The concept of crop water requirements has emerged simultaneously with the above views that established a strong case for the hypothesis that the relationship between crop yield and evapotranspiration (ET) is linear with varied intercepts and slopes for various crops and localities (De Wit, 1958; Dorenboos and Kassam, 1979; Bucks *et al.,* 1985; Sharma *et al.,* 1990; Sharatt, 1994). The other group of scientists (Grimes *et al.,* 1969; Musick *et al.,* 1976; Stewart and Hagan, 1973; Hargreaves, 1975; Follett *et al.,* 1978; Kumar and Khepar, 1980; Sharma and Neto, 1986; Stone and Nofzicer, 1993) maintained that the functional relation between yield and seasonal irrigation depth is curvilinear, that could be expressed in the form of a quadratic, square root, parabolic and Mitscherlich function.

The resulting scientific works have yielded many important insights into the relationship between crop plants and water. Virtually all of these insights have contributed towards the crucial understanding of the role of water in irrigated agriculture. Despite the quite impressive availability of knowledge and experience about

the water-agriculture relationship, the works done for rainfed cropping, particularly in east Africa, is limited (Dancette, 1978). Therefore, the study of crop water requirements, which takes account of soil, crop and climatic parameters such as solar radiation, temperature, relative humidity and wind speed is becoming a widely applicable area in operational farming.

4.1.2 Definition of crop water requirement

Crop water requirement is defined as the amount of water that is required to replenish the water lost through evaptranspiration (ET) processes. The cumulative seasonal values of the two terms (evapotranspiration and crop water requirement) are therefore identical except of opposite sign. In other words, knowing the amount of ET per unit time and space equals the amount of water that crop requires to grow and develop successfully. In most cases, crop water requirement studies need the daily or seasonal water balance information which should take account of the soil water stored from the foregoing season at planting time, followed by sequences of rainfall throughout the season (Bidinger, 1978, Ritchie, 1991).

In this study, determination of ET has followed a standard procedure, using the FAO-Penman-Monteith equation (Allen *et al.,* 1998), which was developed for irrigated crops. However, as the principle involved is relevant to any soil-plant-atmosphere continuum (SPAC) the same procedure was employed for studying rain-fed grain sorghum water requirement for various planting dates in the CRV of Ethiopia. This presumes that the crop water requirement could be satisfied through either irrigation or other modifications like *in situ* or *ex situ* water harvesting to increase the amount of crop extractable soil water. Other crop management regimes include those that reduce the water requirements such as adjusting planting date or using varieties with lower water demand (Williams, *et al.,* 1991).

According to Smika (1990), to benefit from dryland farming one must understand the techniques of capturing and storage of soil water to cope with times of water deficit, which is universal in arid regions of the world. One popular misconception related to dryland farming involves the impossibility of making water available for farming under these conditions, as there is no control over the weather. Rimmington and Connor

(1991) asserted that maximum yields in a water-limited environment could come from improving the water use efficiency. For instance, dryland farming is responsible for changing what was named on maps as the Great American Desert in U.S.A to the Great Plains (Hayman, 2001). It was also largely responsible for the massive wind erosion of the 'dirty thirties' in U.S.A, where the subsequent stubble mulching and zero till emerged from dust mulching (Hayman, 2001).

4.1.3 Crop water requirement research in Ethiopian dryland farming

In Ethiopian dryland farming, research on improved soil water management practices has been one of the scientific focuses over the last few decades (Reddy and Georgis, 1994). 'Tied ridge' is a proven technology in conserving *in situ* soil water and increasing the depth of wet soil (Reddy and Georgis, 1994). The postulated premise is grounded on the fact that ridges linked at certain intervals increases the capture of rainwater in the field through reducing runoff loss from certain soil types.

The stored soil water due to tie ridging, seasonal rainfall amounts and the observed total biomass was linearly and positively related to yield during poor rain seasons (Reddy and Georgis, 1994, Mesfin, 2004) while this technology could negatively influence stand establishment during the heavy storms, as explained by water logging and the associated lack of aeration. Under Ethiopian conditions, the progress in enhancing soil water use by crop plants through alternative techniques of water harvesting is limited, as improved soil water management techniques have not been studied in detail. This in turn constrained the optimal use of the available water for crop yield optimisation under Ethiopian semi-arid regions (Kibret, 2003).

Sorghum, 'the camel of the crop world' is the major food crop of the rural community in semi arid regions of the world (Borrell *et al.*, 2003). In Ethiopia, sorghum production covers about one million hectare and it contributes about 20% of the annual food production (EARO, 2000). As sorghum is mostly grown with sub-optimal inputs, the productivity of this crop is low and its potential is usually not reached. The national average productivity of sorghum is of the order of 1.2 t ha^{-1}. In the Central Rift Valley, grain sorghum production is limited to the Asebot-Miesso plain, Abomssa, Arsi Negele and small areas of Iteya-Gonde valley.

Except for heavy losses from *Quella quella,* the region should be efficient for sorghum production. Therefore, in view of its actual and potential benefits to national food security, especially in drought prone areas, water requirement information should be made available to promote successful sorghum cropping. This information could help in changing or modifying one or more key crop and soil management decisions at various growth stages. The sequential aim to be achieved is multi-faceted: (1) to ensure food security, (2) to produce more food, (3) to increase crop productivity, and (4) to improve sustainability through maintaining production, despite natural variability in climate.

A critical point to be raised is that rainfed farmers, researchers and decision makers in Ethiopia are limited by lack of crop water requirement information and procedures for using it to make choices related to successful cropping. The belief however is that there exists sufficient knowledge to determine the water requirements for any crop during all growth stages at any location. This information can be used to effectively evaluate the gap and promote alternate crop and soil water management techniques that can meet crop water needs when the forecast probability is high for any of the probabilities. For agro-meteorology as a discipline, it appears to be a sensible strategy to dwell on models for handling risk and decision analyses related to soil, crop and climate variability (Hayman, 2001).

4.1.4 Water Requirement Satisfaction Index (WRSI)

The water requirement satisfaction index (WRSI) is calculated using a water stress index calculation scheme that helps determining whether an agricultural season has performed well and a given crop has had sufficient water to achieve potential yield (Hoefsloot, 2004). WRSI was mainly developed for monitoring seasonal crop performance through its growth and development to final yield prediction well in advance. WRSI indicates the extent to which the water requirements of a given crop have been satisfied in a cumulative way at any growth stage (Mukhala, 2002). FAO studies (Doorenbos and Pruitt, 1977) have shown that WRSI can be meaningfully related to crop production in semi-arid regions, using a linear-yield reduction function specific to a crop. More recently Senay *et al.* (2001) have reported a GIS-based WRSI in northwestern Ethiopia, while Verdin and Klaver (2001) have also demonstrated a

regional implementation of WRSI in a grid-cell based modelling environment and found useful results. Awoke (1991) also studied WRSI for maize production in central Ethiopia and found useful relationships between maize yield and WRSI.

A number of inputs are required to calculate WRSI over the course of a growing season. These include the start of the growing season (SOS), end of the growing season and length of the growing season (LGS). Among the soil factors, water holding capacity and water balance are essential. Meteorological parameters include rainfall and potential evapotranspiration, while crop coefficients (Kc) that define the water requirements of a specific crop at the different growth stages are also important. WRSI starts with a value of 100% at SOS, while water deficits and excesses above the soil water holding capacity have a negative impact on the crop performance and therefore decrease the value in proportion to the degree of water deficit or water excess (Mukhala, 2002).

4.1.5 Water Production Function (WPF)

In order to apply any water based yield optimisation technique, an understanding of the functional form of the relationship between yield and some measure of water use by crop plants, is necessary. The information is usually obtained by calculations using different climate elements (Stewart, 1972, Stewart *et al.,* 1974). Regression analyses of field experiments in which water or its surrogates, including WRSI, are taken as predictor variables is one way of integrating such relations. This functional relationship is called crop-water production function (WPF) (Monteith and Virmani, 1991).

Crop water production functions can be used to estimate the impacts on the yield expected from insufficient rainfall (Stewart, 1972; Stewart *et al.,* and Hagan 1973).Dorenboos and Kassam, (1979) and Abate (1994) have also used the concept of yield reduction to classify their study areas into suitable sorghum and maize production zones as given in the following equation.

$$\left(1 - Ya/Ym\right) = KY\left(1 - ETa/ETm\right)$$

(4.1)

Where:
Ya = actual yield
Ym = maximum yield
KY = yield response factor
ETa = actual evapotranspiration

$$ETm = \text{maximum evapotranspiration}$$

In rainfed cropping, water production function analyses have been widely used in dealing with the issue of physiology and agronomics of crop-water relations. Moreover, it is useful in modeling the yield response of crops to different ET values and maximizing the knowledge of how to optimize the 'desirable level of water use' under a variable climate. The specific objectives of this chapter are:

a) To map tempo-spatial patterns of the seasonal total sorghum crop water requirement satisfaction index (WRSI) for various sorghum maturity groups under different planting dates in Central Rift Valley of Ethiopia.

b) To develop a long-term yield prediction equation from experimental yields of two maturity group sorghum cultivars grown at Miesso, Melkassa and Arsi Negele, under experimental conditions.

4.2 Materials and Methods

4.2.1 Seasonal crop water requirement

The seasonal crop water requirement was calculated for 5 possible planting dates (March, April, May, June and July) combined with the 4 possible cultivars maturity groups (90 day, 120 day, 150 day and 180-day duration). Accordingly, there are 5 chances to grow a 90-day cultivar, 4 in case of 120-day cultivar, 3 for a 150-day cultivar and 2 for a 180-day cultivar, all together forming 14 possible concurrent growing seasons. The formula for the crop water requirement (CWR) computation is :-

$$\text{CWR} = \text{Seasonal } ETc = \sum_{d=1}^{d=n..} Kc * ETo \qquad (4.2)$$

Where:
CWR = Crop water requirement for the season (mm season^{-1})
ETc = Total season crop water requirement (mm season^{-1})
ETo = daily reference crop evapotranspiration (mm day^{-1})
Kc = Crop water requirement coefficient (dimensionless)
d=1---d=n = day 1 to last day at the end of the season.

ETo is defined as the water loss from the hypothetical extensive surface of green, well-watered, actively growing grass of 0.12 m height with a fixed surface resistance of 70 s m-1 and albedo of 0.23 (Allen et al., 1998). ETo represents the evaporative demand of

the atmosphere and as such, it is independent of the crop type, crop development and soil as well as management practices. Being a climatic parameter, ETo values can be calculated either from weather data or can be obtained from lysimeter experiments, or by aerodynamic or by energy balance measurements over grass (Kaihla, 1983, Doorenbos and Pruitt, 1977).

In this study, the grass ETo was computed using the observed daily historical climatic data namely minimum and maximum temperature, relative humidity and wind speed at 2 meter height. Alfalfa is used as a reference grass, because of the many aerodynamic and surface resistance studies done on it. The solar radiation was estimated from the minimum and maximum temperature following a series of standard procedures given in a REF-ET program (Allen, 2002).

The generic formula to compute ETo is

$$\text{ETo} = \frac{0.408\,\Delta(Rn - G)}{\Delta + \gamma(1 + 0.34u_2)} + \frac{\gamma u_2(e_s - e_a)(900/(T + 273))}{\Delta + \gamma(1 + 0.34u_2)} \tag{4.3}$$

Where

ETo = Reference evapotranspiration (mm d^{-1})
Δ = slope of vapour pressure curve at mean air temperature (kPa °C^{-1})
Rn = net radiation at the crop surface (MJ m^{-2} day^{-1})
G = soil heat flux density (MJ m^{-2} day^{-1})
γ = psychrometric constant (kPa °C$^{-1)}$
T = mean daily air temperature at 2 m height (°C)
u_2 = wind speed at 2 m height (m s^{-1})
e_s = saturation vapour pressure (kPa)
e_a = actual vapour pressure (kPa)
$e_s - e_a$ = saturation vapour pressure deficit (kPa)

Crop evapotranspiration (ETc) is calculated from ETo and Kc (crop coefficient) under standard conditions that represent the water loss from a disease free, well fertilized crop, grown in a large field which,under optimum soil water conditions, achieves full production potential under a given climatic condition (Allen *et al.*, 1998). For practical purposes, ETc can then be considered as a maximum crop water requirement, which is determined by the genetic code, and to which the crop grown under water stress could be compared (Bidinger, 1978).

The grass ETo and crop ET (ETc) are integrated through the single crop water requirement coefficient (Kc). In the single crop coefficient approach, ETc is calculated by

multiplying ETo by Kc. Since most of the effects of weather conditions are incorporated into the ETo estimate, and ETo is an index of climatic demand, Kc varies predominately with the specific crop characteristics and only to a limited extent with climate variations. The Kc integrates the effects of characteristics that distinguish a typical field crop from the reference grass, which has a constant appearance and complete ground cover. Consequently, different crops would have different Kc values. Moreover, the changing characteristics of the crop growth through the growing season as well as the changes in evaporation from the soil influence the Kc.

Accordingly, ETc and therefore seasonal crop water requirement was computed, which was used in the computation of the crop water requirement satisfaction index (WRSI). The Kc values and the proportionate duration of each of the growth stages of various maturity categories in sorghum cultivars in this study are summarized in Table 4.1.

Table 4.1 Summary of Kc values and duration of stages (number of days) for various sorghum cultivars with different length of growing season

Sorghum Varietal Group	Duration of the growth stage (days)			
	Initial stage (K_c= 0.30)	Developmental stage (K_c=0.3-1.05)	Grain filling stage (K_c = 1.05)	Late season stage (K_c = 0.55)
90-day	15	25	35	15
120-day	20	35	45	20
150-day	25	45	55	25
180-day	30	55	65	30

Source: Allen *et al*., (1998), Doorenbos and Kassam (1979).

Total seasonal WRSI was then computed from the corresponding crop water requirement values and soil water balance for various grain sorghum cultivars. In this study, a value of 100 mm per meter depth of available soil water (PAW) is used. WRSI for a season is calculated as the ratio between total seasonal water deficit or excess, and the seasonal crop water requirement (CWR). For the excess rainfall, WRSI decreases by 3% for every 100 mm excess water (Mukhala, 2002).

The soil water balance is calculated through a simple mass balance equation where the water content is monitored in a bucket defined by the water holding capacity of the specific soil. Therefore, if the seasonal rainfall total exceeds the crop water requirement,

any excess amount would be retained by the soil. On the other hand, any amount of rainfall above the soil water holding capacity would be considered superfluous and therefore poses negative influence on the crop performance by 3% for each 100 mm of excess water. Since the purpose of these analyses is to establish a gross feature of the potential of rainfall behavior for cropping in the study area, losses from surface runoff and deep percolation are not taken into account.

This analysis supposes that if the index falls below 50%, essentially there is a total crop failure *i.e.* it is unsuitable for crop production during that particular season. The WRSI values from 51 to 75% are considered as moderately suitable, while WRSI values larger than 75% indicates adequately available water for a sorghum grown at a given location during that particular season.

4.2.2 WRSI by growth stages and water production function

In addition to the total seasonal WRSI computed for the different seasons as discussed above, a more detailed WRSIs were also studied across a series of sorghum growth stages under contrasting environments in the study area where sorghum variety trials have been regularly conducted. These are Miesso and Melkassa for the 120-day cultivars (76-T1#23 and Gambella-1107) under inadequate rainfall conditions and Arsi Negele for the 180-day cultivar (ETS-2752) that represents adequate rainfall conditions. The growth stages considered are initial, developmental, mid-season and late part of the growing season, as defined for Kc.

The sorghum water production function (WPF) was also computed for the same stations and sorghum cultivars using long-term climatic data and measured historical/experimental grain yield productivity (kg ha^{-1}) data for the above listed released sorghum cultivars. The historical yield data of these cultivars were partly obtained from the published reports and partly from the data archive of the sorghum-breeding program at Melkassa Agricultural Research Centre (MARC).

The weighted average WRSI from the 4 growth stages of the 120 day maturity cultivar grown during June-September period was used as an independent variable for computing sorghum-water production function at Miesso and Melkassa. In the case of

Arsi Negele, the same procedure was used for the 180-day cultivar grown during May to October season.

In the computation of the WPF, the weighted average WRSI values were used instead of using WRSI of the individual growth stage, on the principle ground that the final yield is a function of not only WRSI of a given growth stage, but is a result of the combined contribution from each of the growth stages. In fact, WRSI from any growth stages could largely influence the final yield expression. Under this condition, that particular growth stage would be given more weight as compared to the WRSI from the rest of the growth stages.

In finding the best equation, 11 logical alternatives were attempted for each station (for details see appendices A, B and C). Then, the one having the best linear association with the grain yield of the respective cultivars and locations was considered for detailed analyses for each station. Table 4.2 presents basic information pertaining to the two sorghum cultivars used in the water production function analyses.

Table 4.2 Summary of the sorghum cultivars used for water production function construction for different locations (Data source: MARC)

Location	Sorghum cultivar	Maturity category	Historical yield records	Growing season
Melkassa	76-T1#23	120-day	16 years (1983-2000)	June-September
Miesso	76-T1#23	120-day	8 years (1990-2000)	June-September
Arsi Negele	ETS-2752	180-day	10 years (1988-2000)	May-October

4.3 Results and Discussion

The following sections present detail accounts of the results and discussion pertaining to the sorghum water requirement satisfaction and water production functions. The figures provide the schematic view of spatial differences and similarities of varying maturity groups for grain sorghum water requirement satisfaction computed for early March to September in the study area. From the maps, one can note widely differing sequences of the spatial scenario of water availability in sorghum fields and the amounts of water required over the 7 month period.

4.3.1 WRSI and various grain sorghum cultivars

4.3.1.1 WRSI for a 90-day cultivar

The analyses show that it is hard to meet the 75% level of the water required for a 90-day cultivar planted in March (Fig. 4.1a) with the exception in the extreme southern part of the Central Rift Valley. For the southeastern parts (like Kulumsa and Abomsa areas) about 60 % of the sorghum water requirement is met during this same season. Fig. 4.1b shows the increased spatial coverage of the April to June rainfall across Langano and Ziway from the southern direction along the northwestern borders until Debre Zeit. During April-June period, these areas experience a WRSI value of the order of 59 to 64% for the same 90-day sorghum.

For a 90-day sorghum cultivar planted during May, both the southern (except Adami Tulu) and central parts, as well as Kulumsa areas in the south eastern meet 75 to 100 % of the sorghum water requirement (Fig. 4.1c). However, the northeastern part of the study area (zone 4) including areas extending until Miesso (extreme northeast) still remains under a risky situation with WRSI less than 50%. For June and July planting dates, approximately half the Central Rift Valley gets rainfall giving 75 to 100% WRSI. This shows that the cultivation of a 90-day sorghum cultivar can be practiced during these two concurrent seasons (Fig. 4.1d and Fig. 4.1e). During these two seasons, the southern, western and central parts of the study area provide 94-100% of the 90-day sorghum water requirements. In the northeast, Miesso receives 83% WRSI for JJA and 98% for JAS seasons. The rest of the eastern part in zone 4 (Metehara, Werer, and Nura Era) cannot support growing a 90-day sorghum under rainfed cropping.

From comparisons, JJA and JAS seasons are found more conducive to growing a 90-day sorghum over the entire study area, except sections of zone 4 (Metehara, Werer, and Nura Era). March planting is least preferred, except for areas like Awasa, Arsi Negele and to a certain extent for Abomssa and Kulumssa. April and May planting are moderately suitable for planting a 90-day sorghum in the southern, southeastern and central parts of the study area.
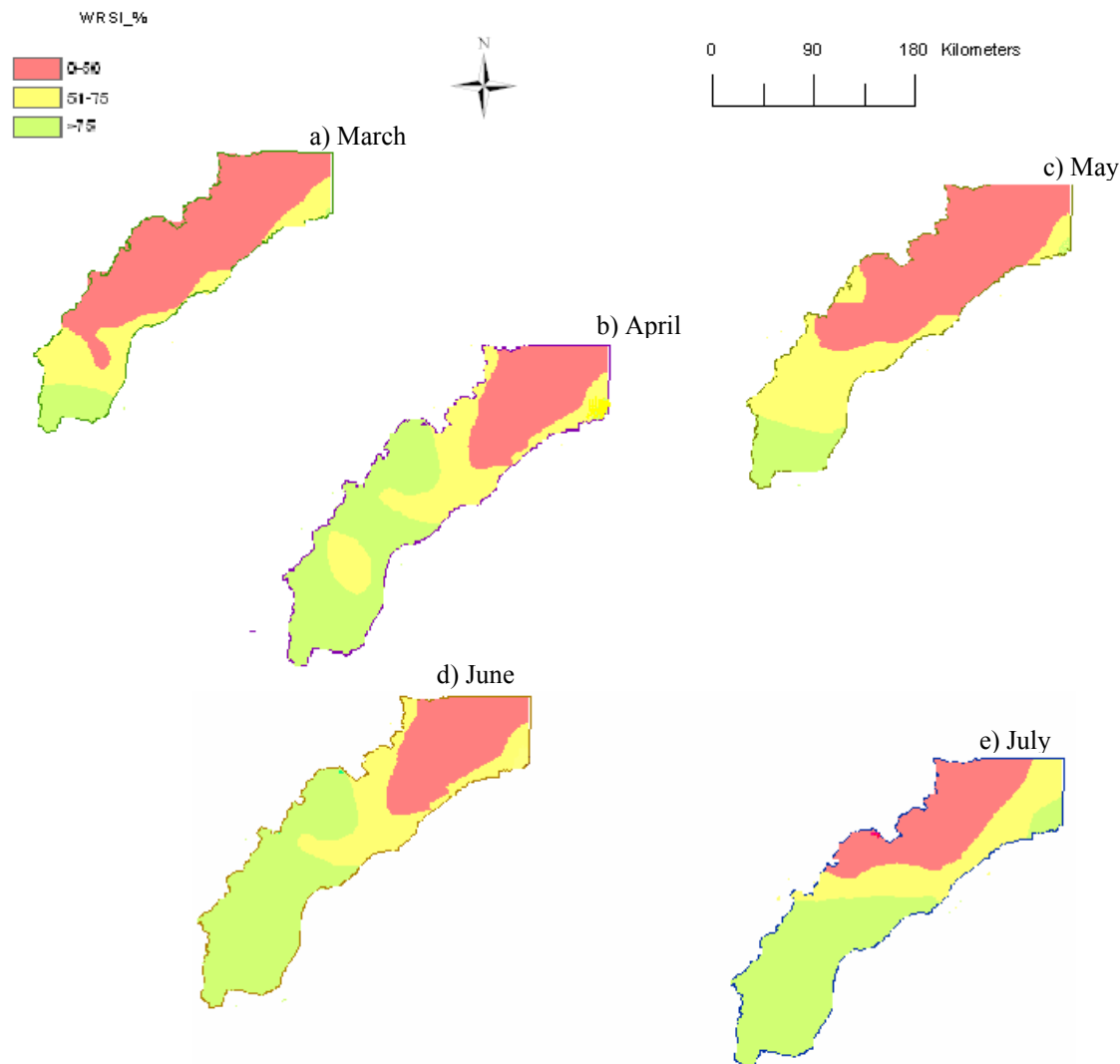
Figure 4.1 Seasonal crop Water Requirement Satisfaction Index (WRSI) for a 90-day grain sorghum cultivar grown under CRV climate, Ethiopia (a) March-May; (b) April-June; (c) May-July; (d) June-August and (e) July-September

4.3.1.2 WRSI for a 120-day cultivar

The WRSI for a 120-day sorghum planted between March and June period shows that a larger area has less than 50% indices (Fig 4.2a). For April, May and June planting dates this area is shown to be smaller and limited to the northeastern section (Fig. 4.2b.and Fig. 4.2c). As indicated in Fig. 4.2a, the WRSI performance for the March-June season is satisfactory in the South at Arsi Negele and Awasa (80 to 100%), while moderate at Abomsa, Kulumsa and Ziway (58 to 60%). For Langano, this value is 54%; essentially sorghum would not experience a total failure every year. The WRSI value for Miesso is

49.1%, indicating a high chance of total failure for a 120-day sorghum grown under rainfed. Over the rest of the study area, March-June season rain cannot ensure comfortable growth and development of a 120-day sorghum.

The degree of WRSI for a 120-day sorghum during the April-July season (Fig. 4.2b) shows that Awassa, Arsi Negele, Abomsa, Kulumsa, Debre Zeit and Mojo areas ensures a WRSI value of above 75%. Areas like Langano, Adami Tulu and Ziway from the southern part receive a WRSI value between 63% and 73%. The central parts, Alem Tena, Dera, Melkassa, Nazreth, Wenji and Koka areas maintain WRSI values ranging from 57 to 73%. This shows in general that much of the CRV would be able to support growing a 120-day sorghum cultivar.

The third scenario examines the possibility of growing a 120-day sorghum during the May-August season (Fig. 4.2c). During this season, almost all of the southern, southeastern, central and western part maintains WRSI value of greater than 75%. From the economic production point of view, the northeastern part does not provide useful rainfall amount, except Miesso, which meets 68% WRSI. The final possible season for growing a 120-day sorghum is the June-September period (Fig. 4.2d), where except for the northeastern part (excluding Miesso-Assebot plain) the whole area receives adequate rainfall, so that growers can generally use a 120-day sorghum during this season.

From comparison of different planting dates, March planting date is difficult for a 120-day cultivar almost all over the study area, except for the southern, southwestern and southeastern, where water requirement could be moderately met. In April, there is a gradual enhancement of the rainfall performance towards the central and northwestern. May and June are almost equally suitable all over the area, except the northeastern.
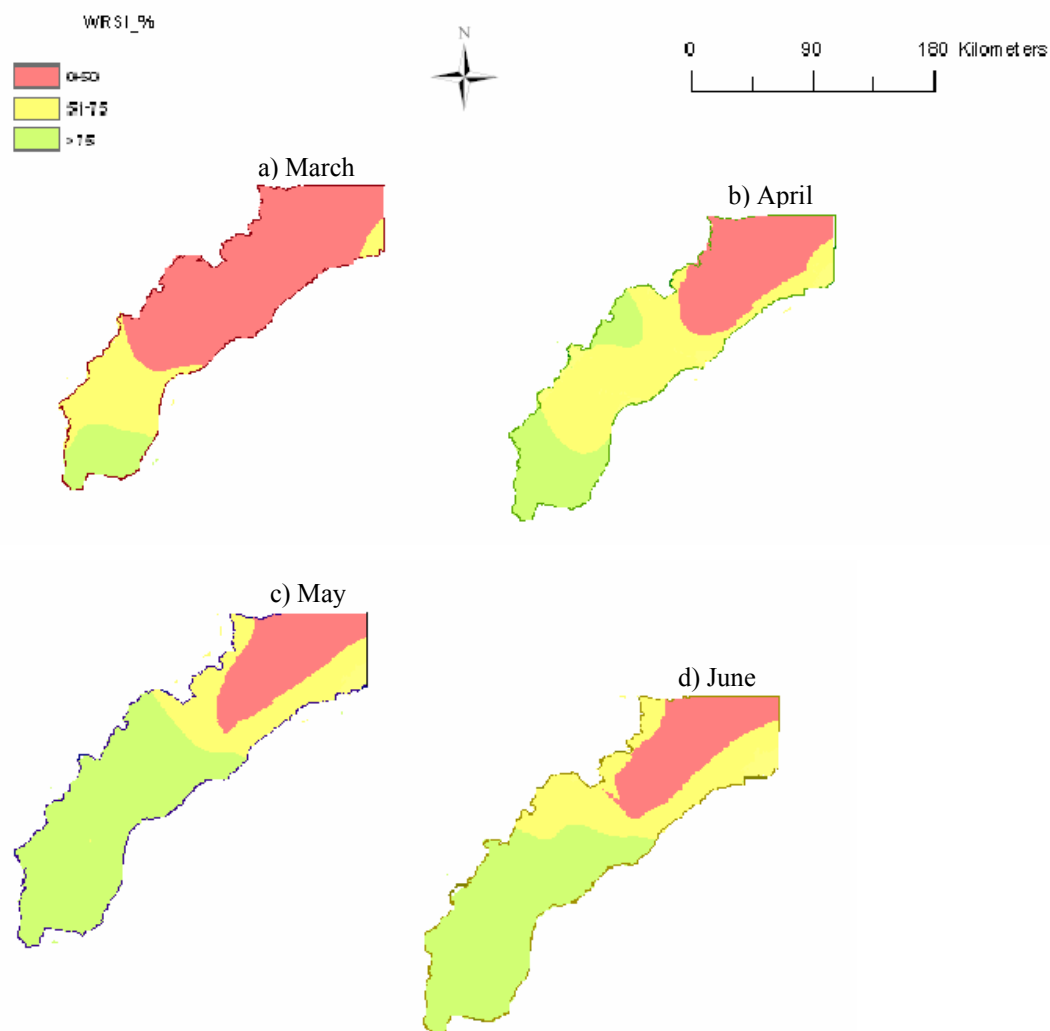
Figure 4.2 Seasonal crop Water Requirement Satisfaction Index (WRSI) for a 120-day grain sorghum cultivar grown under CRV climate, Ethiopia (a) March-June; (b) April-July; (c) May-August and (d) June-September

4.3.1.3 WRSI for a 150-day cultivar

Another sorghum cultivar considered in this study is one that needs a 150-day period from planting to maturity. Based on the premise of planting grain sorghum on a monthly time step from March, this cultivar group has 3 possible concurrent seasons. These are March to July, April to August and May to September (Fig. 4.2a, b, c).

As in the preceding cases, during March to July planting (Fig. 4.3a) the southern (Awasa, Arsi Negele), south eastern (Abomsa and Kulumsa) and the northern-central sections of the study area (Debre Zeit, and Mojo) ensure the WRSI values well above

75%. On the other hand, areas extending from Adami Tulu through Meki-Ziway valley to Koka, as well as the Nazreth, Melkassa, Dera and Wenji belts receive WRSI values from 55 to 70%. In the extreme northeast, Miesso maintains 60% of WRSI, often enough not to threaten total crop failure. The rest of the areas in the eastern sub-region receive much less than this value and cannot support successful growth of a150-day sorghum during this season under rainfed condition.

The second and third opportunities to grow a 150-day grain sorghum are April-August (Fig. 4.3b) and May-September seasons (Fig. 4.3c). During these seasons, with the exception of the eastern sub-region (excluding Miesso), the remaining parts receive adequate rain (with WRSI between 76.and 100% for April-August and 80 to 100% for May-September. Miesso maintains WRSI of 76% and 73% during April-August and May-September respectively. Generally, April-August and May-September seasons are adequate for growing of a 150-day sorghum rather than March-July season. For all the planting dates, the northeastern part, except Miesso, cannot support growing a 150-day sorghum cultivar.
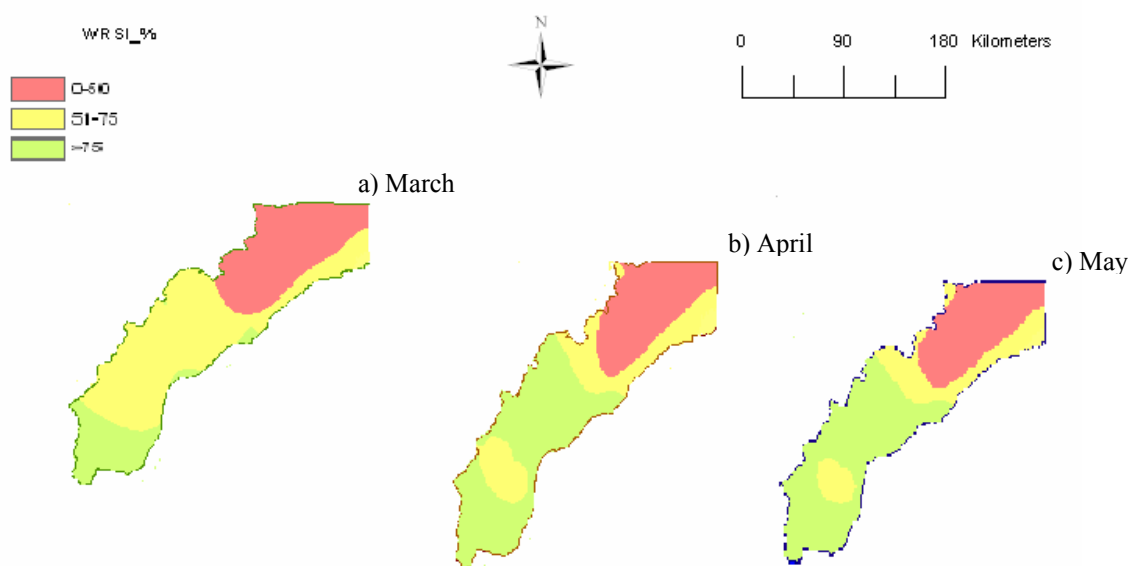
Figure 4.3 Seasonal crop Water Requirement Satisfaction Index (WRSI) for a 150-day grain sorghum cultivar grown under CRV climate, Ethiopia (a) March-July; (b) April-August and (c) May September

4.3.1.4 WRSI for a 180-day cultivar

The WRSI values for a 180-day grain sorghum grown either during March-August or during April- September seasons (Fig. 4.4a and Fig. 4.4b) indicates that more than 75% of the sorghum water requirement could be met at Arsi Negele, Awasa, Debre Zeit, Kulumsa, Mojo, Nazreth, Wenji and Ziway during both seasons. Typically, the longer season receives more rainfall and so, as long duration cultivars also need higher amounts of water, this is a useful matching. It is reasonable to expect higher yields from long duration sorghum groups, provided factors other than soil water do not vary substantually. Generally, growing a 180-day sorghum cultivar can be planned for March planting in the southern and southeastern, while April planting could be planned for the rest of the areas, except the northeastern part.
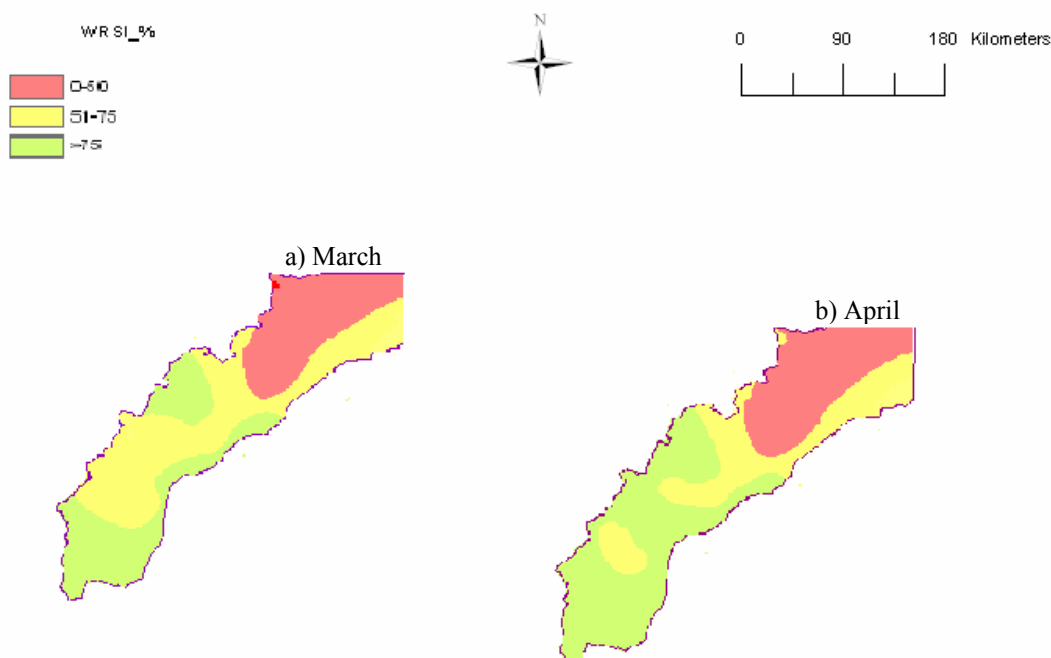
Figure 4.4 Seasonal crop Water Requirement Satisfaction Index (WRSI) for a 180-day grain sorghum cultivar grown under CRV climate, Ethiopia (a) March-August and (b) April-September

4.3.2 WRSI analysis by sorghum growth stages

The purpose of the above WRSI analyses in a cumulative way (season total) was to characterize the study area in terms of the overall space-time rainfall potential and constraints in growing a range of grain sorghum cultivars. While the seasonal WRSI provides a gross picture for long-term research and development planning, it cannot give detailed information on the timing of the growth stages and rainfall adequacy or

deficit. Most crops are more sensitive to water stress during the mid-season or flowering stage, as compared to the vegetative stage. Therefore, water stress during flowering could result in significant yield reduction or total crop failure, even if there was adequate rainfall during the vegetative stage.

The knowledge of the variation in crop water requirement over a series of critical crop growth phases can help in this discussion. Therefore, a 120-day grain sorghum crop grown at Melkassa and Miesso and a 180-day grain sorghum grown at Arsi Negele will illustrate the performance in relation to the prevailing water requirement satisfaction across a sequence of growth stages.

4.3.2.1 WRSI of a 120 day sorghum cultivar grown at Melkassa (zone 3)

At Melkassa, no risk free sub-growing seasons or growth stages exist (Fig 4.5a*)*. March-June planting does not ensure adequate water for any of the growth stages. This means, growing a 120-day sorghum during March-June season is practically difficult under rainfed without supplementary irrigation. However, with the subsequent three growing seasons, cropping a 120-day sorghum is possible, but appropriate soil water and other crop management practices need to be employed almost through all the growth stages. Particular focus on the development stage of April-July and May-August seasons, as well as the mid-season stage of the April-July period is very important. On the other hand, with June-September cropping both the development and final stages would be satisfied with the water requirement, while the initial stage and the mid-season stage faces water shortage of the order of 40 to 60%.

The point of interest given this variability in crop water requirement satisfaction index, is how it is possible to respond appropriately to utilise opportunities and minimize losses. Overall, a minimum package of useful soil water and other crop management technologies should be in place, so as to pick only the winning combinations as deemed necessary during any of the growing seasons. A good example is a practice in the Liverpool Plains of the North Eastern region of Australia, where in-crop rainfall is rarely adequate and evaporation is high and a wheat-10 months fallow-sorghum-15 months fallow-wheat cropping sequence is widely adopted. With this practice, farmers ensure maximum water use efficiency and paying returns from farming (Hayman, 2001). Botha

et al. (1999) employed an in-field water harvesting technique at Glen, Free State of South Africa, making use of a 'tram line' row spacing (1 m by 2 m), whereby in-field runoff from the 2 m strips between the plant rows is captured in micro basins.

4.3.2.2 WRSI of a 120-day sorghum cultivar grown at Miesso (zone 4).

The analytical result of the March-June and April-July seasons sorghum water requirement for a 120-day sorghum grown at Miesso would be satisfied for the initial (seedling establishment) and the final stage (leaf senescence and maturity phase), each of which span about 20 days (Fig 4.5b). Similarly, the critical growth stages (developmental and the mid-season) that correspond to pre-flowering and flowering stages would be under severe stress, as reflected in a reduced sorghum productivity. With May-August cropping, the mid-season WRSI reduces further to the order of 60% followed by another decrease to 52% for June to September mid-season. Likewise, the developmental (60% satisfaction) and mid-season (63% satisfaction) phases of the same season pose a moderate level of risk in a sequence of the crop growth and development. In the case of May-August, the worst-case scenario is during the developmental stage, which experiences a water deficit of the order of 80%. The point of interest is how the standing crop plants survive this severe dry spell until the relief period (the stress is relieved to the extent of 64.8% during the mid-season and 80% by the final stage).

Generally, it is important to note that by the time of the developmental and mid-season stages, quite a significant portion of the growing period has been lapsed and the crop plants have undergone fundamental changes in terms of biomass production and cycle completion. At these stages it is too late to make decisions like 'quit farming'. Thus, proposed alternative advice is to make use of the risk management tools (see details chapter 5 and chapter 6). More specifically, the control over the future by managing stored soil water would be good. If accurate seasonal climate forecasts go a step ahead and indicate whether the rainfall performance of the pursuing season would be risky or not, this will provide synergy for the impact of modern field level management. In the Miesso case, this reflects that growing a 120-day sorghum during the specified seasons is possible, but specialized field level crop and soil water management actions should be taken at all the risky growth stages.

4.3.2.3 WRSI of a 180- day sorghum cultivar grown at Arsi Negele (Zone 2)

The other sorghum growing zone covered here was Arsi Negele. Since this zone benefits from the southward exiting inter-tropical convergence zone (ITCZ) during September and October months, there is a longer duration of rainfall. A more reasonably timed rainfall pattern through the season is the main characteristic of this zone. Accordingly, farmers grow the preferred long duration (180-day and longer) grain sorghums. Fig. 4.5c further depicts that Arsi Negele, besides having the advantage of longer rains, has growing seasons facing only minor deficits of water. Viewing different aspects of WRSI at various growth stages indicates that only the mid-season (flowering stage) of the grain sorghum grown during all the planting seasons face a relative water shortage. The rest of the growth stages across the possible growing seasons meet a 75% and above level of water requirement. One may judge, how it would be possible to boost yield with the available opportunities of the good seasons in this zone.

In comparing the seasonal total and the growth stages based WRSI one can realize the existence of difference in outputs. For instance, in the case of a 120-day cultivar grown at Melkassa during June-September season, the result from the seasonal WRSI analyses states that the crop water requirement is met satisfactorily (Fig 4.2d). However, the calculation of WRSI at various growth stage components detects the existence of water deficit at flowering (mid-season), while the rest of the growth stages receive an adequate amount (> 75% WRSI). The same problem prevails at Miesso and Arsi Negele, in which the mid-season stage suffers from water scarcity.

Therefore, the need is to learn precisely what the risks of crop water requirement or crop loss are with cultivars of different maturities requiring different amounts of water in different growth sequences. It is worth noting that maybe different growth stages actually have different levels of sensitivity to water stress. Detail understanding of the system and building experience on how to take advantage of the potentials embodied in the season, crop and place is vital. It is this basic difference that warrants the need for detailed WRSI analyses rather than the whole season total. This is also important for the water production function analyses, which establish association between the water used and the corresponding crop yield. It is only then that one can confidently pinpoint

the most suitable season out of the range to select the most suitable crop maturity group for any one time.
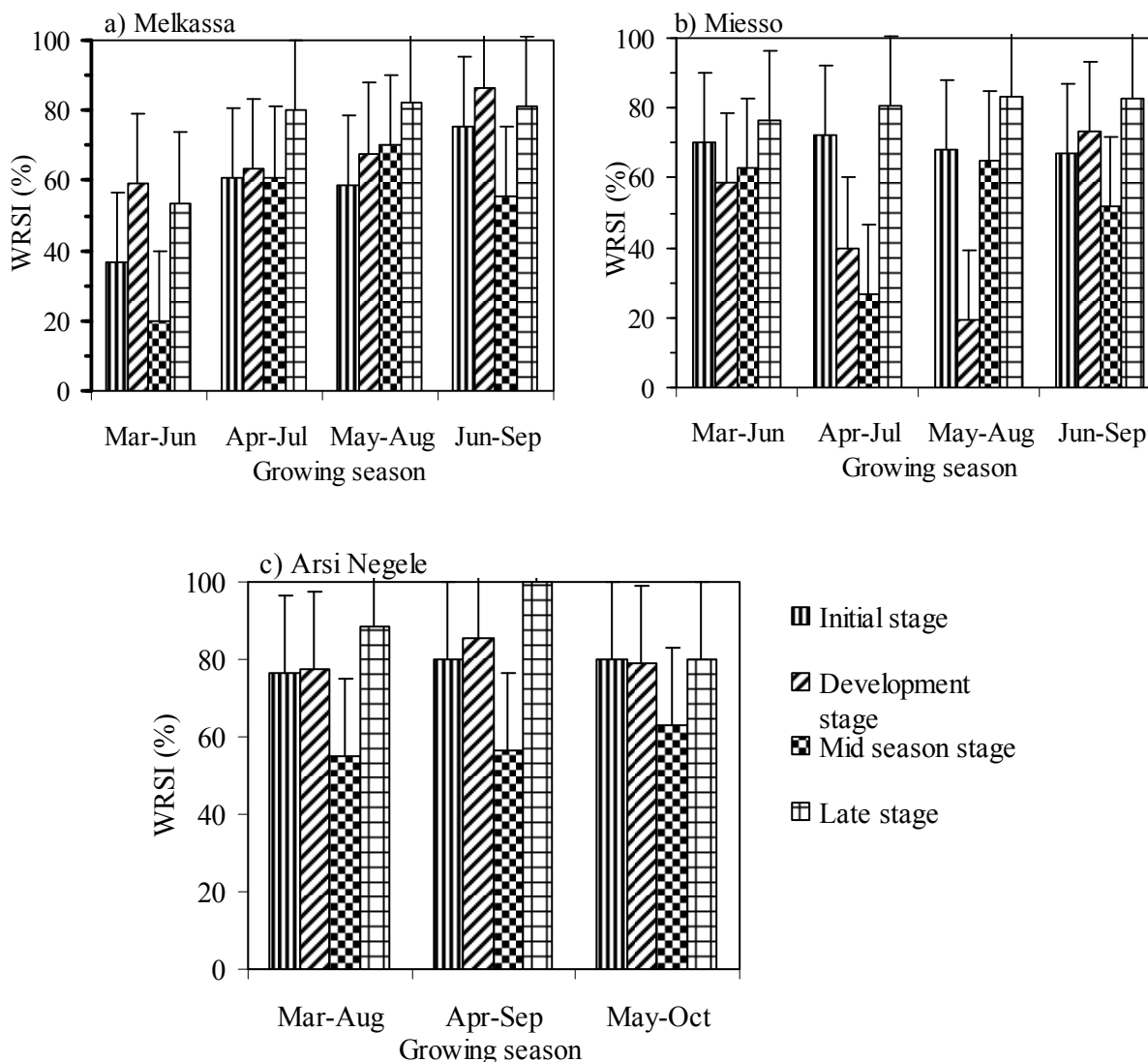
Figure 4.5 Growth stages based Water Requirement Satisfaction Index (WRSI) for a grain sorghum cultivar grown during March to October season in CRV of Ethiopia (a) Melkassa; (b) Miesso and (c) Arsi Negele

4.3.3 Sorghum water production function

Sorghum production in Ethiopia is rather a function of the climate variability than technological changes (Awoke; 1991, Yehualawork, 1989). The water production function (WPF) shows the functional relationship between water use and grain yield. The following section presents the water production function curves to show yield

estimation from the weighted average WRSI equations for 2 cultivars grown at 3 experimental sites (Table 4.3, Fig. 4.6a & b). These regression equations were chosen from among the constructed weighted average WRSIs (Appendices A, B and C).

The weighted average WRSI for Miesso reveals that grain yield is three times more sensitive to the mid-season / flowering stage than the WRSI of the other growth stages (Equation 4.4 in Table 4.3). The prediction error quantifiers given in Table 4.3 and the 1:1 line in Fig. 4.7 also highlights a reasonable level of agreement (D-index = 0.945) with the overall RMSE of 551.8, RMSEs of 352.7 and RMSEu of 424.4.

Similarly, the slope (*b* value) for Melkssa (Equation 4.3 in Table 4.3) shows that the weighted average WRSI during the mid-season/ flowering stage (WRSI 3) is more sensitive to yields of June-September grown cultivar 76-T1#23 by a factor of three or more than as compared to WRSIs from the other growth stages. Similar results were obtained for Arsi Negele as well (Equation 4.5 in Table 4.3). Fig 4.6 elaborates the observed yields as a function of the weighted average WRSI for the cultivar 76-T1#23 at Melkassa and Miesso planted in June and ETS-2752 planted in May at Arsi Negele.

For Melkassa, the agreement index (D-index) and the RMSE components given in Table 4.3 and Fig. 4.7 demonstrate how the observed yield was fairly well approximated by the predicted yield (D-index = 0.954 with RMSE = 530.6, RMSEs = 226.4 and RMSEu = 479.9). The systematic component of the RMSE (RMSEs) together with the 1:1 line (Fig. 4.7) also shows the extent to which the model has slightly overestimated yields at the lower tail and underestimated at the upper tail in the entire distribution. The lower the RMSEs and the closer the RMSEu are to the total RMSE indicates the existence of better agreement between the observed and predicted yields.

Fig. 4.7 also compares the observed and predicted grain yield of ETS-2752 grown at Arsi Negele. The statistics (D-index = 0.91 close to 1:1 line; RMSEu = 873.1 approaching RMSE = 1044.2; RMSEs = 572.2) show good agreement between predicted and observed yields for Arsi Negele. This is reflected in the over-estimation of the lower parts of the data series and under-estimation of the upper parts of the series. While the

RMSEu represents the true magnitude of random error, knowing the RMSEs values helps improve the predictive accuracy of the model (Wilmott, 1981 & 1982).

Table 4.3: Summary of the best linear regression equations for the Water Production Functions

Site & sorghum cultivar used	Weight for each growth stages (WRSI 1, 2, 3 & 4)*				Liner regression coefficient		Eq. #	Sample size	Prediction error quantifiers				
	1	2	3	4	a	b			r²	D-index	RMSE (kg/ha)	RMSEs (kg/ ha)	RMSEu (kg/ha)
Melkassa 76-T1#23	1	1	3	1	-7834.7	117.53	4.3	16	0.834	0.954	530.6	226.4	377.5
Miesso: 76-T1#23	1	1	3	1	-4303.1	68.9	4.4	8	0.776	0.945	551.8	352.7	424.4
A. Negele ETS-2752	1	1	3	1	-17879	250.98	4.5	10	0.699	0.910	1044.0	572.6	873.1

* WRSI 1 to 4 represents initial, developmental, mid- and late-season growth stages respectively
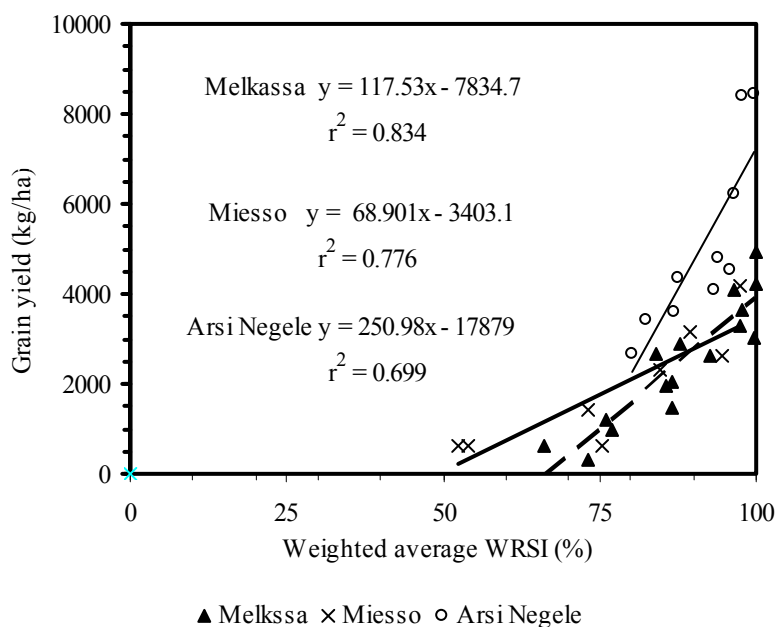
Figure 4.6 Water production function (WPF) for sorghum cultivars - 76-T1#23 planted during June at (▲) Melkassa and (X) Miesso and ETS-2752 planted in May at (o) Arsi Negele in CRV of Ethiopia

From these diagnostic measures pertaining to Fig. 4.7, the most probable explanation for the disagreements between the observed and predicted yields involve the slight difference in planting dates and the corresponding growth stages experienced during those growing seasons. Zere (2003) provides a similar explanation for a weak relationship between observed and predicted maize yields data series at Glen in the Free State province of South Africa.

Further, the available historical yield records are so limited that it would be difficult to achieve a prediction equation closer to certainty. Moreover, because of the simplification in formulation and possible data measurement errors, such data cannot be perfectly used in yield prediction. Under such circumstances, one must recognize how the rainfall pattern behaves and then choose the crop and practices best suited to that pattern.

Overall, it can be summarized that the developed water production functions have demonstrated the potential usefulness of the historical climate data for long-term yield prediction at a specific location that can be improved when data accumulates sufficiently. This in turn enables useful evaluation of sorghum productivity for the stated locations and quantifying the production risks under a variable climate.
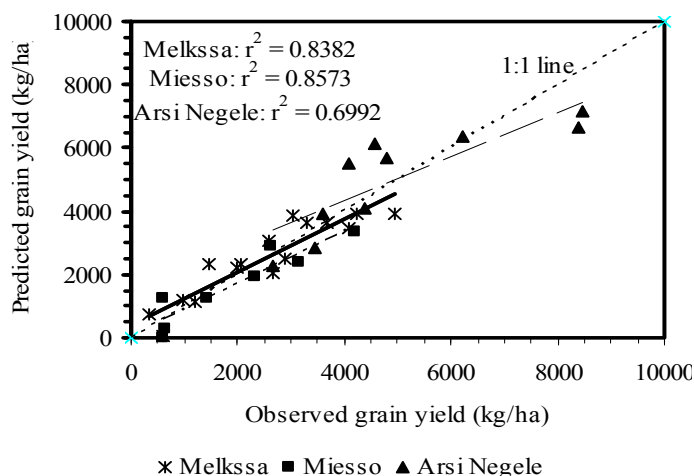
Figure 4.7 Predicted vs observed productivity of grain sorghum at three experimental stations in Central Rift Valley of Ethiopia

4.4 Conclusions

This chapter presented detailed accounts of the tempo-spatial sorghum water requirement satisfaction pattern (seasonal and growth stage based) and water production functions in the variable climate of the study area. For the seasonal WRSI, 14 concurrent sorghum growing seasons were mapped, while the growth stage based WRSI and water production function analyses were computed for 3 experimental sites.

Spatially, the southern and southeastern parts have relatively more favourable seasonal climate for growing the range of sorghum maturity groups considered in this study (90-day, 120-day, 150-day and 180-day cultivars). The northwestern and central parts constitute the next suitable climate for the above listed sorghum cultivars. On the other hand, the wide northeastern dryland plains of the study area, except the pocket section of Miesso-Assebot plain, does not warrant the economic farming of sorghum under rainfed condition. Miesso, although categorized under zone 4, mainly because of its proximity to the areas categorized into dry zone in chapter 3, also experiences a relatively better rainfall condition, most probably because of the influences from the nearest Cherecher highland that can influence the synoptic scale circulation.

It was also found that, while the seasonal map satisfactorily displayed the spatial pattern of WRSI with the progress of the season, it is the growth stage based WRSI that truly detected the existence of water scarcity during the same season. This could be exemplified by the detailed WRSI analyses done for a 120-day sorghum cultivar grown during June-September period at Melkassa. At Melkassa, the seasonal WRSI highlights the adequacy of the water satisfaction for the 120 day sorghum cultivars, but the growth stage based WRSI detected the true risk of water scarcity at the flowering stage. Similar information was obtained for Miesso and Arsi Negele as well.

Temporally, as it is hard to attain the crop water requirement, March planting is the least preferred season for all the sorghum cultivars in the study area, except for the southern and southeastern portions. The study area is well known for its climatic variability, and the risk at various critical crop growth stages for March planting is considerable even for the relatively suitable section. Therefore, the availability and use of an alternative soil water and crop management technique according to the prevailing risk level is crucial.

It was also understood that rainfall performance in terms of spatial coverage and amount improves gradually through April, May and June with a notable peak in July and August. In September, the crop water requirement can be partially met; however, although the level and dimension could vary across the study area, development or introduction of improved technologies still needs serious attention. The water

production function analyses for the three experimental sites also revealed a reasonable level of accuracy in estimating long-term yields, provided the possibility of achieving a reliable model as and when sufficient data sets accumulate in the future.

Therefore, for Miesso and Melkassa, growing a 120-day grain sorghum under improved soil water and crop management practices, together with the area specific rainfall prediction aid, may be rewarding to ensure high yields during the wet season. Likewise, food security for family sustenance may be achieved during below average rainfall years. On the other hand, a focus could be made on specific and potential areas where both the seasons and the crop are efficient that could be combined for the purpose of optimizing yield benefits. Arsi Negele proves the best example for such an effort. These basic differences underscore the need for area specific crop water requirement satisfaction and water production function analyses and for improved decisions in sorghum cropping. Overall, it can be concluded that this chapter's objectives on tempo-spatial mapping of the crop water requirement satisfaction levels of a range of sorghum cultivar maturity group and fitting the water production function have been achieved.

Chapter 5

Risk Analysis for Various Sorghum Planting Windows under Variable Rainfall

5.1 Introduction

Farming is a risky business. Anderson (1974) cited that while farm businesses face the same cost and price risks as any other sectors of the economy, climatic variability makes it turbulent. The main impact of this turbulence is on production risk, though this has far-reaching implications on financial and farm input suppliers' risks as well. The notion of climate variability and defining crop water requirement and satisfaction related risk is more than an academic exercise. Therefore, as it is open to multiple interpretations, finding a clear definition is not that easy (White, 1994). For rainfed agriculture, risk represents the probability of a defined climatic hazard affecting the livelihood of the producers.

At the outset, the risk definition used in this thesis is the one reported by Powell (1994), which is "uncertainty with consequences". This emphasizes that rainfall variability at a given location is a natural phenomenon and does not imply risk in itself, but when coupled with the possible adverse consequences it becomes a real source of risk. Powell (1994) also noted that risk should be considered as a source of opportunity rather than something that should necessarily be avoided.

A more fundamental definition of risk involves a distinction made by Knight (1921) and Heady (1952) between risk and uncertainty situations. Risk refers to a probability that can be estimated from prior information, while uncertainty applies to a situation in which probability cannot be estimated. Abadi *et al.* (1996) used a similar distinction in the context of introducing chickpeas to the farmers in the Western Australia wheat belt. They defined risk as an environmental or economic variability so that if farmers knew the true probability distribution of yield for chickpea they would be making a purely risky decision. On the other hand, uncertainty was taken as being due to the ignorance of the producers. They postulated that, as farmers gained experience with a new crop,

the uncertainty would decrease and the true distribution, i.e. the risk, would be apparent. Therefore, what is chance for the ignorant is not a chance for an educated person (Bernstein, 1996).

Bernstein (1996) further provided the origin of the word 'risk' as being the early Italian *risicare,* which means 'to dare' and emphasizes choice, opportunities, and the desire to avoid or minimize adverse consequences. Anderson (1991) pointed out that, were it not for risk aversion, there would be no need to study variability except for its role in establishing the mean. He added that, if farmers were risk neutral, they would be unconcerned about the degree of variability. Common definitions of risk that emphasize the uncertainty of outcomes are 'the dispersion of actual from expected results' or 'the probability of any outcome different from the expected' (Vaughan, 1986).

However, the concept of risk is derived in recognition of future uncertainty*, i.e* ones inability to see into the future, indicating the degree of uncertainty that is significant enough to notice it. A risk analysis has the capacity to generate the whole probability distribution of uncertain outputs such as yield quickly. Therefore, it offers a decision maker with opportunities to make timely comparisons of not only just the means of alternative strategies but also the lower, risk-laden tails of the probability distributions. Anderson (1974) describes this as 'risk oriented research', in distinguishing it from the 'average oriented research' which focuses on only treatment means and does not show the expected impact of uncertainty of a given input variable, rainfall for instance, on a key output variable such as yield.

5.1.1 Goal of risk analysis

In risk analysis, the procedure extends at least to include the 'worst-case, expected and best-case' scenarios, giving an opportunity to the decision maker to know whether the expected values and the best-case scenario outweigh the worst-case scenario (Hardaker, *et al.*, 1998). At best, risk analysis includes the probability distribution that provides a solution of more than just filling only the worst–case, expected and the best-case values. In other words, a risk analysis determines a correct and a possible range of target output values that are more correct than the worst, expected and best- case range (Hardaker *et al.,* 1998). It also shows the likelihood of occurrence of achieving

specific values, which is very useful for the targeted yield analyses, helping to determine the types and levels of inputs employed to achieve a given target yield.

In general, the primary goal of risk analysis is to support the decision makers who farm at various levels to choose a course of action, given a better understanding of the possible outcomes that could occur. The hypothesis in this chapter is that rainfall variability poses significant risks in farming and emphasizes the need for one or another form of risk analysis. Risk is a chance of loss in the physical scientists' terminology and its analysis guides the rational decision maker to the best choice based on preferences providing a safety 'rationale' in terms of the axioms of the theory (Hayman, 2001).

There is ample evidence from psychology that the unaided human intellect has difficulties dealing with risk and hence human beings are prone to make poor risk assessment. Bernstein (1996) equated risk management with modernity, pointing out that in the distant past, the world had mathematicians, inventors and technologists but no concept of risk. "The revolutionary idea that defines the boundary between modern times and the past is the mastery of risk: the notion that the future is more than a whim of the gods and that men and women are not passive before nature" (Bernstein, 1996). Until human beings discovered a way across that boundary, the future was a mirror of the past or the murky domain of oracles and soothsayers who held a monopoly over knowledge of anticipated events (Hayman, 2001). McCown *et al.* (1991a) pointed out that given the fact that agronomists spend most of their time conducting experiments, running models and giving advice on resource allocation decisions, it is surprising that most agricultural scientists were quite unfamiliar with risk analyses.

Parry and Carter (1988) argued that the climate impact studies which dominated the literature until mid-1970s treated agriculture as a passive exposure unit and they called for a system approach in order to demonstrate the capacity of agriculture to interact with and adapt to a variable climate. Over a third of a century ago, Trewartha (1968) warned against treating climate as 'constant'. While emphasizing that climate study in general could be handed over to the norm (average); but it should be noted that departures, variations and extremes are also important.

Bawden Richard (1990) likened the process of agricultural science in general and the activities of the scientists in particular to a symphony orchestra, "if you enjoy what you do, and can get someone to pay you, good luck to you; but don't confuse this with intervening and improving the situation of farmers". Taylor (1994) underlined that the information and tools for risk management have not been readily available to farmers and that this was a valid role for federal and state governments. Stehr and vonStarch (1995) contrasted the neoclassical economic treatment of climate variability in which a perfectly informed society adopts optimal strategies, with the social construct theory of climate. In such a society, climate risk study is no longer new, it has become an essential ingredient in adopting optimal strategies. For such a society, questions of how the climate science should influence a farming system and appropriate ways of analysing, intervening and improving a given farming system have become a focal point.

5.1.2 Climate variability and Ethiopian farmers' risk management

Throughout history, climate was widely understood to be controlled supernaturally and extraordinary events are taken as a sign of God's wrath (Stehr and vonStarch, 1995). This holds true under Ethiopian agriculture, making the problem more of a social construct than natural. In fact, this problem is global in nature and not unique to Ethiopia. For instance, in recent more secular times, the media and even many scientists were quick to attribute any extreme weather event as a proof of climate change and evidence of the irony of the so called 'human progress' (Hayman, 2001).

Bernstein (1996) was critical of the association of risk with fate or luck. If everything was a matter of luck, then risk management is a meaningless exercise. He states, "invoking luck obscures the truth, because it separates an event from its cause shunning the progress" and this is a deep-rooted part of social construct theory of climate. In essence however, these days' insights are more likely to come by keeping the edges sharp and being clear when moving from one framework to the other and it's likely that such problems could be properly understood and managed in the future (Hayman, 2001).

The traditional Ethiopian farmers' wisdom for climatic variability and risk management involves conservative farming systems. Farmers choose crop cultivars and practices not

for producing high yields during good years, but to produce adequate food on a sustainable basis to supply the family needs. The most likely explanation could be that memories of losses during drought years in particular, inflate farmers' estimate of the riskiness of their farming environment. The gains that are foregone during the good seasons place the longer-term sustainability of many farmers at risk (Donnelly 1997) and make them uncompetitive. Donnelly (1997) concluded that the harsh reality, however, is that the majority of farmers could immediately increase their productivity and efficiency simply by adopting less conservative management practices. According to Uehara and Tsuji (1991), although technology adoption is widely believed to be necessary to improve farm performance, there is also a wide spread agreement that risk aversion is a major deterrent to technology adoption.

This chapter focuses therefore on the concept that a variable rainfall makes Ethiopian agriculture riskier, not only for the farmers but also for the national decision makers. In an Ethiopian context, this statement is commonly taken as obvious and either stated as fact or in passing reference to as *Ethiopia, a land of drought and famine'*. However, given the potential of the existing natural resources, both farmers and the decision makers have to decisively come to terms with the 'true state' of the risks associated mainly with climatic variability. It means climatic risk analysis provides sound management, enabling the decision maker to trade off upside and downside in reducing risks. Wood and Harper (1993) noted that phrases such as "better technical information" leads to better decisions and all the societal groups need 'more information' that relates to risk and risky prospects embedded in farming.

In Ethiopian dryland farming context, this signifies the need for technically sound intervention in terms of in-field water harvesting to accumulate crop root zone soil water content, as well as provision of timely and updated short and long-range rainfall prediction information, particularly for planting related decisions. The updated information on the performance of the season with the lapse of time and growth stages is also vital.

5.1.3 Classic risk analyses techniques

Appropriate ways of measuring risk are still being debated. For example, Mumey *et al.* (1992) measured risk for Canadian producers as root mean square of error (RMSE) of actual and forecast or budgeted income. Wylie (1996) questioned the use of probability in communicating climate risk with farmers and asserted that information from seasonal forecasts needed to be user friendly and not in the form of risk or probability distribution. Malcolm (2000) noted that while the probabilistic way of thinking was useful in farm management, there is ambiguity about the role of probability theory due to the paucity of the necessary information. The following sections present the risk analyses techniques used in this chapter.

5.1.3.1 Cumulative Density Functions (CDFs) and Stochastic Dominance (SD) Analyses

According to Anderson and Dillon (1992) a cumulative density function (CDF) is likely to be the first and most understandable graph of the distribution, in which it is possible to compare the dynamic values of random variables. If two CDFs are identical, one can use a 1:1 line to estimate risk for instance, values above the 1:1 line suggesting an over-estimation and those below a 1:1 line representing under-estimation.

The stochastic dominance (SD) technique that encompasses first degree stochastic dominance (FSD), second degree stochastic dominance (SSD) and third degree or higher order stochastic dominance is also a method used to analyze CDFs. FSD means the cumulative density function (CDF) of the best alternative must always lie below and to the right of the CDFs of the other distribution curves. Fig. 5.1 illustrates that CDFs 'B' and 'C' are dominant relative to CDF 'A' in the FSD sense. This means that for every risk percentile point on the *Y* axis, a farmer gets at least x amount more yield from CDF 'B' or 'C' as compared to the yield obtained from CDF 'A'. In the FSD, the dominating variable would be preferred by any decision maker who prefers "more" to "less", regardless of the attitude towards risk. The FSD analysis requires the pair wise comparison of all the pairs of distributions with the provision that once an alternative has been found to be dominated by another, then the dominated one can be dismissed from all further considerations (Hardaker *et al.*, 1998).
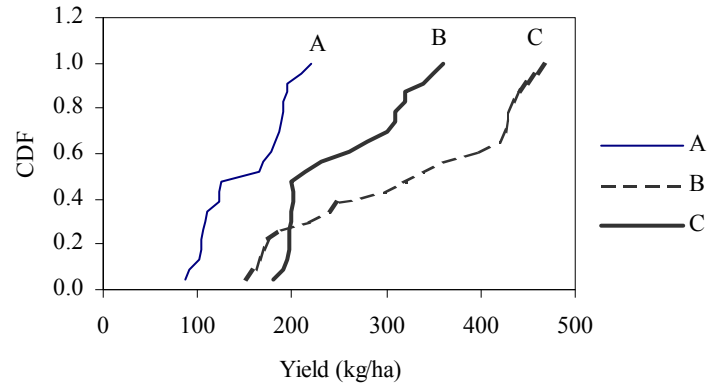
Figure 5.1 Hypothetical data to illustrate first degree and second degree stochastic dominance analyses

On the other hand, decisions are more difficult to resolve when the CDFs interact (cross-over) as shown by CDF 'B' and 'C'. Under such circumstances, neither of them totally dominates in the sense of FSD, indicating the limited discriminatory power of the FSD (McCarl, 1996). Cross-over implies that one strategy could dominate the other at the lower points (bottom tail) of the distribution, but could be dominated at the upper values (top tail) in the distribution or vice versa (see CDF 'B' and 'C' in Fig 5.1). In this curve, CDF 'C' lies to the left of CDF 'B' at the lower level of the data series, meaning that the 'B' alternative is better choice in this range of the data distribution, while CDF 'B' lies to the left of CDF 'C' at the upper tail of the series, meaning that 'C'is a better and less risky choice in the upper range of the series.

The cross-over between CDF 'B' and CDF 'C' implies that curves meet the requirements for SSD and the comparison should be handled using the higher order stochastic dominance techniques. By comparison, the total area under the CDF of 'C' is bigger than CDF 'B' at upper percentile points and therefore 'C' is to be the first choice (McCarl, 1996). McCarl (1996) points to this early cross-over as the main problem with SSD, as distribution may show a vast advantage over all points in the distribution, but the lowest one. As seen in the figure, CDF 'C' falls left of 'B' at the lower points, therefore rendering decision making more complicated to the farmers. Procedurally, the SSD analysis involves comparison between the areas below and above the cross-over point for the two CDFs. The implication is that all the decision makers (risk averse, risk neutral and risk takers) will have to choose the curve with the best outcome, according to their attitude towards risk. In this case, the risk averse (conservative farmer) prefers

CDF 'B' to 'C', because his or her priority concern is to ensure better than lowest yield for the family sustenance. On the other hand, a risk taker always targets the highest possible outcome (not worried about the downside risk) and therefore, prefer CDF 'C' to 'B', giving more weight to the upside risks.

The Kolmogorov-Smirnov test (K-S) also determines if the CDFs differ significantly in terms of the maximum vertical distance between the two CDFs. The K-S has the advantage of making no assumption about the distribution data (it is non-parametric and distribution free). In this test of the distance between two CDFs, p-value would be used to decide whether the difference between the two CDFs is significant. If the reported p is 'small', then the null hypothesis would be rejected, meaning there is significant difference between the two.

5.1.3.2 Sensitivity Analyses

Another risk analysis technique used in this chapter involves the sensitivity analysis, which is a useful way of determining to which input variable or group of input variables the output is most vulnerable. Sensitivity analysis is the process of varying model input parameters over a reasonable range (range of uncertainty in values of model parameters) and examining the relative change in model responses. It is important to recognize that the output of almost any model is sensitive only to a small number of parameters (Penning de Vries and Spitters, 1991).

Regression and correlation techniques are the best ways of analysing sensitivity of the outputs to the input levels. By keeping other variables constant, and varying only a specific variable of interest, sensitivity analysis explains partition of the full risk distribution into good and poor seasons (Hardaker *et al.,* 1998).

5.1.3.3 Crop weather simulation modelling for risk analysis

Simulation of crop growth using dynamic models, which depend on daily weather, is generally an accepted method for assessing the effects of climatic variability on crop production (Hutchinson, 1991). Simulation models are used to estimate potential yield in new areas (Buringh *et al.*, 1975; Patron and Jones, 1989; Aggarwal and Penning de Vries, 1989), to forecast yields before harvest (Duchon, 1986), to estimate sensitivity of crop production to climate change (Parry and Carter, 1988) and to compare

management options (van Keulen and Wolf, 1986) and technology levels (Horie, 1987). A dynamic simulation model that includes a combination of mathematics and logic is used to conceptually represent a simplified crop yield that reflects sufficient detail of the system. This brings agronomic sciences into the information age (Ritchie, 1991).

According to Penning de Vries and Spitters (1991) simulated output is more consistent across environments and more complete than those data obtained from empirical experiments. Consequences of subtle changes in crops or environmental conditions can therefore be simulated better than obtained with measured data (such as trends in weather, modification of crop or soil features and gradients of biological constraints). According to Ritchie (1991), the minimum requisite for a crop simulation model that could be used for climatic risk assessment is the simulation of a daily soil water balance, duration of crop growth, biomass growth rate and partition into harvestable yield. Sinclair and Seligman (1996) suggested that crop simulation modelling was entering a long and productive mature phase, having overcome the confusion and excessive confidence of adolescence. They pointed out that in modern agriculture, field experimentation had not only dominated research but also the extension message. They argued that the complexity of management alternatives and a variable climate had led to limitations in field experimentation which simulation modelling could help overcome.

In crop growth simulation, four levels of crop production are usually distinguished. These are: potential yield, water-limited yield, nitrogen-limited yield and nutrient-limited yield. Key processes for simulation are photosynthesis, respiration, assismilation, partitioning, leaf area growth and phenological development (APSRU, 2005). Several advanced models simulate these processes, with daily or hourly time intervals and considerable details (Loomis *et al.*, 1979; Penning de Vries *et al.*, 1983; Whistler *et al.*, 1986; Wisiol and Hesketh, 1987). Models for research and instruction emphasize integration of process level knowledge, while models for application emphasize extrapolation into new conditions. For research, better model structures lead to improved yield simulation under different conditions. For applications, the answer to whether improvements in models help to improve crop yield simulation is less straightforward. Lack of sufficient field data has limited the full use of models for many years and in many areas (Jeffers, 1976).

On the other hand, there are many complaints about simulation modelling in that simulated numbers are too easily derived and do not represent the real situation. Passioura (1973, 1996) states that biological simulation should be considered primarily as a work of art rather than science, because it usually fails to meet biologists' expectations. Passioura (1996) also gave a bleak assessment of mechanistic simulation models helping farm management, arguing that, if the aim was accurate prediction on which to base sound advice, then delivering this advice with models based on guesses about "essential structures" was like the behaviour of a 'snake' oil salesmen. Similarly, De Wit (1982) argued that crop simulation models are not simplified representations of the conceptual ideas of biologists and warned agronomic modellers that "fools rush in where wise men fear to tread" and "this rushing into simulation in biology is done by agronomists, perhaps because they are fools, and also may be that they deal with systems in which the technical aspects overrule more and more the biological aspects". Dillon (1971) raised a similar criticism in his three laws of simulation: first, you can prove anything with simulation; second, you can prove nothing with simulation; and third, simulation will continue until the money runs out.

Given the above contradictory views of scientists, our aim was to use agrometeorology in the context of simulation modelling in climate risk analysis and produce a series of model outputs for June planting dates at two sorghum experimental sites (Melkassa and Miesso) in the Central Rift Valley of Ethiopia. This agrees with the idea of McCown *et al.* (1991a) that the option of running a field experiment to analyse climate risk is problematic and at the same time, climatic risk can only be adequately quantified by linking crop simulation models to long-term weather data. The issue of appropriate resolution (farm level or regional planning) in simulation models that are to be used for management should be critically considered, as well.

The focus of this chapter is on the production aspect using climate risk analysis in sorghum farming in the Central Rift Valley of Ethiopia (assuming a fixed price). To deal with these analyses, the following three basic research questions were formulated:

> 1) Which planting window/s or rule/s significantly reduce/s rainfall risk and give efficient yields?

2) In terms of sorghum productivity, which rainfall parameter is most sensitive as an indicator?

3) Does the proposed model simulate the observed sorghum yield well enough?

Accordingly, the following specific objectives were set:-

a) To determine the most risk efficient planting season/window;

b) To determine the most sensitive rainwater related input variable/s for sorghum productivity;

c) To evaluate the observed sorghum yields against the simulated output and analyse the reasons for the difference.

5.2 Materials and Methods

In determining risk efficient planting window/s, the linear form of the water production function (WPF) using WRSI-grain yield equations that were developed in chapter 4 are used for the three sorghum experimental sites (Miesso, Melkassa and Arsi Negele). For Miesso and Arsi Negele, the linear regression equations developed using weighted average WRSI for a 120-day cultivars are used. For Arsi Negele, the same procedure was employed for a 180-day sorghum cultivar.

For Miesso and Melkassa there were no observed yield data for seasons with planting date before June. Therefore, the June-September growing season WPF with weighted average WRSI was used to simulate yields. For Arsi Negele too, there was no yield data for seasons with planting date before May. Therefore, the WPF with weighted average WRSI for the May-October growing season was used to simulate sorghum yield for March-August and April-September growing seasons. The assumption in using the predictor WRSI is that it is a dimensionless value that signals 'total crop failure' if it's value is less than 50% and 'good performance' if its value is greater than 75%, despite the seasons differences in terms of rainfall distribution or amount.

5.2.1 Analytical techniques

5.2.1.1 CDFs and Stochastic Dominance

To begin with, the probability distribution of yields for each planting window using CDF was drawn. These were compared using either the first degree stochastic dominance (FSD) or second degree stochastic dominance (SSD), whichever was appropriate, for the particular cultivar and/or location. The K-S statistics were also employed to determine whether there is a significant difference between yields from different planting dates used at Miesso, Melkassa and Arsi Negele.

5.2.1.2 Sensitivity Analyses

The sensitivity analysis was carried out for the 120-day sorghum cultivars planted in June at Miesso and Melkassa and the 180-day sorghum cultivar planted in May at Arsi Negele. Arsi Negele represents the high rainfall area as well as areas supporting longer duration sorghum cultivars that give high yields. Since the rainfall starts early in this zone, farmers prefer to grow a long duration sorghum cultivars. Accordingly, three concurrent planting seasons (planting in March, April and May) were evaluated in terms of productivity.

The input variables include planting date (P), maturity date (M), number of rainy days (R, count of days on which rainfall was recorded), rainfall duration (D, difference between planting date and end of the growing season), crop water requirement (CWR, mm) and $WRSI$ (%). Prior to executing multiple regressions, these six input variables were submitted to the stepwise regression procedure with the aim of avoiding multicolinearity problems and selecting only those variables having significant yield explanatory power.

Further, because data on planting date and maturity date were available in days of year (DOY), these were first categorized into dummy variables (Table 5.1); for instance, planting date was classified into early (P_E), medium (P_M) and late (P_L), while maturity date was classified into extended (M_E), intermediate (M_M) and short (M_S). Number of rainy days (R) in a season was also categorized into longer number of rainy days (R_L), intermediate number of rainy days (R_M) and short number of rainy days (R_S).

Subsequently, these were represented by dummy variables; e.g. 2 was assigned to represent the early (early June) planting date or 150-160 DOY for the 120-day cultivar planted at Meisso and Melkassa, as well as for the 120-130 DOY (early May) in case of the 180-day sorghum cultivar planted at Arsi Negele (see Table 5.1). From the previous findings it was found that early planting date is the most preferred one and that is why the largest weight of 2 was assigned to it, as compared to '0' that was assigned for the late planting date scenario and therefore least preferred. Similar cases hold for maturity date too. The multiple regression equation is:

$$Y = P + M + D + R + CWR + WRSI \qquad (5.1)$$

Where:
Y = sorghum yield (kg ha^{-1}) in a given year

P = planting date (DOY range

M = maturity date (DOY range)

D = rainfall duration in a given year

R = number of rainy days in a given year

CWR = crop water requirement

$WRSI$ = water requirement satisfaction index.

Sequentially, all variables with the largest coefficient of regression and the least multicolinearity were retained as the most critical input (most sensitive) in detecting percentage changes to sorghum yields and constituted the multiple linear equations for the respective cultivars and locations.

Table 5.1 Summary of dummy variables used in multiple regression for a 120-day sorghum cultivar planted in June at Meisso and Melkassa and 180-day grain sorghum cultivar planted in May at Arsi Negele

Experimental Station	Planting date (P) (DOY)			Maturity date (M) (DOY)			Number of rainy days (R) (Number)		
	P_E 2	P_M 1	P_L 0	M_E 2	M_M 1	M_S 0	R_L 2	R_M 1	R_S 0
	best	better	good	best	Better	good	best	better	good
Miesso & Melkassa	151-160	161-170	171-180	>280	271-280	261-270	>40	31-40	20-30
Arsi Negele	120-130	131-140	141-150	>300	291-300	280-290	>70	61-70	50-60

P = Planting date (P_E = early planting date; P_M = medium planting date; P_L = late planting date);
M = Maturity date (M_E = extended maturity date, M_M = medium maturity date, M_S = short maturity date);
R = Number of rain days (R_L = longer number of rain days in a season, R_M = intermediate number of rain days, R_S = short number of rain days).

5.2.1.3 Simulation modelling

To achieve this objective, the Agricultural Productivity Simulator (APSIM version 4.0) was used. APSIM is a dynamic model that takes into account different growth and development processes of a given crop or cropping system. Central to this analysis is that differences between the observed and simulated water-limited yield in any test year could, as an approximation, be used to establish a yield pattern that prevails in response to the seasonally variable climate and soil factors in the study area. The difference between the observed and simulated yields was then assumed to be a management gap that may attract attention from breeders, physiologists and agronomists in adjusting research strategies in the wake of optimising the resource use in the study area. Also, it can be quite useful to the farmers in making improved on-farm level tactical decisions.

As there was no data for the other growth and yield components like biomass and leaf area, only sorghum grain yield data was recorded during simulation. The daily climate records that were used include: maximum and minimum temperatures, solar radiation and rainfall. The measured soil variables like depth (D), bulk density (BD), drainage upper limit (DUL), saturation water content (SAT), lower limit (LL), plant available water capacity (PAWC), organic carbon and pH were obtained by courtesy of Worku Atlabatchew (currently a PhD student at the University of the Free State, Republic of South Africa).

The other essential soil parameters like air dry water content, whole drainage coefficients (SWCO), nitrate level (N0$_3$), ammonium (NH$_4$), humic fraction (FBiom), inert fraction (FInert), initial stage evaporation coefficient (u) and soil reflectivity/albedo (*salb*) were adopted from the APSIM's default values, which were set for sorghum under similar soil characteristics in Australia. Sorghum crop parameters including root water extraction constant (Kl) were adopted from the same source. Subsequently, the model was run, resulting in a harvestable grain yield, which was eventually integrated into a hectare-based product for each year.

Guided by the fact that most planting dates for the observed yields were concentrated around the early days of June, sowing date was set at the first of June for both the

experimental sites. Other factors, including the nitrogen fertilizer, are kept non-limiting (because the cultivars have been grown under a no-fertilizer limited condition) and only climate over the growing periods was different. The rainfall amount at planting was 20 mm received over three consecutive days under which the cultivar has been regularly planted for years at the two experimental sites. The sorghum plant density was set at 6.6 plants m^{-2} (0.75 meter space between rows by 0.20 m space between plants) that represents the field experimental situation (Georgis, 1999).

Following the calibration, diagnostic indices (Wilmott, 1981, 1982) including index of agreement (D-index), total root mean squared error (RMSE) and its partitions *i.e* systematic (RMSEs) and unsystematic (RMSEu) were employed. These help to evaluate how the observed and simulated yields are in agreement. The dimensionless D-index ranges from 0 to 1, with 1 indicating perfect agreement between the observed and simulated, while 0 represents strong disagreement. The latter 3 error quantifiers describe the magnitudes of the major errors. For acceptable agreement between the observed and simulated outputs, the total RMSE should be as low as possible. At the same time, the systematic component of the RMSE *i.e.* RMSE$_s$ is expected to be minimized, while the RMSE$_u$ should approach the total RMSE value. The equations are given below:-.

$$D = (\sum_{i=1}^{N}(P_i - O_i)^2 / \sum_{i=1}^{N}\left[\left|P_i\right| - \left|O_i\right|\right]^2 \qquad 0 \leq D \leq 1 \qquad (5.2)$$

Where:
                    D = agreement index
                    P_i = predicted values
                    O_i = observed values
                    N = number of observations

$$RMSE = N^{-1} \sum_{i=1}^{N} [(P_i - O_i)^2] \qquad\qquad\qquad (5.3)$$

$$RMSE_s = \sqrt{MSE_a + MSE_p + MSE_i}$$

Where:
                    RMSE = root mean squared error
                    RMSEs = systematic root mean squared error
                    MSEa = a^2 = additive systematic error

$$MSE_p = (b-1)^2 [N^{-1} \sum_{i=1}^{N} (O_i)^2] = \text{proportional systematic error}$$

$$\text{MSE}_i \ = \ 2a(b-1)\overline{O} = \text{interdependence factor for proportional and}$$
additive components

a = intercept
b = slope
O_i = ith observed yield (kg ha^{-1})
N = total number of observation
$\overline{O}$ = Mean observed yield

$$\text{RMSE}_u \ = \ \sqrt{MSE - MSE_s}$$

Where: RMSE_u = unsystematic component of RMSE
                                      MSE_s = mean squared error

Moreover, the regression equations and 1:1 line were used to determine whether the observed yields were accurately estimated by the simulated yields. In these multiple sequences of risk analyses, it is believed that the adopted procedures are reasonable, which could be optimised as and when data become sufficiently available.

5.3 Results and Discussion

5.3.1 Stochastic dominance analysis

The CDFs and stochastic dominance analyses output for March, April, May and June planting of two 120-day sorghum cultivars (76-T1#23 and Gambella-1107) for Melkassa reveal that May planting window was dominant in FSD sense in both cultivars, giving a yield of 3900-4000 kg ha^{-1} at 85th percentile point (Table 5.2 and Fig. 5.2). The performance of the two cultivars under the various planting dates reveals a similar pattern in that there is no significant difference between May and June planting dates (Table 5.2), while there are significant differences for instance among April and June planting dates. In other words, as May and June curves converged at the upper tail, but did not cross over (for both 76-T1#23 and Gambella-1107), an alternate advantage expected from June planting date over May case may not be justified (D = 0.38 and p=0.07). It means, all decision makers at Melkassa may prefer May planting date, as it gives the highest outcome as compared to the rest of the planting dates. However, soil water management is important to mitigate the risks associated with a May planting date.
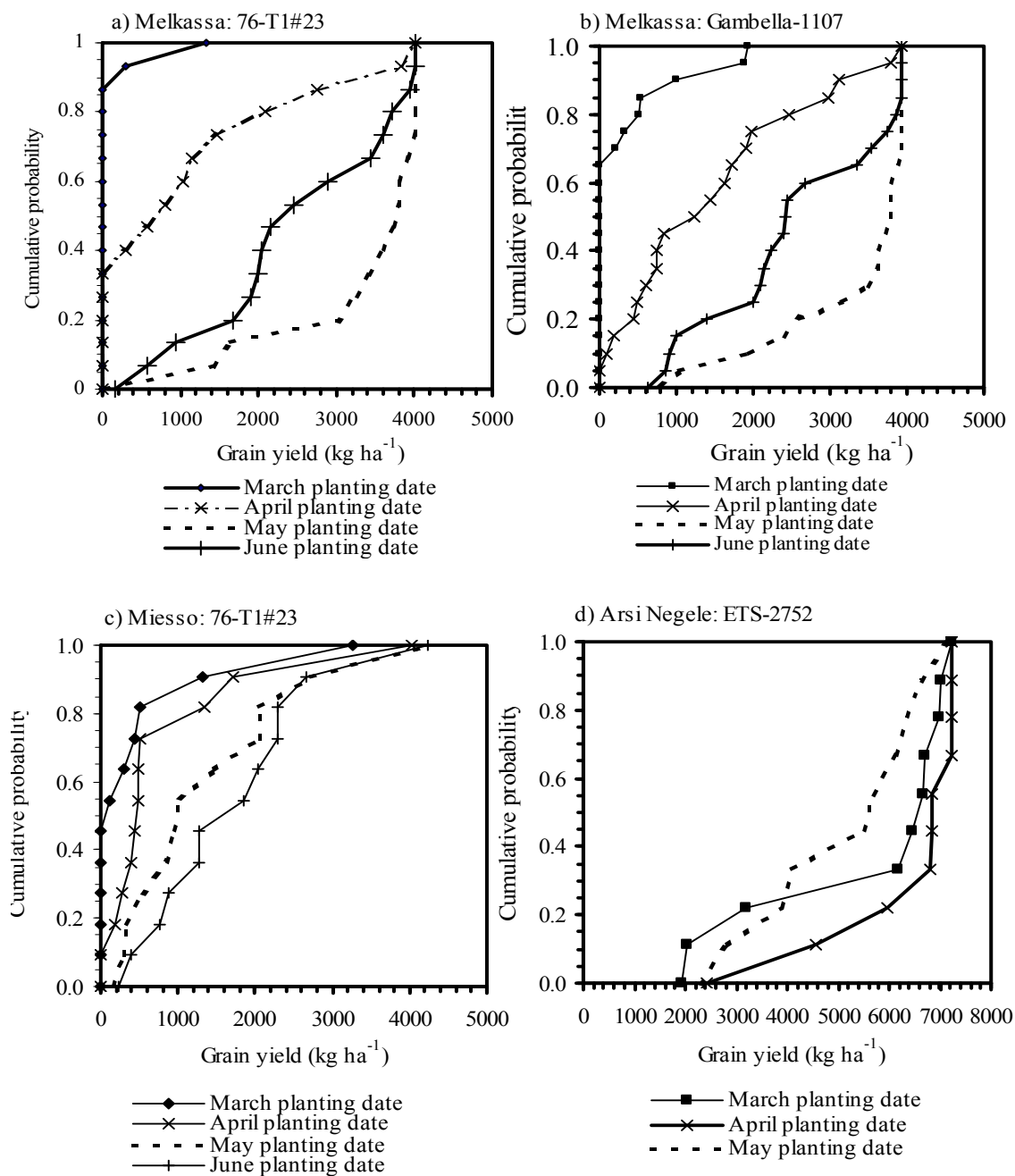
Figure 5.2 Cumulative probability density function of three sorghum cultivars planted in March, April, May and June at (a) Melkassa for cultivar 76-T1#23, (b) Melkassa for cultivar Gambella-1107, (c) Miesso for cultivar 76-T1#23 and (d) Arsi Negele for cultivar ETS-2752

Table 5.2 Kolmogorov-Smirnov test statistics for different sorghum planting dates at Miesso, Melkassa and Arsi Negele in the Central Rift Valley of Ethiopia

Planting date	Miesso						Melkassa 76-T1#23						Arsi Negele			
	April		May		June		April		May		June		April		May	
	D	p	D	p	D	p	D	p	D	p	D	p	D	p	D	p
March	0.4167	0.18	0.58	0.019	0.07	0.005	0.56	0.007	0.94	0.00	0.87	0.00	0.40	0.03	0.40	0.31
April			0.50	0.066	0.58	0.019			0.68	0.00	0.56	0.007			0.60	0.03
May					0.25	0.786										
							Gambella-1107									
March							0.57	0.001	0.90	0.00	0.85	0.00				
April									0.67	0.00	0.52	0.004				
May											0.38	0.07				

D = maximum vertical distance between two CDFs; p = level of significance

It can also be deduced from the same curve that, a farmer targeting 4000 kg ha^{-1} from May and June cropping seasons could achieve the desired quantity, but the associated risk level is of the highest order (85%). In such a targeted yield analyses; any decision maker should therefore be able to increase the soil water content and crop water use efficiency. The same curve shows that the March planting date mostly gives yields of zero order, except that 15% of the time 2000 kg ha^{-1} could be achieved ($p \geq 85\%$).

At Miesso (zone 4), an area where sorghum is known to be the staple food, the crop is produced under not only highly variable, but also a risky rainfall pattern. Fig 5.2c evaluates the CDFs of the predicted yield of cultivar 76-T1#23 for March, April, May and June plantings. Table 5.2 and Fig 5.2c highlight that the March planting date apparently gives a yield of zero order for 50% of the time and therefore, planting sorghum under these conditions is practically impossible. There is a significant difference between the planting dates with the progress of the rainfall season. For instance, the yield level between March and April is non-significant but the yield differences between March and the rest of planting dates are significant. Like the Melkassa case, the difference between May and June planting dates is statistically not significant. However, given that the rainfall pattern at Miesso is lower compared to Melkassa, alternative soil water management techniques should be considered before making planting decisions in May. April planting is also possible, but the risk is much higher than even the May case, particularly from the poor farmers' perspective.

Therefore, except that the curves converged at the upper tail of the distribution (>2600 kg ha^{-1}), Fig 5.2c shows that June planting reveals slightly better output than the May

planting date in FSD sense. Hence, June planting date is to be chosen by any decision maker who seeks higher yields for the cultivar under consideration, regardless of the attitude towards risk. From the same curve, one can also note that 9 years out of 10, the sorghum productivity does not exceed 2600-2700 kg/ha, showing what the potential yields are under the Miesso climate for all the planting dates.

Fig. 5.2d highlights the CDFs of yield distribution for the 180-day cultivar (ETS-2752) under alternative planting windows at Arsi Negele (zone 2). From the CDFs curve, there is significant difference among the three planting dates at 5% probability level. April planting is found to have the best risk efficient set, yielding up to 7220 kg ha^{-1} in 4 out of 5 years *i.e.* for Arsi Negele farmers seeking more payoff this planting date should be the one preferred most in the FSD sense. In examining planting dates vis-à-vis attitude of farmers towards risk, CDFs in Fig. 5.2d show that both risk averse, risk neutral and risk taker farmers invariably prefer the April planting date, as it gives better yields in the FSD sense. With further comparison of March and May planting dates, risk averse prefer May planting, as it yields better at the lowest tail of the series and since the risk averse always worry about the downside risk.

5.3.2 Sensitivity analysis

The equations reflecting four cardinal rainfall related input variables retained after running the stepwise regression which formed the basis for the sensitivity analyses results are summarized in Table 5.2 and discussed in the subsequent sections. For both stations, the rejected input variables were seasonal rainfall duration and crop water requirement.

Table 5.4 and Fig. 5.3 highlight that the productivity of the released sorghum cultivars are more sensitive to the changes in WRSI levels than to any of the other equation components. For instance, with the 'best combination' of inputs (*i.e.* at early planting date (P_E), extended maturity date (M_E), longer rain days (R_L) and 100% WRSI), both cultivars invariably display the highest (3422 - 5148 kg ha^{-1}) productivity in the case of Miesso and Melkassa, while the same was 6469 kg ha^{-1} in case of Arsi Negele. The relative changes in yield (from the yield obtained under the best combinations of inputs)

vary from 21.4 to 100% in case of Miesso, 10.7 to 100% in case of Melkassa and 0.40 to 57.1% for Arsi Negele.

Table 5.3 Multiple regression equation for sensitivity analyses of the important rainfall variables at Miesso, Melkassa and Arsi Negele experimental sites, (CRV of Ethiopia) using planting date (P), maturity date (M), number of rainy days (R) and water requirement satisfaction index (WRSI) as input variables

Experiment Site	Cultivar	# records (n)	Con-stant (α)	Regression coefficients				r^2	F-Test	Eq. # 5.4
				P	M	R	WRSI			
Miesso	76-T1#23	13	-3295	271	79	51	71	0.80	15.5	a
Melkassa	Gambella1107	21	-5458	516	700	114	84	0.85	19.3	b
Arsi Negele	ETS-2752	11	-367	1590	215	1530	63	0.93	22.2	c

From Table 5.4 it could be noted that keeping the other inputs at the best level and changing only WRSI from 100% to 75%, resulted in 49.7 % in the case of Miesso, 40.8% for Melkassa and 24.3% in the case of Arsi Negele. Similarly, keeping the other input variables at the best level, but changing WRSI further down to 50%, resulted in total crop failure at Miesso and Melkassa, while it resulted in 52.8% yield reduction at Arsi Negele.

A similar analysis was done by changing the other input variables from their best level combination to the 'medium' scenario (see Table 5.1). These are: medium planting date, medium maturity date and intermediate number of rainy days. In this case too, the yield level under 100% WRSI was 3056 kg ha^{-1} for Miesso, 4047 kg ha^{-1} for Melkassa and 6195 kg ha^{-1} for Arsi Negele. A change in WRSI from 100% to 75% (keeping the other variables at 'better' level) resulted in 62.2%, 60.8% and 28.5% yield reduction at Miesso, Melkassa and Arsi Negele respectively. A further change in WRSI down to 50% resulted in total crop failure at Miesso and Melkassa and 52.8% reduction at Arsi Negele.

The third scenario in combining different levels of inputs involved late planting date (end of June), short maturity date and short number of rainy days (see Table 5.1) together with different WRSI levels (Table 5.4). The result from these scenario analyses (when WRSI is changed to 75%) indicates that yields decline by over 80% at Miesso, 71.1% at Melkassa and 32.8% at Arsi Negele. With a further change in WRSI to 50% , sorghum productivity was abruptly dropped to zero for cultivar 76-T1#23 at Miesso and

Gambella-1107 at Melkassa (Table 5.4 and Fig 5. 3). On the other hand, the yield reduction with the same treatment combination was 57.1% at Arsi Negele. The percentage change in yield (Fig 5.3) is in relation to the best level treatment combination.

The implication is that, while the optimum combination of yield determining factors is desirable for successful cropping, one factor could be much more important than the others. The large standard errors in Fig 5.3 show how the variability in yield is higher at both experimental sites. However, this sensitivity analyses revealed how WRSI is the most important determinant of yield, as the change in WRSI from 100 through to 50% resulted in significant changes in yield at different experimental sites.

In comparison, while WRSI is most important both at Miesso and Melkassa, in relative terms, sorghum yield response to the change in WRSI is more obvious at Miesso than at Melkassa. The response of sorghum cultivars to a change in WRSI level is lower at Arsi Negele.

Table 5.4 Sensitivity of sorghum cultivars to changes in the levels of input variables at three experimental stations

Input variables combination	Miesso		Melkassa		Arsi Negele	
	Predicted yield kg.ha^{-1}	Relative % change	Predicted yield kg.ha^{-1}	Relative % change	Predicted yield kg.ha^{-1}	Relative % change
P_E+M_E+R_L+100% W	3422		5148		6469	
P_E+M_E+R_L+75%W	1720	-40.8	3047	-49.7	4897	-24.3
P_E+M_E+R_L+50% W	200	-94.1	947	-81.6	3325	-48.6
P_M+M_M+R_M+100% W	3056	-21.4	4047	-10.7	6195	-0.4
P_M+M_M+R_M +75% W	1334	-62.2	1946	-60.8	4623	-28.5
P_M+M_M+R_M +50% W	0	-100.0	0	-100.0	3051	-52.8
P_L+M_S+R_S+100% W	2690	-42.8	2945	-21.4	5920	-8.5
P_L+M_S+R_S+75% W	989	-83.6	844	-71.1	4348	-32.8
P_L+M_S+R_S+50% W	0	-100.0	0	-100.0	2776	-57.1

P_E = early planting date; M_E = extended maturity date; R_L = longer # rain days;
P_M = intermediate planting date; M_M = medium maturity date; R_M = intermediate # rain days;
P_L = late planting date; M_S = short maturity date; R_S = short number rain days;
W = water requirement satisfaction index.

From the sensitivity graph (Fig. 5.3), one useful research question could be advanced with regard to the 100% WRSI. That is, water being an expensive commodity and other factors being kept constant (no negative influence), the expected yields from the use of

adequate WRSI level (>75%) should be in the highest possible range. The question then arises "is it worth using a sorghum cultivar that yields a maximum of 5 t ha^{-1} under a higher range of WRSI ?" or, put differently, "should potentially high yielding cultivars be searched for the benefit of these farmers?"
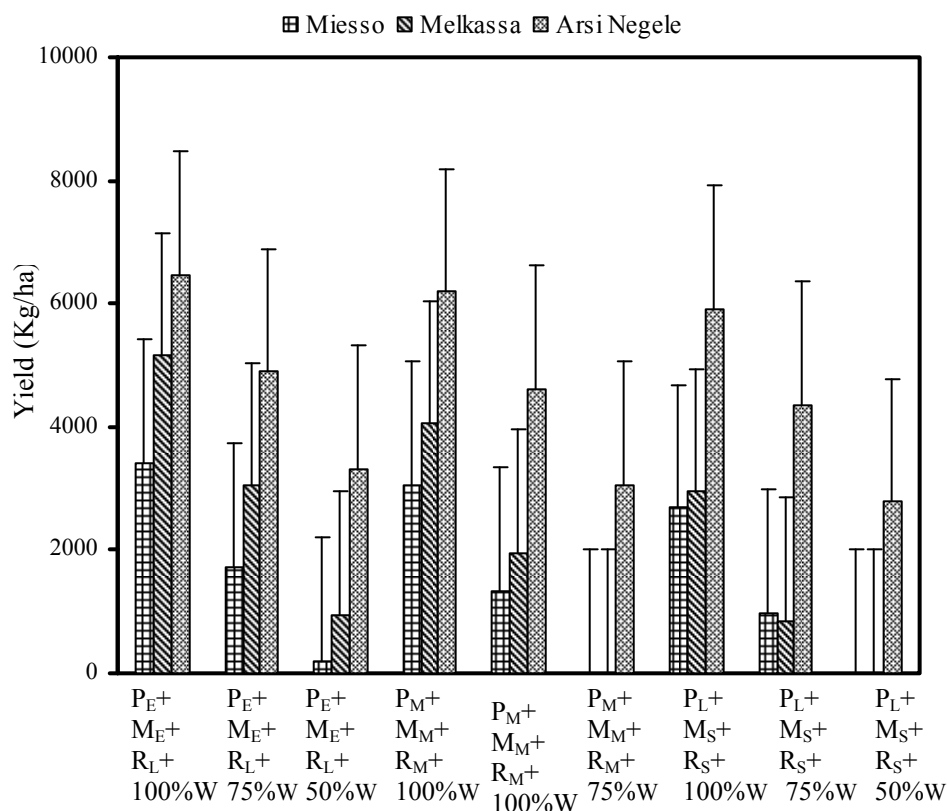
Figure 5.3 Percentage change in yield of sorghum cultivars planted in June at Miesso and Melkassa and in May at Arsi Negele in Central Rift valley of Ethiopia

As explained earlier, farming in the study area is carried out under a highly variable climate. Assuming that farmers always prefer to get more payoffs and can adopt those decision aids and material technologies that are helpful in improving their traditional wisdom of crop management, high yielding cultivars are certainly desirable to them. Therefore, given the timely rainfall prediction information and other decision aids that also contribute to the increased likelihood of WRSI, research targeting high yielding cultivars could be an attractive strategy. However, without decision aids and improved material technologies, as well as for farmers who do not use inputs, stable yielding cultivars and the balanced crop water use information should be targeted.

5.3.3 Simulation modelling

In this section, the relative yield of APSIM simulation output is evaluated against the relative observed yield obtained from sorghum cultivar (75-T1#23) grown in June at Miesso and Melkassa, using Wilmott's (1981, 1982) statistical indices (Fig. 5.4). At Miesso, sorghum yield was over-estimated (75 % of data points appeared above the 1:1 line) with the D-index of 0.82.
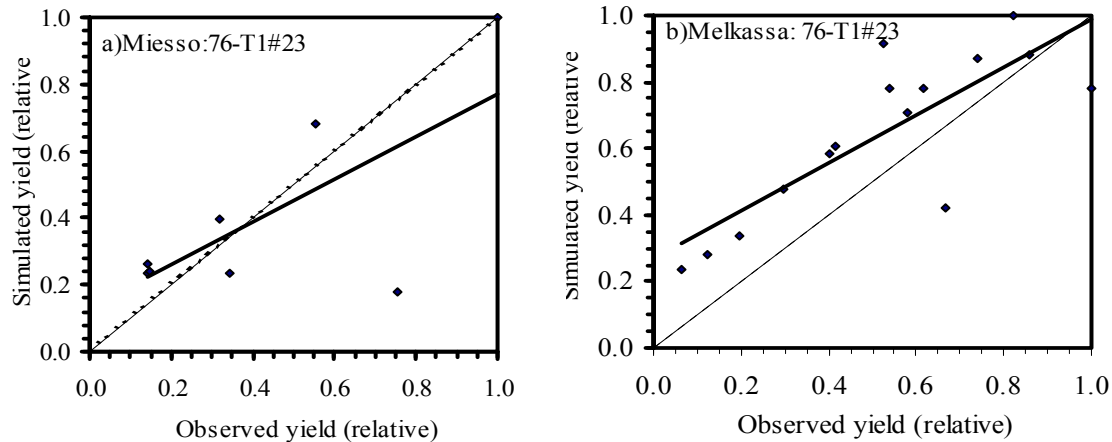
Figure 5.4 Relative observed and relative simulated yield (kg ha^{-1}) of sorghum cultivar (76-T1#23) planted in June at (a) Miesso and (b) Melkassa , CRV of Ethiopia.

At Melkassa, the relative simulated output has over-estimated sorghum yields with the D-index of 0.81, as could be noted from the 1:1 line in Fig 5. 4b with the RMSE of 1148.4 kg ha^{-1} and the corresponding RMSEs and RMSEu of 621.3 and 965.7 kg ha^{-1}. The high RMSEs, reflects a wider difference between the observed and simulated outputs. In accordance with our current argument, possible explanations could be forwarded for the model over-estimated yields. Firstly, the sample size of the observed records used for the simulation was relatively low (n = 8 for Miesso and 15 for Melkassa) and secondly, many crop growth and development related and essential inputs (like leaf area, total dry matter and others) required for the simulation of growth and development processes were missing. This must have contributed to the lack of strong disagreement between the observed and simulated yields.

It is equally important also to note that even with an availability of a sufficiently large sample and a good understanding of the underlying processes, the link between understanding and realistic simulation in such a complex biological-climate system is

problematic and it is difficult to establish perfect reasoning for such a low scale association all at once (Hutchinson, 1991; Monteith, 1996).

Generally, the result from the current simulation run did not produce scientifically useful results at this stage. Nevertheless, new insight and deeper understanding of how the rainfall risk that could form a good ground for the future simulation work has been gained.

5.4 Conclusions

The risk analyses conducted in this chapter provided a framework for using climate risk information pertaining to sorghum productivity at three experimental sites (Miesso, Melkassa and Arsi Negele) in the CRV of Ethiopia. Two 120-day cultivars (76-T1#23 and Gambella-1107) were used for March-September growing season at Miesso and Melkassa, while a 180-day cultivar (ETS-2752) was used for March-October in the case of Arsi Negele.

At Miesso, the stochastic dominance analysis shows that June planting date was the dominant set in FSD sense over the rest of the planting windows. The simulation analysis for a 120-day cultivar planted in June at Miesso shows that APSIM has overestimated the observed yield with an average of 2906 kg ha^{-1} as compared to the 1782 kg ha^{-1} observed average yields with the D-index of 0.82.

At Melkassa, the result from the stochastic dominance analysis (SDA) shows that May planting date was dominant in FSD sense for both cultivars, yielding between 3900-4000 kg ha^{-1} at 85th percentile risk level. The sensitivity analysis conducted for Melkassa using four cardinal rainfall related input variables (planting date, maturity date, number of rainy days and water requirement satisfaction index) shows that yields of Gambella-1107 planted in June was found to be much more sensitive to WRSI than the rest of the input variables. For instance, by keeping other input variables at a given level of combination, and changing WRSI from 100% to 75%, yield was reduced by 40.8%, while further change in WRSI down to 50% resulted in total crop failure. The simulation modelling result for Melkassa also shows that most of the data points

appeared above the 1:1 line which means APSIM has overestimated the observed yields (D-index was 0.81) and this may be useful research information that could be of interest to the sorghum breeders and agronomists working in the study area. Further study is required to arrive at a definitive conclusion.

For Arsi Negele, the CDFs of a 180-day cultivar planted in April was found more risk efficient and this could be adopted by the farmers preferring 'more' payoff to 'less'. The sensitivity analyses conducted for cultivar ETS-2752 planted in May shows that the relative reduction in grain yield due to a change in WRSI from 100% to 75% was only 24.3%. Compared to the Miesso and Melkassa cases however, further reduction in WRSI down to 50% did not result in complete crop failure (2777 kg ha^{-1} could still be realized). Further comparison shows that the response of ETS-2752 to the change in WRSI levels (keeping other variables constant) is lower compared to the Miesso and Melkassa cases. This shows how WRSI is the most important input variable under inadequate rainfall compared to that under adequate rainfall areas.

Overall, although there was a limitation in data that rendered the results not to provide a definite conclusion, this chapter has brought several risk related research questions to the fore and proposed possible solution statements. These need to be taken up as a useful research topic on the way forward.

Chapter 6

Tactical Decision Support Tool for Sorghum Production under Variable Rainfall

6.1 Introduction

The fact that agricultural science is only offering marginal information and material technologies, particularly to help dryland farmers who live with a highly variable climate, is no doubt disappointing. Indeed, the much cited quip of Charles Dudley Walker "everybody talks about the weather but nobody does anything about it" emphasizes the need for re-engineered coping mechanisms and solutions for a variable climate. Russel (1950) observed the arid and erratic rainfall of Australia and stated "I am almost unable to believe that it is beyond the power of science to remedy this …. why should we sit down under such circumstances. If science teaches us anything, it teaches us that there are few circumstances in which we should sit down passively."

As a step towards a solution, Russel (1950) suggested, "if I could control Australian policy, I should establish a college of highly skilled scientists of various sorts, meteorologists, agronomists, nuclear physists to be engaged in a theoretical investigation of what is necessary to increase the fertile area of Australia". He also added, "the people involved should be young, temperamentally hopeful and respected because of their capacity. The same skill that shows us how to exterminate the human race can also help to make the desert bloom like the rose".

As agriculture is in acute competition with the other economic sectors for resources, the need for agricultural science in teaching about better decision making is becoming more crucial (Hayman, 2004). Recent soil-plant-climate-informatics interfaced developments provide an unprecedented opportunity to design and implement improved crop management systems, via what is now known as decision analysis. Goodwin and Write (1991) emphasized the term 'analysis', which originated from the Greek word "to loosen". Analysis involves going deeper into the smaller parts, while synthesis is the

process of putting the decisions and problem situation back together as a whole, but with new understanding.

According to Anderson *et al.* (1977) decision analysis (the classic approach to risky decisions) has been applied to diverse aspects for a long time but has been used elegantly in research on climate risk (Katz *et al.*, 1982; McCown *et al.*, 1991a; Keating *et al.*, 1993; Marshall *et al.*, 1996; Hammer *et al.*, 1996). Decision analysis is vital, because there is a specific time when the crop must either be sown or the land left fallow; and when the crop is sown, there is an optimal rate of fertilizer that should be applied under defined planting density and available soil water (Ackoff, 1981). Likewise, decision theory was applied to businesses in 1960s by Howard Raiffa and Robert Schlaifer of Harvard University's Business School as a way of dealing with uncertainty in decisions (Philips, 1982). This implies that a decision (Greek word means cut-off point) that can be considered as an irrevocable allocation of resources must be made at the right time for the specific farmland.

6.1.1 Decision analysis: Definition and approaches

Barnard (1938) defined decision analysis as a logical process of discrimination and then choice. The three recently redefined stages in decision analysis involve:

First, the sequence of restructuring a problem (establishing a context), allocation of probabilities and making choice from among alternative courses of actions. Structuring the decision situation is a form of system diagnosis or situation description. While there is no argument that system diagnosis is important, there are vast numbers of arguments to be considered, including the appropriate resolution and the choice of methodology. This has led some professionals to the extent of even dismissing decision analysis as an artifact with little relevance to the context of the decision maker. For example, Checkland (1988) suggested that decision analysis is only suitable for those who enjoy playing around with the logic of a situation.

Secondly, by definition tactical decisions are difficult commodities to package and transfer to the farmers, because they are highly uncertain. Therefore, a rule of decision analysis is that all uncertainty can be represented through appropriate use of probability, which is used to express their future behaviour. Norris and Kramer (1990)

defined subjective probabilities as "the beliefs held by individuals that reflect their uncertainty about some idea, event or proposition". They maintained that subjective probabilities are successfully used in fields as diverse as psychology, management science, investment analyses, meteorology and agriculture. Anderson and Dillon (1992) claimed that the use of subjective probabilities further emphasizes the sovereignty of the decision maker.

The third and final stage involves systematically presenting the choices, chances and consequences associated with a particular decision, in which the best choice often becomes either obvious (*i. e.* one choice has much better outcomes than all the others), or marginal (*i.e.* little difference between the projected outcomes). Hayman (2004) calls such a sequence of approaches to the uncertain and therefore risky decisions, a 'decision support system' (DSS) or 'decision support tool' (DST).

Hochman (1995) described a DST as any structured method of using data, information or knowledge to help people reach objective management decisions. Arinze (1992) noted a trend for the term DSS to be applied to problem solving rather than the specific technology of computers. For instance, Nykanen *et al.* (1991) defined DST as "the exploitation of the extended human mind and computer related technologies to improve creatively decisions that really matter". For the purposes of this study, a DST is understood to be a computer based, interactive system which offers both information and decision making procedures, and is designed to support a specific set of decisions (Sage, 1991). This implies that once the goal is properly established there could be more than one way to reach it.

According to Sprague (1980), a DST has always had its greatest value in uncertain environments dealing with missing information. He noted that while many other applications use historical data, a DST is forward-looking in perspective and involves not only data, but also procedures for judgment about future uncertain events. Simon (1983) agrees that the underlying theories of decision analyses are a beautiful object, deserving a prominent place in the world of ideas, but claimed that there exist many uncertainties that make it difficult to employ them in any literal way to making actual human decisions. Woods *et al.* (1993) made a point that while most agricultural DSTs

have a potential to improve farmers' decisions, the means by which these can occur is not clearly established or thoroughly evaluated.

As it is impossible to deal with risks all at once, much of the success of decision analyses has been attributed to the 'divide and conquer' orientation in the sense of using diagrams such as decision trees to disaggregate (analyse) a decision problem (Keeny, 1982). Setting boundaries and hierarchies for a particular problem consistent with time and other resources available is therefore vital. The promise of DST is a means of organizing data into information or knowledge that can be readily used. For example, Hamilton *et al.* (1991) stated "never before have we been able to analyze so much data relating to a specific situation, and arrive at a solution to a complex problem". According to Gaffney (1996) decision analysis is what one has to do when situations become difficult to manage.

As pointed out by Hardaker and Gill (1994) and Hardaker *et al.* (1998), there is little new about decision analyses. Bernouli recognized risk aversion in 1738, while von Neuman and Mongestern developed the central hypotheses of decision analyses in 1947 and Savage wrote a text on subjective probabilities in 1954. On the other hand, Scanlon and McKeon (1993) claimed that the discipline of computerized DST in agriculture is in its infancy and hence it was too early to judge its value. Similarly, White *et al.* (1993) noted the emerging role of DST in agriculture, while it has been used more than 20 years in other industries.

6.1.1.1 Decision analyses: State of the art in developed and developing nations

In developed nations, DST has been a significant way in which agricultural scientists seek to intervene and improve the way farmers manage their enterprises. Although there have always been some diverging ideas, DST is held as a promising means to transfer scientific information and farm management procedures to farmers for instance in America and Australia (Hayman, 2004). This notion has however been challenged with the recognition of the existence of the important pools of knowledge with farmers, extension workers, scientists and others (Rölling, 1988). In their study on the potential of DST in dryland farming of Australia, Hamilton *et al.* (1991) saw a promising future for DST once computers became more common and providing that developers took a

team approach and considered end-users. They concluded "computer based decision aids have not been oversold, but have just been underdeveloped".

What are the implications in relation to farming in developing nations? No doubt, for these nations too, decision analysis represents a useful interface between scientists studying the farming system and farmers managing the systems (Hayman, 2001). However, the relationship between the two has always been a complex one. The Ethiopian research system for instance has an overall objective of developing material technologies (e.g. varieties, fertilizers etc.) and decision aids (ideas, agronomic, resources) to assist farmers deal with crop and livestock production decisions that are greatly affected by climatic risks. It follows from this claim that Ethiopian farms are currently not profitable, but farmers are reliant on food aid and adopt less sustainable agricultural practices not only due to climate variability, but also to the fact that they lack information and procedures for decision-making.

For the Ethiopian research system, this makes a case for a challenging environment in the course of technology 'exchange'. Technology 'exchange' presumes that material technologies and knowledge are expected to be created and transformed into useful information by research and farmers teams in a participatory way. This emphasizes that, as the loop needs to be closed, technology 'exchange' also assumes the preference of co-learning and technology sharing among the stakeholders as opposed to the flow of technologies and ideas from one direction only.

Hochman (1995) noted that farm management is becoming more complex and to deal with the complexity one needs more advanced decision aids. In the case of developing countries, the overwhelming majority of small-scale farmers do not and cannot own computers in the near future. Therefore, whatever computer DST one is referring to can be targeted only at the third party (researchers, extension workers and consultants) and not directly at the farmers themselves. That is not to say that a farmer today who wants access to a DST cannot find one. To bring the DST utility to the level of small-scale farmers however, enormous capacity building needs to be promoted in terms of financial resources and adult learning schemes.

6.1.2 DST and the Ethiopian farmer

This chapter accepts that a climate referenced DST is a valid contribution to the Ethiopian research system, but at the same time exploring the most useful kind of information expected from the analyses needs crucial thinking. For this purpose, decision-making can be conveniently categorized into three sequential groups: strategic, tactical and operational (Russel, 1991). By 'strategic' is meant management practices, which are followed every year in the expectation that it will give maximum benefits over the long-term. On the other hand, 'tactical' application means changing management practices in response to the state of environmental or biological systems (Angus, 1991). This involves decisions pertaining to planting (such as which cultivar to sow and when, determining fertilizer rate, plant population to use, enhancing soil water storage). In contrast, 'operational' or action decisions involve the real time operational work done in the fields (sowing, weeding, spraying and the like) almost as they occur in real time.

Of the three categories, this chapter targets tactical decisions that are characterized by responding to the state of the rainfall (prediction aspect) and soil physical constants. With regard to rainfall prediction, the emerging understanding of the relationship between SSTs and rainfall is expected to improve decision making according to the state of the atmosphere and oceans (Chapter 3). On the other hand, soil properties (drained upper limit, lower limit and plant available water) are the core of the successful cropping system. Robinson and Butler (2002) found that pre-plant soil water content information provided the best prediction of dryland crop yields in the northern Australian grain belt, but relatively few farmers accurately measure soil water content prior to planting.

There are many sources of risk in rainfed farming, but the components of the tactical decisions in the current chapter involve only five: date of sowing, cultivar choice, fertilizer levels, planting density and soil water storage. The main reason for focusing on these proposed components of the tactical decisions is that these involve greater uncertainty and possibilities for change and therefore risky decisions by farm managers in dealing with the a variable climate. Moreover, as they are sensitive to changes in weather patterns and input levels, they are more critical and yield limiting factors. As such, they represent the most important control levels on the farming system and have

an impact not only on the current farm business, but also on the sustainable resource management. Therefore, serious attention has to be paid to these factors.

6.1.3 Determination of the drained upper limit, lower limit and estimation of the soil water content of the target month

In order to estimate PAW for the target month, information on soil drained upper limit (DUL), lower limit (LL) and the measured soil water content of the predictor month (one month lead) are required. Moreover, the statistically predicted rainfall total and long-term average evapotranspiration data for the month preceding the target month are essential. Meinke *et al.* (1993) defined PAW as the sum of the difference between the volumetric water content at drained upper limit (DUL) and lower limit (LL) of plant available water, for all layers within the plant rooting depth.

$$PAW = SWC + ERF - ET - LL \tag{6.1}$$

where:
PAW = plant available water content (mm) of target month
SWC = measured soil water content (mm) of predictor month
ERF = estimated rainfall (mm) for month before target month
ET = Long-term ET (mm) for month preceding target month
LL = Lower limit (mm m^{-1})

$$PAWC = DUL - LL \tag{6.2}$$

where:
$PAWC$= Plant available water capacity (mm m^{-1})
DUL = Drained Upper Limit (mm m^{-1})

Plant available soil water (PAW) can now be evaluated as either less than, equal to or greater than half the PAWC. Alternatively PAW can also be estimated as follows.

$$PAW = \theta - LL \tag{6.3}$$

where:
θ = on-site measured soil water content of predictor month.

6.1.3.1 Measuring and estimating the drained upper limit (DUL)

Ratliff *et al.* (1983) defined DUL as the highest field measured water content of a soil after it has been thoroughly wetted and allowed to drain until drainage becomes practically negligible *i.e.* when the reduction in profile water content is about 0.1 to 0.2% of the water content per day. The drained upper limit, as defined here is exclusively controlled by the water holding properties of the soil profile within a defined depth. DUL therefore depends on the soil texture, porosity, organic matter content and

thickness of each horizon in a soil profile, which constitute the specified rooting depth (Boedt and Laker, 1985).

In practice, DUL is measured in the field by thoroughly wetting a plot of 3m x 3m, and measuring the water content throughout the root zone at time intervals until the reduction in water content becomes negligible. Evaporation loss from the plot is prevented by covering the plot with a plastic sheet (Hensley *et al.*, 1993). This is a huge amount of work and one needs the necessary instrumentation.

Alternatively, efforts have been made to develop empirical regression equations to estimate DUL, based on other soil properties like texture classes and bulk density. Examples of such equations as thoroughly calculated and discussed by Zere (2003) using ten South African soils are given below:-

a) Hutson (1983) developed Equation 6.4 based from water retention data for a large range of South African soils:-

$$\theta_{-10} = 0.0558 + 0.0037\ Cl + 0.0055\ Si + 0.0303\ BD \qquad (6.4)$$

where:
θ_{-10} = volumetric soil water content ($m^3\ m^{-3}$) at a soil water potential of -10 kPa, to represent "field water capacity"
Cl = clay content (%)
Si = silt content (%)
BD = soil bulk density (g cm^{-3})

b) Bennie *et al.* (1994) developed Equation 6.5 based on measurements of different soils in South Africa, mainly fairly coarse textured soils in the Free State:-

$$\theta = 0.0037\ (Si + Cl) + 0.139 \qquad (6.5)$$

where:
θ = volumetric soil water content ($m^3\ m^{-3}$),
Si and Cl are as defined for Equation 6.4

c) Ritchie *et al.* (1999) developed the DUL equation 6.6 from 312 soils in the USA:-

$$\theta_m = 0.186\ (Sa/Cl)^{-0.141} \qquad (6.6)$$

where:
θ_m = gravimetric soil water content (kg kg-1) at DUL for a particular horizon
Sa = sand content (%)
Cl = clay content (%).

Ritchie *et al.* (1999) used Equation 6.7 to determine the volumetric water content (θ, m^3 m^{-3}) at DUL for the specified layer:-

$$\theta = \theta_m \, BD/\rho_w \tag{6.7}$$

where: $\qquad\qquad$ ρ_w = density of water (Mg m^{-3}),
$\qquad\qquad\qquad\qquad\qquad$ and other symbols remain as defined belore.

Streuderst (1985) developed Equation 6.8 to estimate DUL for freely drained medium textured soils:-

$$Y = 0.1243 + 0.0053 \, x_1 - 0.0098 \, \sqrt{x_2} \tag{6.8}$$

where: $\qquad\qquad$ Y = volumetric soil water content (m^3 m^{-3})
$\qquad\qquad\qquad\qquad\qquad$ x_1 = cation exchange capacity (cmol$_c$ kg^{-1}) plus clay %
$\qquad\qquad\qquad\qquad\qquad$ x_2 = very fine sand plus silt content (%).

6.1.3.2 Measuring and estimating the lower limit of plant available water (LL)

The soil water content at a matric suction of −1500 kPa has long been considered by many agricultural scientists to represent the lower limit of plant available water (e.g. Green, 1985). This assumption has provided the foundation for a number of equations for predicting LL. The lower limit of plant available water (LL) has been defined as the lowest field-measured water content of a soil, after plants have stopped extracting water and are at or near premature death or became dormant due to water stress (Ratliff *et al.*, 1983). In dryland crop production, where one cannot "refill" the profile at will, this definition of the lower limit is appropriate. LL depends on the atmospheric evaporative demand, depth and density of root ramification, drought resistance of the crop and the unsaturated hydraulic conductivity and water retention properties of each soil horizon within the rooting zone (Hensley and De Jager, 1982). Several attempts have also been made to estimate LL using empirical regression equations. The following equations as reviewed by Zere (2003) are given below:-

$\qquad$ (a) Hutson (1983):

$$\theta_{-1500} = 0.0602 + 0.0032 \, Cl + 0.0031 \, Si - 0.026 \, BD \tag{6.9}$$

where: $\qquad\qquad$ θ_{-1500} = volumetric soil water content (m^3 m^{-3}) at a soil water
$\qquad\qquad\qquad\qquad\qquad$ potential of −1500 kPa
$\qquad\qquad\qquad\qquad\qquad$ BD = bulk density (g cm^{-3})
$\qquad\qquad\qquad\qquad\qquad$ Cl = clay content (%)
$\qquad\qquad\qquad\qquad\qquad$ Si = silt content (%)

(b) Bennie *et al.* (1998):

$$LL = \sum(0.00385\ (Si + Cl)i + 0.013)\ zi \qquad\qquad (6.10)$$

where:
LL = lower limit of plant available water (mm)
$(Si + Cl)i$ = silt plus clay content of layer i (%)
zi = thickness or depth of layer i (mm)

(c) Ritchie *et al.* (1999):

LL is estimated as the difference between θ (Equation 6.7) and PAW, where

PAW is defined as follows:

$$PAW = 0.132 - 2.5 * 10^{-6} \exp(0.105\ Sa) \qquad\qquad (6.11)$$

where:
PAW = plant extractable water ($m^3\ m^{-3}$)
Sa = sand content (%)

The equations discussed above are useful in getting insight about the need for soil water content information for practical purposes, mainly when measured soil water content data are not readily available.

This chapter argues therefore that the variable climate in the Central Rift Valley of Ethiopia makes farm management decisions not only challenging, but also leads to decisions that are inappropriate or at least unwise. This could be explained from the perspective of the persistently low yields and land degradation in the study area. The farmer's decision-making is most limited by lack of information on the effective start of the rainy season and preferred planting dates and therefore a DST could help by presenting viable options.

The objective of this chapter is therefore to develop a simple, but conceptually strong, reflective and potentially innovative 'what if' and 'seasonal climate' centered DST that could be activated as required. The tool is expected to provide a good starting framework for answering many of the practical farm questions for CRV farmers, researchers and extension workers alike.

6.2 Materials and Methods

The basic structure of the new decision support tool is summarized in Fig 6.1. The monthly (March-September) rainfall prediction output (in the form of 'below normal' = B, 'near normal = N' or 'above normal = A') as obtained from the chapter 3 prediction

model would be used as part of the inputs. During the development stage the name "MARCMET" was used for this DST, derived from Melkassa Agricultural Research Center and the Agromet Research Group of EARO, but the name "ABBABOKA 1.0" was decided on so as to honour of the traditional rainfall predictors.

In the construction of ABBABOKA, monthly (March-September) rainfall data from 25 weather stations situated in the study area were used. However, since the long-range rainfall prediction is full of uncertainties, it was necessary to include the predictive information from the national (NMSA) and regional (ICPAC) centres in the DST. Moreover, as rainfall is only a single aspect of the overall soil water budget, the plant available soil water capacity (PAWC) and the plant available water (PAW) are included as variables.

In Fig 6.1, three groups of logical combinations of the predictive information from different sources (*i.e.* the newly developed prediction model, NMSA and ICPAC models) are used in a 3 letter code. The first decision box (from top) in the figure shows, for instance if the newly developed prediction model states 'A' and if this information is complemented with the 'N' or 'A' from NMSA (*i.e.* AN or AA), then ABBABOKA displays details of planting decisions that could be advised to the target user, even if the ICPAC prediction model returns 'B' and regardless of the soil water content information. One exception is, if ICPAC gives a 'B', then one must consult the PAW. The second decision box (middle, Fig 6.1) shows that if all the 3 models return 'below normal' i.e. 'BBB' or if either of them returns 'A' or 'N' together with the other 2 giving 'B', then ABBABOKA displays a 'keep on fallowing' decision aid, regardless of the outcome of the soil water content information.

The bottom decision box in Fig 6.1 highlights three different conditions under which ABBABOKA displays a 'go for planting' decision. These conditions are:-

      1) when any one of the models returns 'B' and when other 2 give 'A' or 'N' or

      2) when both the three models release 'NNN' or

      3) when the new model and NMSA produce 'NN' followed by 'A' from ICPAC.

However, for the ABBABOKA to display a 'go on planting' decision under the above three conditions, the fact that the estimated PAW of the target month is either equal to or

exceeding half of the PAWC is a necessary precondition, as this information helps in making a reliable decision. ABBABOKA is useful for monthly-based planting related decisions, with the assumption that, once the effective rainfall onset date has passed, monitoring the subsequent rainfall recieved is possible using other weather-forecasting and application models (e.g. EUMETSAT and AGROMETSHELL).
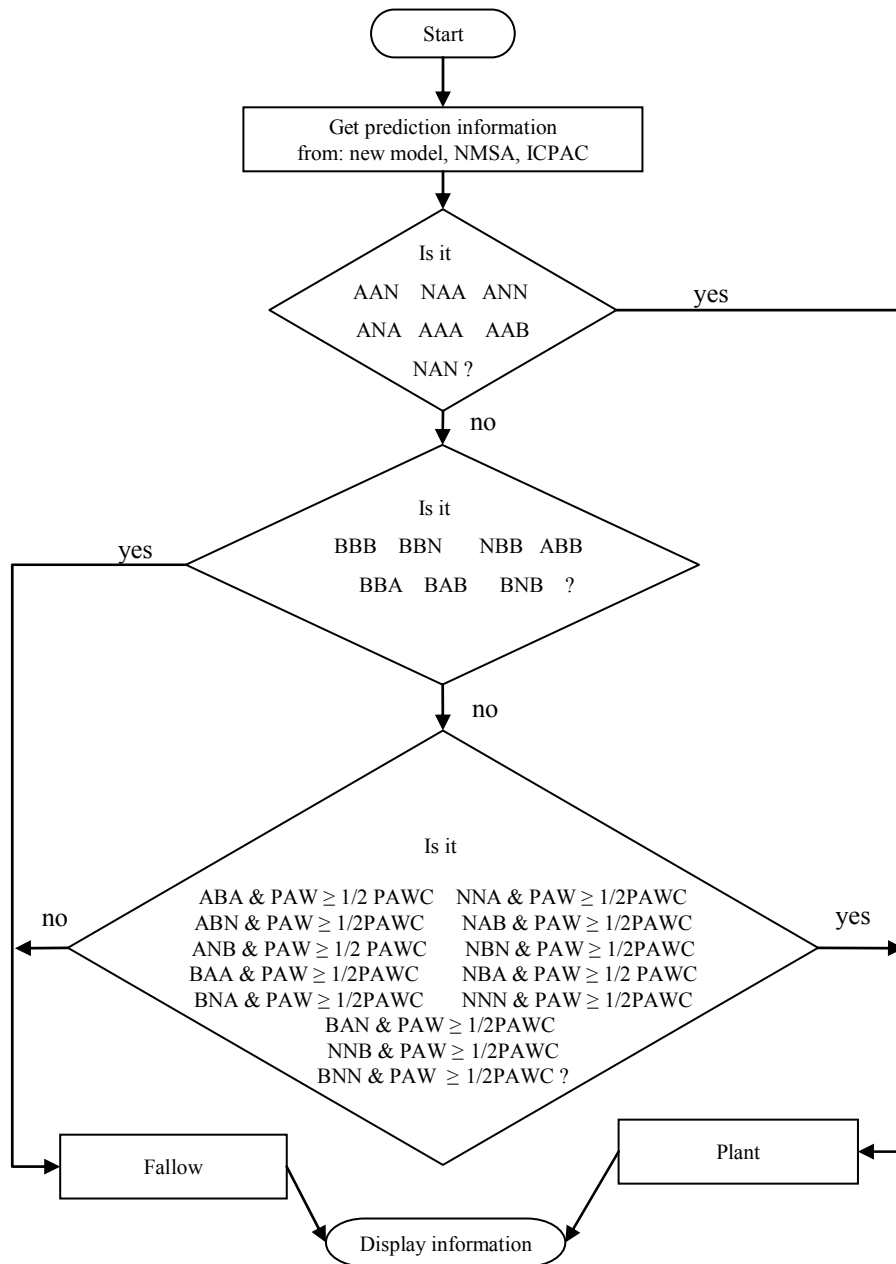
Figure 6.1 Key input variables used in the construction of ABBABOKA 1.0 a decision support for sorghum planting in CRV of Ethiopia

In the construction of ABBABOKA, the Ritchie *et al.* (1999) DUL Equation (6.6 and 6.7) and Equation 6.11 for LL were adapted, mainly because these equations were developed based on the large sample size collected from a range of soil characteristics. Moreover, it has shown a better relationship with DUL measured from the clay soil, which can be useful information for the CRV case. The equation was adapted as follows:-

$$DUL = (\theta_m BD / \rho_w) * Zi \qquad (6.12)$$

Where: $\qquad$ DUL = Drained upper limit (mm m^{-1})
$\qquad$ Zi = soil depth (mm) and others are defined as before.

The PAW from Equation 6.11 was used to calculate LL (Ritchie *et al.* 1999).

6.3 Results and Discussion

This chapter illustrates how decision analyses help using simple examples drawn from the application of ABBABOKA. The interface in Fig 6.2 shows 27 physically possible of planting or fallowing related decisions. An example in Fig 6.2 shows if the new model and the ICPAC predictive products give 'above normal', and NMSA releases 'below normal' rainfall probability information (*i.e.* ABA), for March planting (using January as predictor) for zone 1 that ABBABOKA provides suites of decision aids. The decision states "go on planting a grain sorghum cultivar which needs more than 180-day to mature". It also advises to use 100 kg ha^{-1} DAP (basal), 50 kg ha^{-1} urea (N side dressing) and 33,000 plants ha^{-1}. As the evaluated area is a semi-arid region, ABBABOKA emphasize the importance of enhancing root zone water storage through possible water harvesting techniques, be it traditional or improved or *in situ* or *ex situ.*

On the contrary, if the rainfall predictive information from all three sources states "below normal' (BBB), it could be noted from Fig 6.3 that ABBABOKA unconditionally (regardless of soil water information) releases a 'keep fallow' statement. In other words, the available information does not support March planting of any maturity group of grain sorghum in zone 1.

ABBABOKA also computes the plant available water capacity (PAWC) (Fig 6.4), which is a reference point to which the estimated plant available water (PAW) for the target month is compared for decision making as deemed necessary. As stated, whenever the soil water information is required in planting related decisions, PAW should be either equal

Figure 6.2 ABBABOKA decision aids, when the rainfall predictive information from the new model and the two other institutions (NMSA and ICPAC) states 'above normal', 'below normal' and 'above normal' (ABA) respectively for the month of March in zone 1
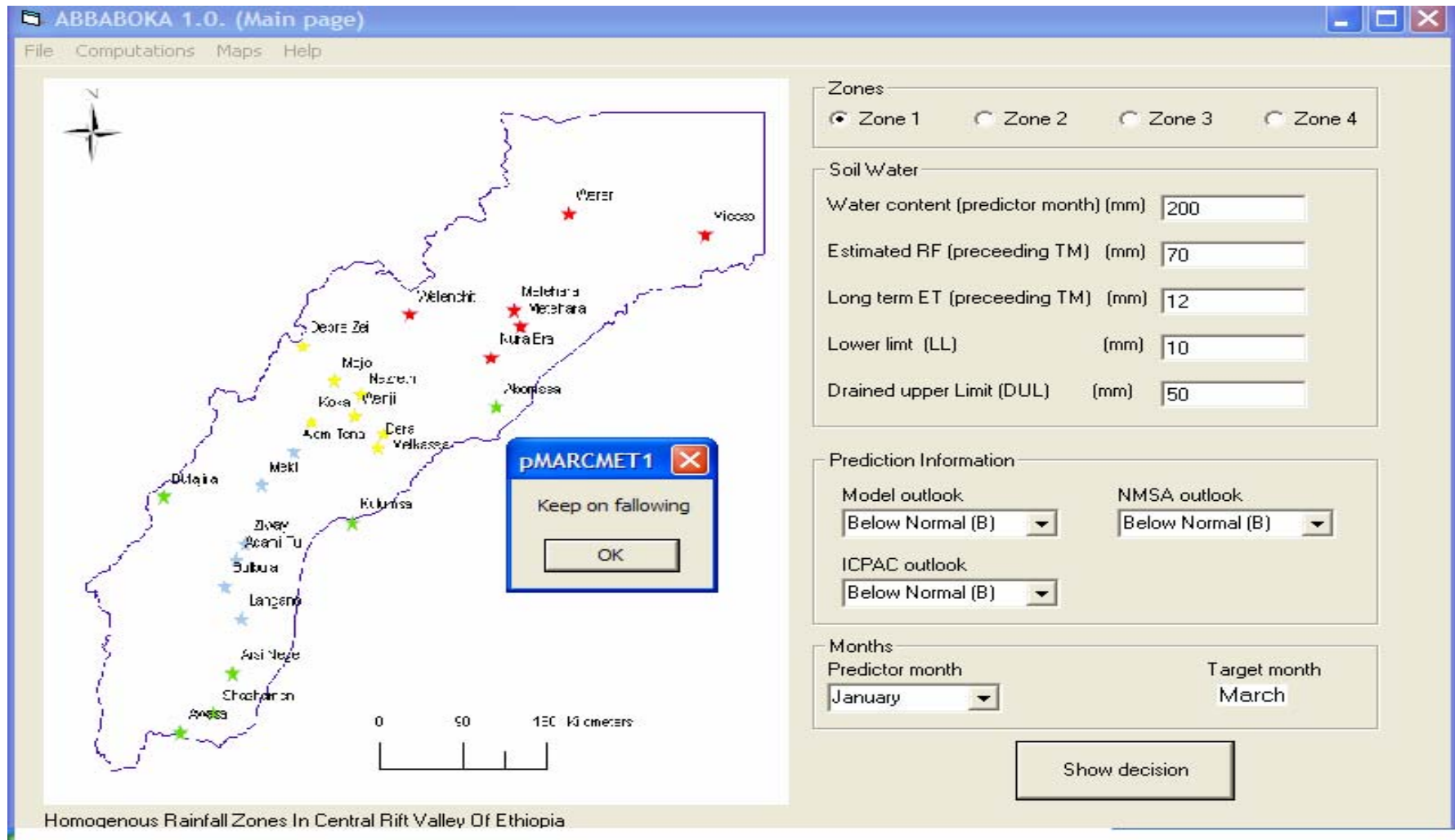
Figure 6.3 ABBABOKA decision aid when the rainfall predictive information from the new model and the other two institutions (NMSA and ICPAC) states 'below normal' (BBB) for March planting in zone 1.

Figure 6.4 Estimation of the available water (PAW) for a given target rainfall month to support sorghum planting decisions in ABBABOKA
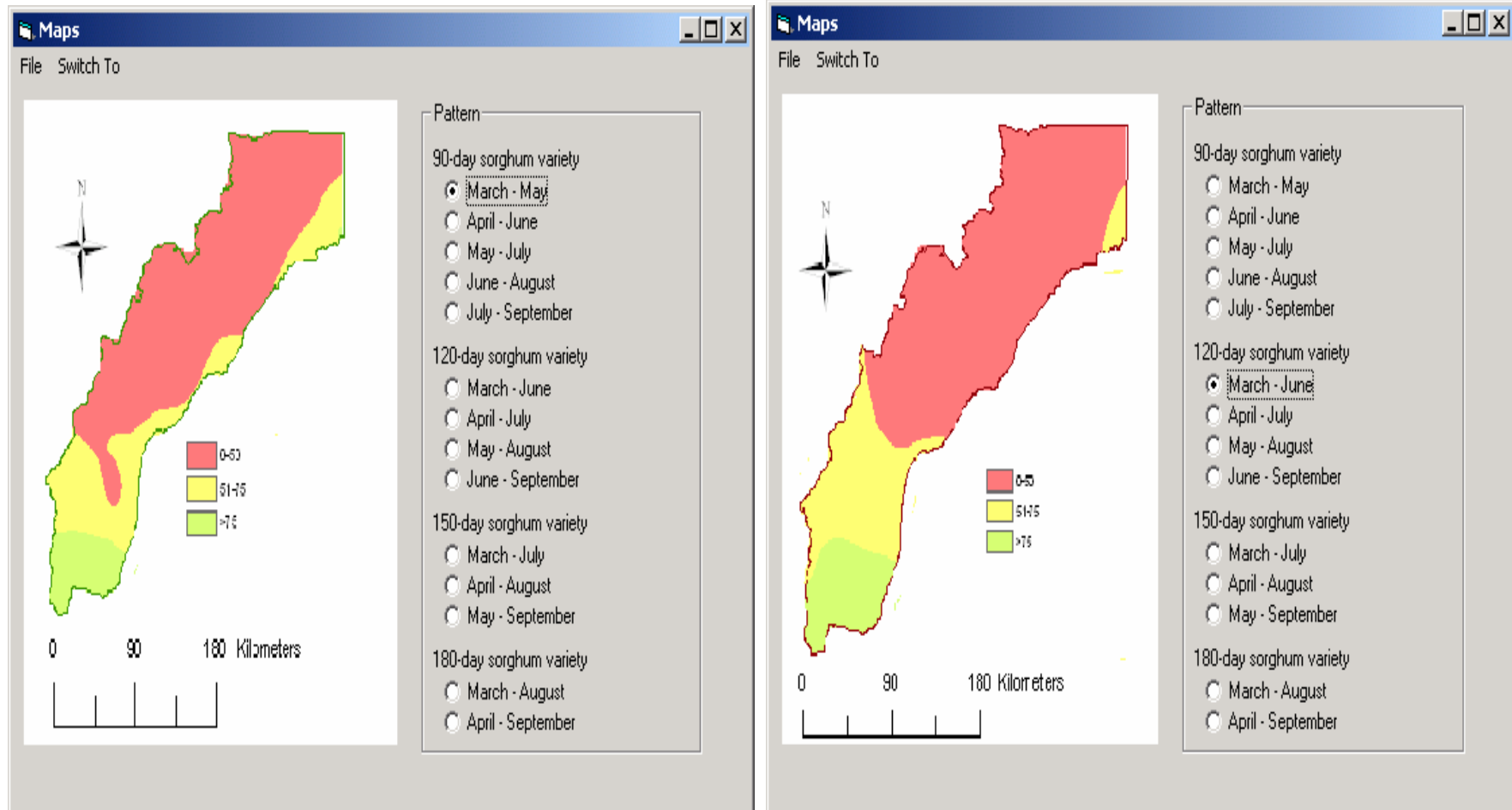
Figure 6.5 Seasonal crop water requirement satisfaction index (WRSI) for a 90-day sorghum cultivar grown (left hand panel) during March-May and a 120-day sorghum cultivar grown (right hand panel) during March-June in zone 1
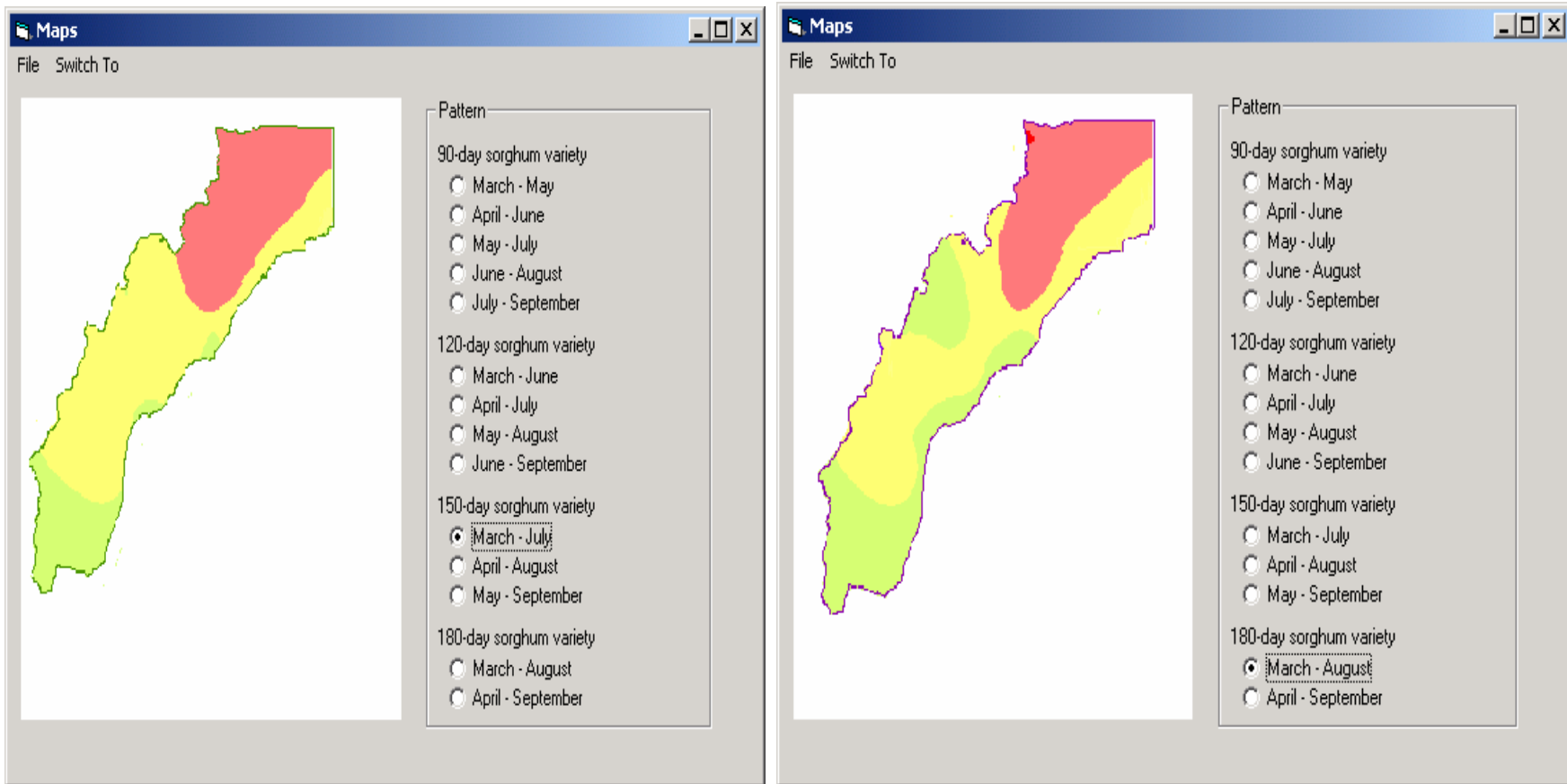
Figure 6.6 Seasonal water requirement satisfaction index (WRSI) for a 150-day sorghum cultivar grown (left hand panel) during March-July and a 180-day sorghum cultivar planted (right hand panel) during March-August in zone 1

to or greater than half the PAWC. Fig 6.4 shows how ABBABOKA is used to compute PAW, which should be compared with PAWC and evaluated for being equal to or greater than half the PAWC, as information which is required to complement the predictive information for planting related decision making, particularly when decision making is difficult from the prediction models alone. Fig 6.5 and Fig 6.6 provide a general impression and first order information regarding the sorghum water requirement satisfaction during given months before the user starts interacting with the DST. This also helps in making improved and final decisions.

6.4 Conclusions

This chapter has discussed the benefits of the decision support tools in the modern field / farm management system in general and the principle ground on which ABBABOKA was developed and the steps used in its development for possible application in the CRV.

The result from 27 decision options (clustered into 3 like groups) shows that flexible planting decisions could be adopted by using the rainfall outlooks and soil water information as input into the appropriate interface. For instance, if the prediction output from the new model and NMSA recommend "above normal" (AA), then regardless of the kind of predictive information from ICPAC model, ABBABOKA advises "continue planting a sorghum cultivar group of interest under the prescribed management practices during a given month in a zone". There are also cases when the rainfall information alone is not sufficient and in which soil water parameters are required for decision making. For instance, when the new model output realizes 'above normal' probability, while the NMSA probability statement is in favor of 'below normal', then this makes a decision difficult. Therefore, in order for ABBABOKA to declare 'go ahead with sorghum planting', supporting information on either 'above normal' or 'near normal' probability from ICPAC, as well as that PAW exceeding ½ PAWC is vital.

In this way, the simple and briefly constructed ABBABOKA is expected to provide a suite of planting decision options to the users. Certainly, this constitutes a significant leap over the fixed 'best bet' recommendations given from the research systems in the past and demonstrates the potential of the internal rigor of ABBABOKA for further development.

If productivity from the rainfed farming is to be improved, it is important that crop yield be increased during the average and above average rainfall years. In the Ethiopian CRV, the magnitude of both the climate and crop yield variability represent a major constraint to increased productivity. In practice, it is also not easy to generate technologies and decision aids for every part of the climate variability spectrum. Therefore, by classifying the historical rainfall records into tercile probabilities expressed in portions of the years (worst one third = below normal, average one third = near normal and wet one third = above normal), the best decision aid, together with the existing improved material technologies corresponding to a given rainfall scenario, can be used for a recommendation. Although the chances to improve yield during 'below normal' rainfall years are marginal, technologies that perform well under the one third driest years could be researched. Further investigated into possible techniques for the average and above average years can also be profitable.

Overall, although climate variability makes the outcome of the decision uncertain and risky, this thesis endorses that decision analyses are potentially useful for combining the understanding of the risks associated with climate and prediction of the future rainfall behaviour. Therefore, developing and delivering scientific knowledge in a way that supports farmers' decision making seems a job worth doing. In this regard, the potential use of ABBABOKA, particularly when linked with the climate database is expected to form a strong base for the future co-learning and generation of conversation among its users. However, as a useful tool of co-learning amongst farmers and researchers, it needs to be expanded with time. Agroclimatology, by using the available DSTs and in collaboration with the related disciplines, is expected to supply such decision support tools in order to influence decision making under risky and uncertain rainfall conditions of Ethiopia.

Chapter 7

Summary, Conclusions and Recommendations

7.1 Summary and Conclusions

Rainfall is an important source of water for crop production in the tropics, especially in sub-Saharan Africa. However rains are unpredictable in terms of onset, amount and distribution and therefore there is a need to understand the basic features of rainfall, prediction for operational farming, crop water requirement, risk and decision analysis using the decision support tools. The above rainfall related issues formed a framework for this thesis, as the knowledge helps to improve productivity over time and space.

The statistical analyses in chapter one have collated essential numerical evidence for the existence of variability in important rainfall features (onset date, end date, duration and the seasonal totals), each of which poses its own specific risk. Of all the rainfall features, onset date and the MAM rainfall total were found to vary for the two weather stations (c.v = 40% for onset date at Abomssa and 42.0% for Miesso; and c.v was 129.9% for Abomssa and 127.7% for Miesso in case of MAM rainfall).

Under rainfed farming, the occurrence of the intermittent dry spells also becomes critical particularly for seedling establishment during the first 30 days after planting. In fact, a dry spell of any length could occur at any stage of crop growth; however, there is higher potential for damage when it coincides with the most sensitive stages such as flowering and grain filling. For the two stations, the probability of dry spells of longer than 15 days from March until the end of the season was found to be less than 10%. This carries useful information for planting decisions by risk taking farmers who work under different capability or resource endowments. For instance, farmer 'A' (risk taker) who may have access to irrigation water or have a crop adapted to suspend its growth under a longer dry spell could decide to plant during the earliest months of the growing season. In this way, one can maximize outputs due to taking risks associated with such a long dry spell. On the other hand, a resource poor farmer 'B' (risk averse) lacking water resources or other soil water management techniques and decision aid to manage

any risk of dry spell length greater than 5 or 7 days, has to wait until there would be sufficient water in the soil.

The bimodality of rainfall in the study area was also studied in relation to the onset date. The result shows that early onset (the start of rainfall any time before June) is associated with an increased seasonal rainfall total. The linear regression line for onset date versus season total rainfall at Abomssa indicates that 45% of the variability in rainfall total is explained by onset date, while 59% is explained for Miesso. As the early start of the rain implies the contribution from the rainfall events occurring before June, this corresponds to a reduction in MAM rainfall totals. Particularly during such a merge of the two seasons, MAM rains cannot meet the amount of water required to sustain a crop or cultivar of any shorter duration to maturity within MAM time. Indications are, and particularly from the economic farming perspective, that the seasonal rainfall pattern in the study area does not have distinct bimodality.

The second part of chapter two dealt with the time series analyses and prediction model fitting to the observed monthly rainfall series. The trend line fitted for both the series indicates the fluctuation of the series with the monthly mean and trend values of 74.4 mm for Abomssa and 62.6 mm for Miesso, indicating the absence of the long-term changes in rainfall pattern. In other words, this study did not find evidence for persistent increase or decrease, particularly for Abomssa. In case of Miesso there is a slight declining tendency. This information is useful for long-term research and development planning. The non-existence of trends for both Abomssa and Miesso formed the basis for the prediction model fitting. Following this premise, a total of 15 time series prediction models (8 for Abomssa and 7 for Miesso) were fitted to March-September/October monthly rainfall totals.

For Abomssa, the time series prediction model shows how the model was reasonably able to capture the-non linear or wavy pattern of March rainfall series (r^2 = 0.886). There is also a better fit for the April prediction model with r^2 value of 0.918 and with the other error quantifier statistics performing reasonably. In case of October, the series-model curves diverge from each other, particularly during 1991, 1994, and 1995, which resulted in the model poorly capturing the pattern during certain years ((r^2 =

0.767). Similar insight could be obtained for the May series-model relationship where association is poor (r^2 = 0.824), particularly during the year 1991. In case of August, the model was found to overestimate the series only during the year 1986 (r^2 = 0.956), indicating a higher degree of agreement between the series and the model. Similar useful trends hold for July and September.

For Miesso also good levels of relationship between the observed and the model were observed for all the months under consideration, except May (r^2 = 0.62). Better relationships were noted particularly for July and August with r^2 = 0.924 and 0.937 respectively. The relationships for March, April, June and September are also quite acceptable with r^2 values ranging from 0.818 to 0.867, indicating the models' agreement with the monthly series of Miesso.

One of the constraints with time series prediction models is that they do not provide the factors underpinning future values. Moreover, because of the high possibility of a change in model structure, the risk associated with predicting outside the observed range of the independent variable could be high. Generally however, the knowledge and understanding of such basic rainfall features and model fitting can further lead to improvements in rainfall risk management practices, by placing into perspective the influences of the current climate variability and sequences on farming system outcomes.

Chapter 3 dealt with the homogenous rainfall zonation and seasonal/temporal prediction using CPT of the IRI. Zonation schemes as one of the most common ways of understanding climate have been employed, which helped to define the study area on the basis of separate research and development units. Accordingly, the area was divided into four homogenous rainfall zones, with the southeastern parts (zone 2) being wet and the northeastern part (zone 4) being drier. The middle parts of the study area were also separated into two with the northwest–northeastern stretching (Debre Zeit-Nazerth-Dera) part receiving a higher amount of rainfall (zone 3) than the south facing Alem Tena-Langano zone (zone 1).

One of the problems with the zonation scheme includes its emphasis on the spatial

rather than temporal variability, which leads to the understanding that a location is either arid or semi-arid or humid, rather than sub-humid one year and arid the next. This is a serious deficiency, since locations with similar plant growth response patterns can have very different probabilities of cropping success during the wet season of one year and dry season of the next year. In fact, emphasis on temporal climatic variability was started after the Sahel drought of the 1970s and attracted wide attention.

Temporally, March rainfall is the least predictable (r=0.25) for zone 2. Moreover, a model that can capture July rainfall pattern was not obtained at all for the same zone. Zone 2 is one with a relatively early onset date and rainfed sorghum water requirement could be reasonably satisfied even with a March planting (chapter 4). Except for zone 1, where r was 0.73, July rainfall prediction is the most problematic for the rest of the zones, followed by another problematic month (May) for zone 4 (r = 0.38). On the other hand, June and July rainfall anomalies are the most predictable for zone 1 (r = 0.73). In case of zone 2, months including May (r = 0.70), August (r = 0.54) and September (r = 0.77) have highly predictable rainfall anomaly patterns, while for zone 3 and zone 4, the April rainfall anomaly is highly predictable (r = 0.79 for zone 3 and 0.72 for zone 4).

Forecasting rainfall in a terrain of complex topography poses serious difficulty particularly over tropical regions. A major impediment to predictive skill is derived from the primarily convective nature of tropical rainfall. The difficulties increase during the wet season when extreme rainfall events (for example dry spell in the middle of the wet season) regularly occur on a localized basis. It is also recognized that rainfall prediction involving smaller scale convective processes presents a far greater prediction problem than the ones explained by the synoptic scale systems.

Therefore, a perfect model that can fully capture variability in the midst of such chaos cannot be achieved at ease. Accordingly, the skill measures produced using CPT hindcast technique are inevitably not of a very high range. The efficiency of these lower hindcast measuring indicators can also be attributed to the fact that the ocean observing instruments have been changed over time such that the discrepancy between the earliest observations and the recent ones could be wide in explaining the values observed under different time scales. Local factors like the windward or leeward facing

mountains including Chilalo and Chercher highlands, Mount Fantale, Mount Boset and Mount Ziquala could also significantly influence the regional atmospheric circulation pattern.

In this study, useful understanding of the climatic determinants of Central Rift Valley's March-September rainfall has been gained. The study disclosed that, with the increased observing networks and data availability, operational climate prediction of definite utility could be achieved for such a smaller spatial and with a short lead prediction scheme. To begin with, areas around Miesso, Abomssa and Arsi Negele, which currently produce sorghum on a significant scale, could represent a good starting point for extension of the prediction information. Other areas could be targeted in a medium term plan to help them establish sorghum production schemes.

Generally, the statistical relationships established here are intended as a good starting point towards the long-term goal of integrating the teleconnections with underlying oceanic phenomena into the background of the Ethiopian agriculture research and development arena. It is believed, despite the above listed time-space difficulties, that most of the models carry useful information that could be translated into farm level decision making and can therefore form part of the operational national or regional prediction formula.

In chapter 4, a detailed account of the tempo-spatial water requirement satisfaction pattern and sorghum water production function in the variable climate was studied. For the seasonal WRSI, 14 concurrent sorghum growing seasons were calculated and mapped, while the growth stage based WRSI and water production function analyses were computed only for 3 sorghum experimental sites.

Spatially, the southern and southeastern parts constitute the most favourable seasonal climate for growing ranges of sorghum maturity groups considered in this study (90-day, 120-day, 150-day and 180-day cultivars). The northwestern and central parts constitute the next most suitable zone. However, the wide northeastern drylands of the study area, except the pocket of Miesso-Assebot plain, does not warrant economic farming of sorghum under rainfed condition.

It was also found that, while the seasonal WRSI gives a reasonable picture, it is the growth stage based WRSI that truly detects the existence of water scarcity in a growing season. This could be exemplified by the detailed WRSI analyses done for a 120-day sorghum cultivar grown during June-September period at Melkassa. At Melkassa, the seasonal WRSI highlights the adequacy of the water satisfaction for the 120-day sorghum cultivars, but the growth stage based WRSI detected the true risk at the flowering stage. Similar information holds for Miesso and Arsi Negele as well.

Temporally, March planting is the least preferred season for all the sorghum cultivars in the study area except the southern and southeastern parts. The study area is well known for climatic variability and even for those relatively favourable sections the risk at the crop critical growth stages for March planting is considerable. Therefore, the availability and use of alternative soil water and crop management techniques in accordance with the prevailing risk level is crucial.

It was also understood that rainfall totals and spatial coverage gradually improve through April, May and June with a notable peak in July and August. In September, the crop water requirement can be partially met; nonetheless, since the level and dimension could vary across the study area, the use of improved technologies still needs serious attention.

The water production function analyses for the three experimental sites did not reveal a high level of accuracy in estimating long-term yields. Nevertheless, it was found that WRSI at the flowering stage influences the expected yield by 3 times more than WRSI during the rest of growth stages. The low level accuracy could be due to the differences in sorghum planting dates, inadequate sample size and the inevitable measurement errors. Nevertheless, the generated yield prediction models for the 3 experimental stations demonstrate the potential for achieving a reliable model as and when sufficient data sets are acquired in the future.

Therefore, for Melkassa and Miesso, growing a 120-day grain sorghum cutlivar under improved soil water and other crop management practices, together with the area

specific rainfall prediction information, could ensure high yields during a good rainy season (wet years). Likewise, food for family sustenance could also be ensured during a poor rainy season (below average rainfall years). On the other hand, a focus could be made on areas like Arsi Negele, where during all the seasons and with a variety of crops its efficiency is evident and this could be combined to synergise the yield benefits or optimise production from such areas. This basic difference underscores the need for area specific crop water requirement satisfaction and water production function studies to enable one to improve decisions for the sorghum cropping in the study area.

Chapter 5 covers the risk aspect of the climate variability in the study area. The risk analysis provided significant climate and soil information pertaining to sorghum productivity at three experimental sites (Melkassa, Mieso, and Arsi Negele). Two 120-day cultivars (76-T1#23 and Gambella 1107) were used for the June-September season at Melkassa and Miesso, while a 180-day cultivar (ETS-2752) was used for the May-October season at Arsi Negele.

At Melkassa, the result from the stochastic dominance (SD) analysis shows that May planting date was dominant in first degree dominance sense for both cultivars, yielding between 3900-4000 kg ha^{-1} at 85th percentile risk level. The sensitivity analysis conducted for sorghum grown at Melkassa using four cardinal rainfall related input variables (planting date, maturity date, number of rainy days and water requirement satisfaction index (WRSI)) shows that yields of Gambella-1107 planted in June was more sensitive to WRSI than the rest of the input variables. For instance, by keeping the early planting date constant, but changing WRSI from 100% to 75%, yield was reduced by 46.2%, while a further change in WRSI down to 50% or below, resulted in total crop failure. The simulation modelling result for Melkassa also shows that the data points appeared 100% above the 1:1 line which means APSIM had overestimated the observed yields (D-index was 0.81) with an average observed yield of 2500 kg ha^{-1} as compared to an average simulated yield of 3410 kg ha^{-1}. This has yielded useful research information for sorghum breeders, agronomists and physiologist working in the study area.

At Miesso, a similar scenario holds. The stochastic dominance analysis shows that June planting date was the dominant set in the first degree dominance sense over the rest of

the planting windows, but the risk level is high when compared to the Melkassa case. The simulation analysis for a 120-day cultivar planted in June at Miesso shows that APSIM has overestimated the observed yield; the model average was 2029.5 kg ha^{-1} compared to an average of 1781.9 kg ha^{-1} observed yields with the D-index of 0.82.

For Arsi Negele, the CDFs of a 180-day cultivar shows the April planting to be risk efficient and therefore could be adopted by the farmers preferring 'more' payoff to 'less'. For the same station, the sensitivity analyses conducted for cultivar ETS-2752 planted in May shows that the relative yield reduction in grain yields due to a change in WRSI from 100% to 75% was 46.1%. Compared to Melkassa and Miesso's cases however, further reduction in WRSI down to 50% did not result in complete crop failure (456.7 kg ha^{-1} could be realized). Further comparison shows that the response of ETS-2752 to the early planting date, in combination with the 100% WRSI, short maturity date and few rainy days, was not as sensitive as it was for Melkassa and Miesso for the same level of inputs combination. The yield level for these input combinations in Arsi Negele case was 2050 kg ha^{-1}, while it ranged between 3109 and 3272 kg ha^{-1} for Melkassa and Miesso. This shows how WRSI is the most important indicator of the adequacy of crop water requirement.

Chapter 6 assembles all the necessary information generated in chapter 3 through to chapter 5. In this chapter, the decision support tool known as ABBABOKA 1.0 was introduced. It captures the most important climatic and soil water related risk factors for sorghum farming in the study area. The result from 27 physically possible decision options (clustered into 3 like groups) shows that by using the probability of rainfall status (either above normal, near normal or below normal) and soil water information as input data for the prediction output for the interface, flexible planting decisions could be advised. For instance, if prediction output from the newly developed prediction model (chapter 3) and NMSA both say 'above normal' (AA), then ABBABOKA advises "continue planting a sorghum cultivar group of interest (90, 120, 150 or 180-day sorghum cultivar) under the prescribed crop management practices during a given month and in a given zone".

There can also be a scenario where the rainfall information alone does not suffice, a case in which soil water parameters need to be consulted for decision making. For instance, when the new model realizes 'above normal' probability, while the NMSA probability statement is in favor of 'below normal', it makes decisions difficult. Therefore, supportive information of either 'above normal' or 'near normal' probability from ICPAC, as well as PAW exceeding ½ PAWC, should be obtained in order for ABBABOKA to declare 'go ahead with sorghum planting' in a given zone. In this way, the simple and briefly constructed ABBABOKA is expected to provide a suite of planting decision options to the users. Certainly, this constitutes a significant departure from the fixed best bet recommendations given from the research system in the past and the potential of ABBABOKA for further development.

If productivity is to be increased, it is important that crop yield be increased during the average and above average years. The magnitude of both the crop yield and the rainfall variability represents a major constraint to increased productivity and in practice it is not possible to generate technologies and decision aids that fit every section of the variability spectrum. Therefore, one can classify the historical rainfall records into a tercile probabilities (one third worst-case scenario/ below normal, one third average / near average and one third wet / above average) years that help to fit the best decision aid and material technologies that correspond to a given rainfall category. Although chances are marginal to improve yield during 'below average' rainfall years, technologies that perform well under the one third driest years could also be researched as done for the average and above average years separately.

While climate variability may make the outcomes of decisions more uncertain, this thesis endorses that developing and delivering scientific knowledge in a way that supports farmers decision making, seems to be a job worth doing. Therefore, the start of ABBABOKA is good news that forms useful ground for the future co-learning and generation of conversation among the users for water risks solving purposes. However, as a tool of co-learning among farmers and researchers, the internal rigor of ABBABOKA, particularly linking it to the national climate and soil database, needs to be done with time.

7.2 Recommendations

This thesis endorses the fact that for agricultural sciences to continue intervening in the management of climate risk in Ethiopian agriculture, the most important factors must be given due attention, mainly the soil and climate aspects. Moreover, as it is inappropriate to mitigate soil water related problems in rainfed cropping systems from one angle alone (unless the problem is solved elsewhere in the system), it is essential to build on past efforts, while encouraging a multidisciplinary approach among soil, crop and climate researchers. This paves the way for technically sound and cooperative problem-solving projects to be developed. In agricultural research (crop cultivar choice / agronomy / soils / entomological/pathological) the final results are always linked to some effect of water availability. In this regard, a focus needs to be made on the following research aspects:-

(i) To extend the classifying of agricultural areas into spatial and temporal homogeneous rainfall zones mainly as it suits agricultural production and research.

(ii) To develop tailored rainfall prediction to help in tactical decision making.

(iii) To employ newly emerging technologies, including satellite imagery. In the medium term, this will enable assessing the economic value of the seasonal rainfall forecast in relation to operational farming in the study area.

(iv) To perform focused research on climate risks, crop water requirements and simulation modelling since these approaches provide a deeper understanding of the underlying factors of a cropping system and increased possibilities for solving water-related farming constraints.

(v) To build a network of weather stations and a soil database in order to promote soil-crop-climate research in Ethiopian agriculture.

(vi) To perform detail studies pertaining to the local factors, mainly ecotopes (homogenous soil, topography, and climate pattern) that affect the soil water balance.

(vii) To expand the use of decision support tools and well established models (eg. APSIM) in the agricultural research and development effort.

Finally, it is recommended that strengthening an inter-institutional partnership, mainly between EARO and NMSA, needs to be brought to an operational level. This would enable a more meaningful assessment of the impact of seasonal climate prediction on agriculture and form a strong foundation for the future strengthening of the value of climate forecasting in economic farming and climate change studies.

References

Abadi, G.A.K; D.J. Pannell; A. Bennettt & V. Stewart (1996). Farmers' risk perspective on adopting legume crops. In: M. Asghar (Ed). Proceedings 8th Australian Agronomy Conference. p60-63.

Abate, K. (1994). The Climatology of Drought over Parts of Ethiopia and their Impacts on Crop Production with Special Reference to the Impact of Drought on the Production of Barley and Maize. PhD thesis (Climatology), University of Nairobi, Kenya.

Ackoff, R.L. (1981). Creating the Corporate Future. John Wiley and Sons, New York.

Addis Ababa University (2001). Introductory Geography of Ethiopia, Geo 101, Teaching text, Department of Geography.

Aggarwal, P.K. & F.W.T. Penning de Vries (1989). Potential and water limited wheat yields in rice-based cropping systems in Southeast Asia. *Agric. Systems* **30**: 49-69.

Alves, O.; G. Wang; A. Zhong; N. Smith; F. Tzeirkin; G. Warren; A. Schiller; S. Godfrey & G. Meyers (2003). POAMA: Bureau of Meteorology Operational Coupled Model Seasonal Forecast System. In: Proceedings National Drought Forum, Science for Drought, Brisbane. p49-56.

Allen, R.G.; L.S. Periera; D. Raes & M. Smith (1998). Crop Evapotranspiration: Guidelines for Computing Crop Water Requirement. FAO Irrigation and Drainage Paper No. 56. FAO, Rome.

Allen, R.G. (2002). Reference Evapotranspiration Calculator. . http://www.kimberly.uidaho.edu/ref-et/. Viewed on 30th October 2005.

Amedie, S. (2000). Seasonal forecast of the March-April-May 2000 rainfall over Ethiopia using empirical statistical model. Drought Monitoring Center, Nairobi (DMCN). pp12.

Anderson, J.R. (1974). Risk efficiency in the interpretation of agricultural production research. *Rev. Market. Agric. Res.* **42**: 131-184.

Anderson, J.R. (1991). A framework for examining the impacts of climate variability. In: R.C. Muchow, and J.A Bellamy (Eds). Climatic Risk in Crop Production. Models and Management for the Semi-Arid Tropics and Sub-Tropics. CAB International. p315-330.

Anderson, J.R., J.L. Dillon & J.B. Hardaker (1977). Agricultural Decision Analysis. Ames: Iowa State University Press.

Anderson, J.R. & J.L. Dillon (1992). Risk Analyses in Dryland Farming Systems. FAO Farming Systems Management Series 2. Rome: FAO. pp109

Angus, J.F. (1991). The evolution of methods for quantifying risks in water limited environments. In: R.C. Muchow and J.A. Bellamy (Eds). Climatic Risk in Crop Production: Models and Management for the Semi Arid Tropics and Sub-Tropics, Brisbane, CAB International. p39-54.

APSRU (Agricultural Productivity Systems Research Unit) (2005). (http://www.apsru.gov). Viewed on 20th November 2005.

Arinze, B. (1992). Decision support systems (DSS) development using a model of user inquiry types: Methodological proposals and a case study. *Sys. Prac.* **5**: 629-647.

Attia, B.B. & A.B. Abulahoda (1992). The ENSO phenomenon and its impact on the Nile's hydrology. In: M.A. Abul Zeid and A.K. Biswas (Eds). Climate Fluctuation and Water Management. Butterworth Hernemann. p71-79.

Awoke, D. (1991). Rainfall Variability and Crop Yield over Ethiopia. MSc thesis (Meteorology), University of Reading, U.K. pp111.

Babu, A. (1991). The influence of El Nino/Southern Oscillation on the Ethiopian seasonal rainfall. Paper presented at ICTP/WMO International Technical Conference on Long Range Weather Forecasting Research (Trieste, Italy, 8-12 April,1991).

Babu, A.; D. Koricha; S. Amedie; B. Gizaw; G. Mekuria & D. Tarekeng (2004). Evaluation of economic Contributions of Seasonal Cimate Outlooks for Power Industry in Ethiopia, Report, Drought Monitoring Center (DMC), Nairobi. p89-128.

Barnard, C.I. (1938). The Function of the Executive. Harvard University Press, Cambridge, MA.

Barnston, A.G. (1994). Linear statistical short-term climate predictive skill in the Northern Hemisphere. *J. Climate* **7**: 1513-1564.

Barnett, T. P. & W. Preisendorfer (1987). Origin and levels of monthly and seasonal skill for United States air temperature determined by canonical correlation analyses. *Mon. Wea. Rev.* **115**: 1825-1850.

Barnston, A.G. (1994). Linear statistical short-term climate predictive skill in the Northern Hemisphere. *J. Climate* **7**:1513-1564.

Barnston, A.G. & C.F. Ropelewsky (1992). Prediction of ENSO using canonical correlation analyses. *J. Climate* **5**: 1316-1345.

Barnston, A.G. & T.M. Smith (1996). Specification and prediction of global surface temperature and precipitation from global SST using CCA. *J. Climate* **9**: 2660-2697.

Bawden, R. (1990). Towards action researching systems. In O. Zuber-Skerritt (Ed). Action Research for Change and Development, CALT, Griffith University, Queensland.

Bennie, A.T. P; J.E. Hoffman, M.J. Coetzee & H.S. Vrey (1994). Storage and Utilization of Rain Water in Soils for Stabilizing Crop Production in Semi-Arid Areas. [Afrikaans]. WRC Report No. 227/1/94. Water Research Commission, Pretoria.

Bennie, A.T.P., M.G. Strydom & H.S. Vrey (1998). The Applications of Computer Models for Agricultural Water Management at Ecotope Level. [Afrikaans, with English abstract]. WRC Report No. 625/1/98. Water Research Commission, Pretoria.

Beltrando, G. & P. Camberlin (1993). Inter-annual variability of rainfall in the Eastern Horn of Africa and indicators of atmospheric circulation. *Int. J. Climatol.* **13**: 533-546.

Bernstein, P.L. (1996). Against the Gods. The Remarkable Story of Risk. John Wiley, New York.

Bernouli, D. (1738). Exposition of a new theory on the management of risk. English translation of the Latin by L. Somer. *Econometrica* **22**: 23-36, (1954).

Bethke, S. (1976). Basic zonal rainfall patterns in Ethiopia. REHAB: Drought and Famine in Ethiopia. International African Institute in Association with the Environment Training Program UNEP-IDEP-SIDA, African Environment Special Report 2.

Bidinger, F.R. (1978). Water stress effects on crop-environment interactions. In: R.H.Shaw, M.V.K. Kumar and S.M. Virmani (Eds). Proceedings Agroclimatological Research Needs of

the Semi-Arid Tropics. International Crops Research Institute for Semi-Arid Tropics (ICRISAT), Patancheru, India. p147-153.

Bi P, X., K. Wu, A.K. Parton & S.L. Tong (1998). Seasonal rainfall variability, the incidence of the morrhagic fever with renal syndrome and prediction of the diseases in low lying areas of China. *Amer. J. Epidem.* **148**: 276-281.

Bjerknes, J. (1969). Atmospheric teleconnection from the tropical Pacific. *Mon. Wea. Rev.* 97: 103-172.

Boedt, L.J.J. & M.C. Laker (1985). The Development of Profile Available Water Capacity Models. WRC Report No. 98/1/85. Water Research Commission, Pretoria.

Bograd, S., F. Schwing, R. Mendelssohn & P. Green-Jesson (2002). On the changing seasonality over the north pacific. *Geophys. Res. Lett.* **29**. (9)1333.

Borrell, A., E.V. Oosterom, H. Graeme, J. David & H. Bob (2003). Using science to combat drought: a case study of stay-green in sorghum. In: R. Stone and I. Partridge (Eds). Science for Drought. Proceedings of the National Drought Forum. p120-123.

Botha, C.A.J., G.J. Steyn & J.B. Stevens (2000). Factors which Influence the Acceptability of Irrigation Scheduling with Specific Reference to Scheduling Models. WRC Report No. 2000/893/1. Water Research Commission, Pretoria.

Briggs, L.J. & H.L. Shantz (1913). The water requirement of plants. I. Investigations in the Great Plains in 1910 and 1911. Bull No. 284. U. Bur. Plant Ind., Washington DC.

Briggs, L.J. & H.L. Shantz (1917). The water requirement of plants as influenced by environment. *Proc. Pan Amer. Sci. Congr.* 3: 95-107.

Broad, K. & S. Aggrawala (2000). The Ethiopia food crises: Uses and limits of climate forecast's. *Science* **289**: 1693-1694.

Brunt, A.T. (1968). Forecasting rainfall for agriculture. In: Agricultural Meteorology. Proceedings WMO seminar, Melbourne p523-534.

Bucks, D.A.; F.S. Nakayama; O.F. French, W.W. Legard & W.L. Alexander (1985). Irrigated guayule-production and water use relationship. *Agric. Water Manage.* **10**: 95-102.

Buringh, P.H.; D.J. van Heemst & G.J. Staring (1975). Computation of the absolute maximum food production of the world. Department of the Tropical Soil Science. Wageningen Agricultural University, Wageningen.

Camberlin, P. & N. Philipon (2001). The East African March-May rainy season associated atmospheric dynamics and predictability over the 1968-1997 period. *Amer. Meteorol. Soc.* **15**: 1002-1019.

Cane, M.A.; G. Eshel & R.W. Buckland (1994). Forecasting Zimbabwean maize yield using eastern equatorial Pacific sea surface temperature. *Nature* **21**: 370: 204.

Carberry, P.S; A. Hochman; R.L. McCown; N.P. Dalgliesh; M.A. Foale; P.L. Poolton; J.N.G. Hargreaves; D.M.G. Hargreaves; S. Cawthray; N. Hillcoat & M.I. Robertson (2002). The FARMCAPE approach to decision support: Farmers, advisors, researchers monitoring simulation, communication and performance evaluation *Agric. Systems* **74**: 179-220.

Checkland, P.B. (1988). Soft system methodology: An overview. *J. App. Sys. Analy.* **15**: 27-30.

Clements, R.J. (1991). Preface. In: R. C. Muchow and J.A. Bellamy (Eds). Climatic Risk in Crop Production: Models and Management for the Semi-Arid Tropics and Sub-Tropics, Brisbane. CAB International.

Dancette, C. (1978). Water requirements and adaptation to the rainy season of millets in Senegal. In: R.H. Shaw, M.V.K. Kumar and S.M. Virmani (Eds). Proceedings Agroclimatological Research Needs of the Semi-Arid Tropics. International Crops Research Institute for the Semi Arid Tropics (ICRISAT), Patancheru, India. p106-120.

Degefu, W. (1987). Some Aspects of meteorological drought in Ethiopia. In: M.H. Glantz (Ed). Drought and Hunger in Africa: Denying Famine in the Future. Cambridge University Press, Cambridge. p23-36.

Dent, M., S. D, Lynch & H. Tarboton (1990). Detailed delimitation of rainfall regions in Southern Africa. *Water SA* **16** (1): 1-4

De Wit, C.T. (1958). Transpiration and Crop Yields. Verslag. Landbook, onderz. Report No. 64. Wageningen. The Netherlands.

De Wit, C.T. (1982). Simulation of living systems In: F.W.T. Penning de Vries and H.H van Laar (Eds). Simulation of Plant Growth and Crop Production. Simulation Monograph Series, PUDOC, Wageningen. p3-8.

Dillon, J.L. (1971). Interpreting Systems Simulation Output for Managerial Decision Making. Sydney, Wiley, Australia.

Dilley, M. (1997). Warning and intervention. What kind of information does the response community need from the early warning community? *Internet J. African Studies* 2. http://www.dir.ucar.edu/esig/ijasno2/dilley.html.

Dilley, M. (2000). Reducing vulnerability to climate variability in Southern Africa: The growing role of climate information. *Climatic Change* **45**: 63-73.

Dilman, A. C. (1931). The water requirement of certain crops and weeds in the Northern Great Plains. *J. Agric. Res.* **42**: 187-238.

Donnelly, J.R. (1997). Managing the impact of climate variability on temperate agricultural systems in Southern Australia. In: R.K. Munro and L.M. Leslie (Eds). Australian Academy of Science Conference, Canberra. p305-318.

Doorenbos, J. & W.O. Pruitt (1977). Crop Water Requirements. FAO Irrigation and Drainage Paper No. 24. FAO, Rome.

Dorenboos, J. & A.H. Kassam (1979). Yield Response to Water. FAO Irrigation and Drainage Paper No. 33. FAO, Rome.

Duchon, C.E. (1986). Corn yield prediction using climatology. *J. Climate & App. Meteorol*. **25**: 581-590.

EARO (Ethiopian Agricultural Research Organization) (2000). National Sorghum Strategy Document. pp28.

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

Efron, B. (1982). The Jackknife, the Bootstrap, and Other Resampling Plans, Philadelphia P.A: Society for Industrial and Applied Mathematics.

Efron, B. & G. Gong, (1983). A leisurely look at the bootstrap, the jackknife, and cross validation. *Amer. Stat.* **37**: 36-48.

Ethiopian Delegation (1984). Climatic and drought conditions in Ethiopia. Scientific Round Table Discussion on the Climatic Situations and Drought in Ethiopia. Addis Ababa, Ethiopia. 20-23 Feb 1984, Mimograph.

FAO (Food and Agriculture Organization) (1984). Assistance to land use planning in Ethiopia: geomorphology and soil. Report prepared and submitted to the Government of Ethiopia. AGDA. ETH/78/003, Field Document 3.

FAO (1989). Assistance to land use planning of Ethiopia: Physiography and soils of the Hykoch and Butajira and Yerer and Kereyu Awurajas (Shewa). FAO/AG: DP/ET/87/006. Field Document No. 37.

Finan, T.J. & D.R. Nilson (2001). Making rain, making roads, making do: Public and private and adaptations to drought in Ceara, North East Brazil. *Climate Res.*19: 97-108.

Fleming, M.C. & J.G. Nellis (2000). Principles of Applied Statistics: An Integrated Approach Using MINITAB and Exel. Thompson Learning, U.K. pp474.

Folland, C.K.; T.N, Palmer & D.E. Parker (1986). Sahel rainfall and worldwide sea temperatures 1901-1985. *Nature* **320**: 602-607.

Follett, R. F.; L.C.Benz; E. J. Doering & G.A. Reichman (1978). Yield response of corn to irrigation on sandy soils. *Agron. J.* **70**: 823-828.

Gadgil, S.; P.R.S. Rao; N.V. Joshi & S. Sridhar ((1995). Forecasting rain for groundnut farming. How good is good enough? *Current Sci.* **68**: 301-309.

Gaffney, J. (1996). Workbook for decision analyses seminar. QDPI (Queensland Department of Primary Industry), Toowoomba.

Gemechu, D. (1977). Aspects of climate and water budget in Ethiopia. Addis Ababa University Press. pp77.

Geological Survey of Ethiopia (1972). Geological Map of Ethiopia 1:2000000, compiled by V. Kazmin, Ministry of Mines, Addis Ababa.

Georgis, K. (1999). Crop modeling within the semi-arid areas of Ethiopia. In Proceedings Highveld Ecoregion Workshop. Grain Crop Institute of the Agricultural Research Council, South Africa. p51-55.

Gissila, T. (2001). Rainfall Variability and Teleconnections over Ethiopia. MSc thesis (Meteorology), University of Reading, U.K. pp109.

Glantz, M.H. (1993). Introduction: Forecasting El Niño: Science's gift to the 21st century. In: M.H. Glantz (Ed). Workshop on usable science. Food security, early warning and El Niño. 25-28 October 1993. Budapest, Hungary, National Center for Atmospheric Research, Boulder. p3-11.

Glantz, M.H. (2001). Currents of Change: El Niño and La Niña Impacts on Climate and Society. 2nd Ed. Cambridge University Press, New York. pp252.

Glantz, M.H.; R.W. Katz & N. Nicholls (1991). Tele-connections Linking World Climate Anomalies. Cambridge University Press, New York. pp527.

Goddard, L., S.J. Mason, S.E. Zebiac, C.F. Ropelewski, R. Basher & M.A. Cane (2001). Current approaches to seasonal-to-interseasonal climate prediction. *Int. J. Climatol.* **21**: 1111-1152.

Gonfa, L. (1996). Climatic classification of Ethiopia. NMSA, Addis Ababa, Ethiopia.

Goodwin, P. & G.I. Write (1991). Decision Analyses for Management Judgment. Chichester. Willey, New.York.

Graham, N.E.; J. Michaelsen & T.P. Barnett (1987a). An investigation of the El Niño-Southern Oscillation cycle with statistical models 1. Predictor field characteristics. *J. Geophy. Res.* **92**: 14251-14270.

Graham N.E.; J. Michaelsen & T.P. Barnett (1987b). An investigation of the El Niño-Southern Oscillation cycle with statistical models 2. Model results. *J. Geophy. Res.* **92**:14271-14289.

Green, G.C. (1966). The Evaluation of Methods of Rainfall Analyses and the Application to the Rainfall Series of Nelspruit. MSc thesis (Agrometeorology) University of the Orange Free State, Bloemfoentein. pp147.

Green, G,C. (ed) (1985). Estimated irrigation requirement of crops in South Africa. Part 1. Mem. Agric. Nat. Resour. S. Afr. No. 2. Department of Agriculture and Water Supply, Pretoria.

Grimes, D.; W.N. Yamada & N.L. Dickens (1969). Functions for cotton production from irrigation and nitrogen fertilization variables I. Yield. and ET. *Agron. J.* 61: 769-773.

Haile, T. (1986). Climatic Variability and Support Feedback Mechanisms in Relation to the Sahelo-Ethiopian Droughts. MSc thesis (Meteorology), Reading University, UK.

Haile, T. (1988). Causes and characteristics of drought in Ethiopia. *J. Agri. Sci.* **10** (1-2): 85-97.

Hamilton, W.D.; D.R. Woodruff & A.M. Jamison (1991). Role of computer based decision aids in farm decisions making and agricultural extension. In: R.C Muchow and J.A Bellamy (Eds) Climate Risk in Crop Production: Models and Management for the Semi-Arid Tropics and Sub-Tropics. Brisbane, CAB International. p411-424.

Hammer, G.L.; D.P. Holzworth & R. Stone (1996). The value of skill in seasonal climate forecasting to wheat crop management in a region with high climatic variability. *Aust. J. Agric. Res.* **47**: 717-737.

Hansen, J.W. (1998). ENSO influence on agriculture in the southeastern United States. *J. Climate* **11**: 404-411.

Hardaker, J.B. & R. Gill (1994). Risk analyses in agriculture developments in research and training. In: Proceedings Conference on Risk Management in Australian Agriculture. UNE, Armidale.

Hardaker, J.B.; R.B.M. Huirne & J.R. Andrson (1998). Coping with Risk in Agriculture. CAB International. pp274.

Hargreaves G. H. (1975). Water requirements manual for irrigated crops and rainfed agriculture. EMBRAPA and Utah State University. Publication 75-D 158. pp40.

Hastenrath, S. (1985). Climate and Circulation of the Tropics Atmospheric Sciences Library ASL 8.D Reidel. Dordrecht.

Hayman, P.T. (2001). Dancing in the Rain: Farmers and Agricultural Scientists in a Variable Climate. PhD thesis (Environmental Management and Agriculture), University of Western Sydney, Australia. pp282.

Hayman, P.T. (2004): Decision support system: The promising past, the disappointing present and the uncertain future. In: Proceedings 4th International Crop Science Congress. September 26 to 1 October 2004. Brisbane, Australia. pp15.

Heady, E.O. (1952). Economics of Agricultural Production and Resource Use. Prentice-Hall, New York.

Henricksen, B.L. & J.W. Durkin (1986). Growing period and drought early warning in Africa using satellite data. *Int. J. Remote Sensing* **7**: 11.

Hensley, M. & J.M. de Jager (1982). The Determination of the Profile Available Water Capacities of Soils. WRC Report. University of Fort Hare, Alice.

Hensley, M., H.W. Hattingh & A.T.P. Bennie (1993). A water balance modeling problem and a proposed solution. In: M. Kronen (Ed). Proc. 4th Ann. Sci. Conf. Windhoek, Namibia, 11-14 Oct. 1993. SADC-Land and Water Management Research Program, Windhoek, Namibia. p479-482.

Hochman, Z. (1995). Action Plan for Decision Support Systems. NSW Agriculture, Orange, Australia.

Hoefsloot, P. (2004). Agrometshell software, Version 1.0, FAO, Rome, Italy.

Horie, T. (1987). Dynamic Models for Evaluating and Predicting the Growth and Yield of Rice and Sunflower Crops from Weather. Food and Fertilizer Technology Center. Technical Bulletin 99, Taipi.

Hoshmand, A.R. (1998). Statistical Methods for Environmental and Agricultural Sciences, 2nd ed. CRC Press. pp439.

Hunt, B.G. (1997). Prospects and problems for multi-seasonal predictions: Some issues arising from a study of 1992. *Int. J. Climatol.* **17**: 137-154.

Hutchinson, M.F. (1991). Climatic analyses in data sparse regions. In: R.C. Muchow and J.A. Bellamy (Eds). Climatic Risk in Crop Production: Models and Management for the Semi-Arid Tropics and Sub-Tropics. CAB International. p55-71.

Hutson, J.L. (1983). Estimation of Hydrological Properties of South African Soils. PhD Thesis (Soil Science), University of Natal, Pietermaritzburg.

Indeje, M. (2004). Status of climate forecasting in the Greater Horn of Africa and review of current global climate system. Paper presented at Greater Horn of Africa Climate Outlook Forum 13 (COF-13), Nairobi, Kenya.

Ininda, J., B. Dessalegne & A. Befekadu (1987). The characteristics of rainfall in Ethiopia and its relationship to El Niño-Southern Oscillation. In: Proc. First Technical Conference on Meteorological Research in Eastern and Southern Africa, Nairobi, Kenya, 6-9 January, 1987. p133-135.

Itanna, F. (2005). Sulfur distribution in five Ethiopian Rift Valley soils under Humid and Semi-Arid Climate. *J. Arid Environ.* (Article in Press). www.elsvier.com/locate/jnlabr/yjare, pp16.

Jean, L.S., M.S. Jeanne, D.G. Jurgen & J.Z. Xunchang (2004). Climate forecasts: Emerging potential to reduce dryland farmers' risks. In: Challenges and Strategies for Dryland Agriculture. CSSA Special Publication. No.32. Crop Science Society of America and American Society of Agronomy, Madison, U.S.A. p47-65.

Jeffers, J.N.R. (1976). Future prospects of systems analyses in ecology. In: G.W. Arnold and C.T. de Wit (Eds). Critical Evaluation in Ecosystem Research and Management. Simulation Monograph Series, PUDOC, Wageningen. p98-108.

Ji, M., A. Kumar & A. Leetmaa (1994). Multi-seasonal climate forecast system at the National Meteorological Centre. *Bull. Amer. Meteorol. Soc.* **75**: 569-577.

Jury, M.R., H.M. Mulenga; S.J. Mason & A. Brandao (1997). Development of an Objective Statistical System to Forecast Summer Rainfall over Southern Africa. WRC Report No. 672/1/97. Water Research Commission, Pretoria. pp45.

Kaihla, A.H. (1983). A Study of Evaporation Pan Factoring at Katumani, Kenya. MSc thesis (Geography), University of Nairobi, Kenya. pp139.

Kassahun, B. (1990). Prediction of Seasonal Rainfall in the Sahel Region. MSc thesis (Meteorology), University of Reading, U.K. pp148.

Katz, R.W.; A.H. Murphy & R.L. Winkler (1982). Assessing the value of frost forecast to orchardists: A dynamic decision making approach. *J. App. Meteorol.* **21**: 518-531.

Keating, B.A., R.L McCown & B.M. Wafula (1993). Adjustment of nitrogen inputs in response to a seasonal forecast in region of high climate risk In: F.W.T. Penning de Vries (Ed.). Systems Approach for Agricultural Development, Kluwer Academic Publishers, Netherlands. p233-252.

Keating, B.A., P.S. Carberry, G.L. Hammer, M.E. Probert, M.J. Roberston, D.P. Holtzworth, N.I. Huth, J.N.G. Hargreaves, H. Meinke, Z. Hochman, G. McLean, K. Verburg, V.Snow, J.P. Dimes, M. Silburn, E. Wang, S. Brown, K.L. Bristow, S. Asseng, S. Chapman, R.L. McCown, D.M. Freebairn & C.J. Smith (2003). An overview of APSIM, a model designed for farming system simulation. *Euro. J. Agron.* **18**: 267-288.

Keeney, D.R. (1982). Nitrogen management for maximum efficiency and minimum pollution. In: F.J. Stevenson (Ed.). Nitrogen in Agricultural Soils. p605-641.

Kibret, K.T. (2003). Estimating Water Retention for Major Soils in the Hararghe Region, Eastern Ethiopia. PhD thesis (Soil Science), University of Free State. pp178.

Kidson, J.W. (1977). African rainfall and its relation to the upper air circulation. *Quart. J. R. Meteorol. Soc.* **103**: 441-456.

Kisselebach, T A. (1916). Transpiration as a factor in crop production. *Stn. Bull. Nebr. Agric. Exp. Stn.* **6**: 1-214.

Knight, F.H. (1921). Risk, Uncertainity and Profit. Century Press, New York.

Koricha, D. (1999). Seasonal rainfall prediction over Ethiopia. (June to September 1999). Report: Capacity Building Workshop for the Eastern Africa sub-region. Drought Monitoring Center (2-22nd May, 1999), Nairobi, Kenya.

Koricha, D. (2002a). Seasonal rainfall prediction of Ethiopia for the periods September–December 2002. Report: Pre-forum Capacity Building Training Workshop for the Greater Horn of Africa., Drought Monitoring Center (DMC), 12-24th August 2002). Nairobi, Kenya. pp28.

Koricha, D. (2002b). Climate Atlas of Ethiopia. Drought Monitoring Center - Nairobi, Kenya. pp158.

Krzysztofowicz, R. (1983). Why should a forecaster and a decision maker use Bays theorem. *Water Resour. Res.* **19**: 327-336.

Kumar, R. & S.D. Khepar (1980). Decision models for optimal cropping patterns in irrigations based on crop water production functions *Agric. Water. Manage.* **3**: 65-76.

Lamb P.J. (1978a). Case studies of tropical Atlantic surface circulation patterns during recent sub-Saharan weather anomalies: *Mon. Wea. Rev.* **106**: 791-802.

Lamb P.J. (1978b). Large scale Tropical Atlantic surface circulation patterns associated with sub-Saharan weather anomalies. *Tellus* **30**: 240-251.

Landberg, H. (1960). Physical Climatology, 2nd Ed.: Gray Printing Co., Inc., Dubois, Pensylvania

Landman, W.A. & S.J. Mason (1999). Operational long-lead prediction of South African rainfall using canonical correlation analyses. *Int. J. Climatol.* **19**: 1073-190.

Landman, W.A., S.J. Mason, P.D. Tyson & W.J. Tennant (2001). Retroactive skill of multi-tiered forecasts of summer rainfall over southern Africa. *Int. J. Climatol.* **21**: 1-19.

Landman, W.A. & L. Goddard (2002). Statistical recaliberation of GCM forecasts over Southern Africa using Model Output Statistics. *J. Climate* **15**: 2038-2055.

Legler, D.M., K.J. Bryant & J.J. O'Brien (1999). Impact of ENSO related climate anomalies on crop yields in the U.S. *Climatic Change* **42**: 351-375.

Lemma, M. (2003). Time Series Analyses of the Variable Seasonality in Ethiopian Rainfall. MSc thesis (Meteorology), University of Reading, U.K. pp66.

Letson, D., I. Llovet, G. Podesta, F. Royce, V.Brescia, D. Lema & G. Parellada (2001). User perception of climate forecast: Crop producers in Pergamino, Argentina. *Climate Res.* **19:** 57-67.

Loomis, R.S., R. Rabbinge & E. Ng (1979): Explanatory models in crop physiology. *Ann. Rev. Plant Physio.* **30**: 339-367.

Maelzer, D.A. & M.P. Zalucki (2000). Long range forecasts of the numbers of *Helicoverpa punctigera* and *H. Armigera* (Lepidoptera: Noctuidae) in Australia using the Southern Oscillation Index and the Sea Surface Temperature. *Bull. Entomol. Res.* **90**: 133-146.

Malcolm, L.R. (2000). Farm management economic analyses: A few disciplines, a few perspectives, a few figuring, a few futures. Invited paper presented to the annual conference. Sydney, Australia.

Makridakis, S., S.C. Wheelbright & V.E. McGee (1983). Forecasting Methods and Applications, 2nd ed., John Wiley and Sons, New York. pp923.

Mamo, G. (2003). History and the need for institutionalizing agrometeorological research in the national Agricultural Research System In: E. Mersha (Ed). Proceedings National Sensitization Workshop on Agrometeorology and GIS, Ethiopian Agricultural Research Organization (EARO). p15-31.

Markin, M.J., T.J. Kingham, A.E. Waddams, C.J. Brichall & T. Tamene (1975). Development prospects in the Southern Rift Valley, Ethiopia. Volume 2. Land Resource Division, Land Resource Study 21. Ministry of Overseas Development, Tolworth Tower, Surbiton, Surrey, England.

Marshall, G.R., K.A. Parton & G.L. Hammer (1996). Risk attitude, planting conditions and the value of seasonal forecasts to dryland wheat grower. *Aust. J. Agric. Econ.* **40**: 211-234.

Mason, S.J. (1998). Seasonal forecasting of South African rainfall using a non-discriminant analyses model. *Int. J. Climatol.* **18**: 147-167.

Mason S.J.L., N.F. Goddard, E. Graham, S.L. Yelaeva & P.A. Arkin (1999). The IRI Seasonal climate prediction system and the 1997/98 El Niño event. *Bull. Amer. Meteorol. Soc.* **80**: 1853-1873.

Mason, S.J. & K. Tippett (2005). Climate Predictability Tool (CPT): Version 4.01. http://iri.columbia.edu/outreach/software/. Viewed on 1st November 2005.

McCown, R.J., G.L. Hammer & D.R. Woodruff (1991a). The contribution of crop models. In: Workshop on Crop Production Decision Making. APSRU, Toowoomba.

McCown, R.L., B.M. Wafula, L. Mohammed, J.G. Ryan & J.N.G. Hargreave (1991b). Assessing the value of a seasonal rainfall predictor to agronomic decisions: The case of response farming in Kenya. In: R.C. Muchow and J.A. Bellamy (Eds). Climatic Risk in Crop Production: Models and Management for the Semi-Arid Tropics and Sub-Tropics, CAB International, p383-409.

McCarl, B.A. (1996). Stochastic Dominance Notes: RiskRoot program documentation. Department of Agricultural Economics, Texas A & M University.

Meinke, H., R.C. Stone & G.L Hammer (1996). Using SOI phases to forecast climatic risk to peanut production: A case study for northern Australia. *Int. J. Climatol.* **16**: 783-89.

Meinke, H. (2003). Options for cropping systems management at a range of time scales. In: R.C. Stone and I. Partridge (Eds). Science for Drought. Proceedings of the National Drought Forum. p82-87.

Meinke, H., G.L. Hammer and P. Want (1993). Potential soil water extraction by sunflower on a range of soils. *Field Crops Res.* **32**: 59-81.

Mersha, E. (2003). Agroclimatic belts of Ethiopia: Potentials and constraints. In: M. Engida (Ed). Proceedings National Sensitization Workshop on Agrometeorology and GIS, Ethiopian Agricultural Research Organization (EARO) p32-48.

Mesfin, T. (2004). Effect of *in-situ* Water Harvesting on the Growth, Yield and Water Use Efficiency of Sorghum (*Sorghum bicolor (L.*) (Moench)). MSc thesis (Agronomy), Alemaya University, Alemaya, Ethiopia.

Michaelsen, J. (1987). Cross validation in statistical climate forecast models. *J. Appl. Meteorol.* **26**: 1589-1600.

Mjelde, J.W, H.S.J. Hill & J.F. Griffiths (1998). A review of current evidence on climate forecast and their economic effects in agriculture. *Amer. J. Agric. Econ.* **80**: 1089-1095.

Monteith, J.L. (1996). The quest for balance in crop modeling. *Agron. J.* **88**: 695-697.

Monteith, J.L. & S.M. Virmani (1991). Quantifying climatic risk in the semi-arid tropics: ICRISAT experience. In: R.C. Muchow and J.A. Bellamy (Eds). Climatic Risk in Crop Production: Models and Management for the Semi-Arid Tropics and Sub-Tropics, CAB International, p183-204.

Mukhala, E.(2002). Manual for calculation of water requirement satisfaction index. Training paper series. SADC Regional Remote Sensing Unit, Harare, Zimbabwe.

Mukhala, E. & P. Hoefsloot (2004). Agrometshell Manual: Version 1.0. Southern African Development Countries (SADC) Food Security Program, Regional Remote Sensing Unit, Harare, Zimbabwe. pp58.

Mumey, G., B. Burden & A. Boyda (1992). Measurement of farm risk: Alberta crop production. *Can. J. Agric. Econ.* **40**: 71-91.

Murphy, A.H. (1977). The value of climatological and probabilistic forecasts. *Mon. Wea. Rev.* **105**: 803-816.

Musick, J.T., L.L. New & D.A. Dusek (1976). Soil water depletion–yield relationship of irrigated sorghum, wheat and soybeans. *Trans. ASAE* **2**: 489-493.

Mutai, C. & M.N. Ward (2000). East African rainfall and the tropical circulation / convection in inter-seasonal to inter-annual time scale. *J. Climate* **13**: 3915-3939.

NRRD / MOA (Natural Resources Regulatory Department of the Ministry of Agriculture). (2000) Agroecological Zones of Ethiopia. pp129.

Norris, P.E. & R.A. Kramer (1990). The elicitation of subjective probabilities with applications in agricultural economics. *Rev. Market. Agric. Econ.* **58** (2-3): 127-147.

NMSA (National Meteorological Services Agency) (1996a). Climate and agroclimatic resources of Ethiopia. Meteorological Research Report Series. Vol.1, No.1, Addis Ababa. pp137.

NMSA (National Meteorological Services Agency) (1996b). Assessment of drought in Ethiopia: Meteorological Research Report Series. Vol.1, No.2, Addis Ababa. pp259.

Nicholls, N. (1986). Use of the Southern Oscillation to forecast Texas winter wheat and sorghum crop yields. *Agric. Forest. Meteorol.* **38**: 9-15.

Nykanen, P.; S. Chowdhury & O. Wigertz (1991). Evaluation of decision support systems in medicine. *Comp. Methods Pro. Biomedicine* **34**: 229-238.

Ogallo L.J., J.E. Janowiac & M.S. Halpert (1988). Tele-connection between seasonal rainfall over East Africa and Global Sea Surface Temperature anomalies. *J. Meteorol. Soc. Japan* **66** (6): 807-821.

Olsen, D.A., N.W. Junker & B. Korty (1995). Evaluation of 33 years of quantitative precipitate on forecasting at NMC. *Wea. Forecast* **10**: 498-511.

Oludhe, C. (2004). Standard procedures for seasonal climate prediction. Pre-Forum Capacity Building Training Workshop for the Greater Horn of Africa Sub-Region, Narobi, Kenya.

Palmer, T.N. (1986). Influence of the Atlantic, Pacific and Indian Oceans on Sahel rainfall. *Nature* **322**: 251-253.

Palmer T.N. & D.L.T. Anderson (1994). The prospects of seasonal forecasting - a review paper. *Quart. J. Roy. Meteorol. Soc.* **120**: 755-193.

Parry, M.L. & T.R. Carter (1988). The assessment of climatic variations on agriculture: A summary of results from studies in semi-arid regions In: M.L. Parry, T. R. Carter, and N.T. Konjin (Eds). The Impact of Climatic Variations on Agriculture. Vol. 2: Assessment in Semi-Arid Region. Dordretcht: Kluwer. p9-60.

Passioura, J.B. (1973). Sense and non-sense in crop simulation. *Aust. Inst. Agric. Sci.* **39**: 181-183.

Passioura, J.B. (1996). Simulation models: Science, snake oil, education or engineering. *Agron. J.* **88** (5): 690-694.

Patron, S.R. J.& G.W. Jones (1989). Soybean production in the tropics - a simulation case for Mexico. *Agric. Systems* **29**: 219-231.

Penning de Vries, F.W.T. & C.J.T. Spitters (1991). The potential for improvement in crop yield simulation. In: R.C. Muchow and J.A. Bellamy (Eds). Climatic Risk in Crop Production: Models and Management for the Semi-Arid Tropics and Sub-Tropics. CAB International. p123-140.

Penning de Vries, F.W.T., H.H. van Laar & M.C.M. Chardon (1983). Bioenergetics of growth of seeds, fruits, and storage organs. In: Potential Productivity of Field Crops under Different Environments. IRRI Los Banos. p37-59.

Pezzulli S., D.B. Stephenson & A. Hannachi (2003). The variability of seasonality. *J. Climate* (http://ugamp.nerc.ac.uk/promise/research/conferenc2003/abstract-pdf/pezzeulli.pdf). Viewed on 1st November 2005.

Pfaff, A., K. Broad & M. Glantz (1999). Who Benefits from Seasonal-to-Interannual Climate Forecast?. *Nature* **397**: 645-646.

Philander, S.G.H. (1985). El Niño and La Niña. *J. Atm. Sci.* **42**: 2652-2662.

Philander, S.G.H. (1990). El Niño, La Niña and the Southern Oscillation. Academic Press. Inc: San Diego, California. pp293.

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

Philips, L.D. (1982). Requisite decision modeling. *J. Oper. Res. Soc.* **33**:303-312.

Potgieter, A.B, G.L. Hammer, H. Meinke, R.C. Stone & L. Goddard (2003). El Niño through the 'eyes' of a wheat crop. In: R.C. Stone and I. Partridge (Eds). Science for Drought. Proceedings, National Drought Forum. p74-77.

Powell, R. (1994). Background on risk in Australian agriculture. In: Proceedings Conference on Risk Management in Australian Agriculture, UNE, Aramidale.

Raman, C.V.R. (1974). Analyses of commencement of Monsoon rains over Maharashtra State for agricultural planning. Scientific report 216, India Meteorological Department, Poona, India.

Rasmusson, E.M. & T.H. Carpenter (1982). The relationship between Eastern Equatorial Pacific Sea temperature and rainfall over India and Srilanka. *Mon. Wea. Rev.* **111**: 517-528.

Ratliff, L.F., J.T. Ritchie & D.K. Cassel (1983). Field measured limits of soil water availability as related to laboratory-measured properties. *Soil Sci. Soc. Amer. J.* **47**:770-775.

Reddy, M.S. & K. Georgis (1994). Overview of dryland farming research of IAR: Objectives and focus: In: M.S. Reddy and K. Georgis (Eds). Development of techniques for the dryland farming areas of Ethiopia. Proceedings of the First National Workshop on Dryland Farming Research in Ethiopia. Nazreth, Ethiopia. 26-28 November 1991.

Rimmington, G.M. & D.J. Connor (1991). Strategies and tactics for managing Australian crops . In: Proceedings Conference on Agricultural Meteorology, Melbourne. p275-278.

Ritchie, J.T. (1991). Specification of the ideal model for predicting crop yields. In: R.C. Muchow and J.A. Bellamy (Eds). Climatic Risk in Crop Production: Models and Management for the Semi-Arid Tropics and Sub-Tropics. CAB International. p97-122.

Ritchie, J.T., A. Gerakis & A. Suleiman (1999). Simple model to estimate field-measured soil water limits. *Trans. ASAE* **42**: 1609-1614.

Robinson, J.B & D.G. Butler (2002). An alternative methods for assessing the value of the Southern Oscillation Index (SOI), including case studies of its value for crop management in dryland farming systems. *Agric. Systems* **76**: 929-948.

Rölling, N.G. (1988). Extension Science Information System in Agricultural Development. Cambridge University Press.

Rosamond, L., P.N. Walter, D.R. Falcon & W. Nikolsa (2001). Using El Niño / Southern Oscillation Climate data to Predict Rice Production in Indonesia. *Climatic Change* **50**: 255-265.

Rowell, D. (1998). Assessing potential seasonal predictability of an ensemble of multi-decadal GCM simulations. *J. Climate* **11**: 109-120.

Russel, B. (1950). Bertrand Russel in Australia. ABC Sound Archive. ISBN 0 642-55803-9.

Russel, J.S. (1991). Prospects for incorporation of long-term weather forecasting into crop decision support systems. In: R.C. Muchow and J.A. Bellamy (Eds). Climatic Risk in Crop Production: Models and Management for the Semi-Arid Tropics and Sub-Tropics. CAB International. p467-487.

Sage, A.P.C. (1991). Decesion Support System Ingineering. Willey, New York.

Sandford, S. (1978). Toward a definition of drought. Symposium on Drought in Botswana. National Museum, Gaborone.

Scanlan, J.C & G.M. McKeon (1993). Tropical pasture establishment. *Trop. Grassland*. 27: 414-19.

Seleshi, Y. (1996). Stochastic Predictions of Summer Rainfall Amounts over the North African Highlands and over India. PhD thesis (Water Resources Engineering), Virjie University of Brussles, Belgium. pp352.

Senay, G., J. Verdin & R. Smith (2001). Crop yield Estimate comparison between two methods: Energy balance (EWBMS) and water balance (WRSI). FEWSNET, USGS/ EROS Data Center Sioux Falls, South Dakota. (http://www.ears.nl/ewbms/E-result_FEWS.html).

Sharma, D.K., A. Kumar & K.N. Singh (1990). Effect of irrigation scheduling on growth, yield and evapotranspiration of wheat in sodic soils. *Agric. Water Manage*. **18**: 267-276.

Sharma P.N. & P.B A Neto (1986). Water production functions of sorghum for North-East Brazil. *Agric. Water Manage*. **11**: 169-180.

Sharratt, B.S. (1994). Observations and modeling of interactions between barley yield and evapotranspiration in the subaretic. *Agric. Water Manage*. **25**: 109-119.

Shiskin, J., A.H. Young & J.C. Musgrave (1967). The X-11 variant of Census Method II seasonal adjustment program. Technical paper No. 15, Bureau of the Census, US.

Simane, B. & P.C. Struick (1993). Agroclimatic analyses: a tool for planning sustainable Wheat (*Triticum turgidum var. durum*) production in Ethiopia. *Agric. Eco. Enviro*. **47**: 31-46.

Simetar Inc. (2005). http://www.simeter.com. Viewed on 01 November 2005.

Simon, H.A. (1983). Reason in Human Affairs. Standford University Press.

Sincich, W.M.T. (1993). A Second Course in Statistics: Regression Analyses, 5th Edition. Prentice-Hall, Inc. pp899.

Sinclair, T.R. & N.G. Seligman (1996). Crop modeling from infancy to maturity. *Agron. J.* **88** (5): 698-704.

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

Smika, D.E. (1990). Fallow management practices for wheat production in Central Great Plains. *Agron. J.* **82** (1-3): 319-323.

Sprague R.H. (1980). A framework for the development of DSS. *MIS Quarter* **4**: 1-26.

Stehr, G.T. & H. von Starch (1995). Perspective of climate. *Climatic Change* **27**: 17-24.

Streuderst, G. J. (1985). A Regression Model for the Prediction of Soil Water Potential in Selected Soils. [Afrikaans]. MSc thesis (Soil Science), University of Orange Free State, Bloemfontein.

Stern, R.D. & R. Coe (1982). The use of rainfall models in agricultural planning. *Agric. Meteorol.* **26**: 35-50.

Stern, R.D. & R.Coe (1984). A model fitting analyses of daily rainfall data. *J. Royal Stat. Soc.* (A). **147**: 1-34.

Stern, R., J. Knock, D. Rijks & I. Dale (2002). Instat+ (Interactive Statistics Package). Statistics Services Center. University of Reading, U.K. pp530.

Stewart, B.A. & J.I. Steiner (1990). Water use efficiency. *Adv. Soil Sci.* **13**: 151-173.

Stewart, J.I. (1972). Prediction of Water Production Functions and Associated Irrigation Programs to Miinimize Crop Yield and Profit Losses due to Limited Water. PhD thesis, University of California, Davis. pp200.

Stewart, J.I. (1980). Effective rainfall analyses to guide farm practices and predict yields. In Proceedings 4th Annual General Meeting of the Soil Science Society of East Africa, Arusha, Tanzania. pp34.

Stewart, J.I. (1988). Response Farming in Rainfed Agriculture. The WHARF Foundation Press. pp103.

Stewart, J.I & R.M. Hagan (1973). Functions to predict effects of crop water deficits. *J. Irrig. Drain. Div. ASCE* **99**: 421-439.

Stewart, I.J. & C.T. Hash (1982). Impact of weather analyses on agricultural production and for the semi-arid areas of Kenya. *J. App. Meteorol.* **21**: 479-495.

Stone, R.C. & A. Aulciems (1992). SOI phase relationships with rainfall in eastern Australia. *Int. J. Climatol.* **12**: 625-d36.

Stone, R.C., G.L. Hammer & T. Marcussen (1996). Prediction of global rainfall probabilities using phases of the Southern Oscillation Index. *Nature* **384**: 252-55.

Stone, J.F. & D.L. Nofzicer (1993). Water use and yields of cotton grown under wide-spaced furrow irrigation. *Agric. Water Manage.* **24**: 27-38.

Taddesse, T. (2000). Drought and its predictability in Ethiopia. In: D.A. Wilhite (Ed). Drought: A Global Assessment, Vol. 1, Rougtledge. USA. p135-142.

Tanco, R.A. & G.J. Berri (2000). Climlab2000 Manual, English Version. International Research Institute for Climate Prediction (IRI). pp61.

Tapp, R.J. & G.F. Mnamara (1989). Experiments using model output statistics to predict precipitation at tropical location. *Aust. Met. Mag.* **37**: 129-39.

Taylor, M. (1994). Training for Risk Management in Victorian Agriculture. In: Proceedings of Conference on Risk Management in Australian Agriculture.

Tesfaye, K.F. (2004). Field Comparison of Resource Utilization and Productivity of Three Grain Legume Species under Water Stress. PhD thesis (Agrometeorology). University of the Free State.

Tilahun, K. (2005). Analyses of rainfall climate and evapotranspiration in arid and semi-arid regions of Ethiopia using data over the last half a century. *J. Arid Enviro.* (article in press). (www.elsvier.co/locate/jnlabr/yjare)

Todd, C. (1893). Meteorological work in Australia: A review. In: Report 5th meeting Australian Association, Advancement of Sciences. p246-270.

Trewartha, G.T. (1968). An Introduction to Climate, 4th ed.. McGraw-Hill, New York.

Trenberth, K.E. (1991). General characteristics of El Niño-Southern Oscillation. In: M.H. Glantz, R.W. Katz and N. Nicholls (Eds). Teleconnections Linking Worldwide Climatic Anomalies: Scientific Bases and Societal Impact. Cambridge University Press, New York. p13-42.

Tuker, C.J. & S.N. Goward (1987). Satellite remote sensing of drought conditions: In: Planning for Drought: Toward a Reduction Societal Vulnerability. West View Press, Boulder and London.

Uehara, G.& G.Y. Tsuji (1991). Progress in crop modeling in the IBSNAT Project. In: R.C. Muchow and J.A. Bellamy (Eds). Climatic Risk in Crop Production: Models and Management for the Semi-Arid Tropics and Sub-Tropics, CAB International. p143-156.

United States Geological Survey (USGS), 2005. . http://publs.usgs.gov/publications/text/East_Africa.html

Van Keulen, H. & J. Wolf (Eds) (1986). Modeling of Agricultural Production: Weather, Soils and Crops. Simulation Monograph Series, PUDOC, Wageningen.

Van Loon, H. & D.J. Shea (1985). The Southern Oscillation Part IV: The precursors south of the 15o S to the extremes of the oscillation. *Mon. Wea. Rev.* **113**: 2063-2074

Van Loon, H. & D.J. Shea (1987). The Southern Oscillation Part VI: Anomalies of sea level pressure on the Southern Hemisphere and of Pacific sea surface temperature during the development of a warm event. *Mon. Wea. Rev.* **115**: 370-379.

Vaughan, E. J. (1986). Fundamentals of Risk and Insurance. John Wiley and Sons, New York.

Verdin, J. & R. Klaver (2001). Grid cell based crop water accounting for the famine early warning system. Hydrological Processes.

Von Neuman, J. & O. Mongenstern. (1947). Theory of Games and Economic Behavior. Princeton University Press, Princeton.

Walker, S.G. (1923). Correlations of seasonal variations of weather. VIII. A preliminary study of world weather. *Mem. Indian Meteorol. Department* **24**: 75-131.

Walker, G.T. & E.W. Bliss (1932). World Weather V. *Mem. Roy. Met. Soc.* **4** (36): 53-84.

Walker, G.T. & E.W. Bliss (1937). World Weather VI. *Mem. Ro. Met. Soc.* **4** (39): 119-139.

Walker, S., G.E. Yohannes, K. Tesfaye, G. Mamo, A. Yeshanew & E. Bekele (2003). The use of agroclimatic zones as a basis for the cropping system in the Central Rift Valley of Ethiopia. (www. climateadapation.net/docs/papers). Climate and Societal Interactions Divison of NOAA of the Global Programs.

White D.H. (1994). Climate variability, ecologically sustainable development and risk management. *Agric. Sys. Info. Tech.* **6**: 7-8.

White, D.H., D. Collins & S.M. Howden (1993). Drought in Australia, prediction, monitoring, management and policy. In: D.A Wilhite (Ed). Drought Assessment Management and Planning: Theory and Case Studies. Kluwer Academic Publishers. p213-236.

Whistler, F.D., B. Acock, D.N. Baker, R. Efye, H.F. Hodges, J.R. Lambert, H.E. McKnion & V.R. Reddy (1986). Crop simulation models in agronomic systems. *Adv. Agron.* **40**: 141-208.

Wilks, D.S. (1995). Statistical Methods in Atmospheric Sciences. Academic Press. pp467.

Wilks, D.S. (1989). Conditioning stochastic daily precipitation models on total monthly precipitation. *Water Resou. Res.* **25**: 1429-1439.

Wilmott, C.J. (1981). On the validation of models. *Physical. Geog.* **2**: 184-194.

Wilmott, C.J. (1982). Some comments on the evaluation of model performance. *Bull. Amer. Meteorol. Soc.* **63**: 1309-1317.

Williams, J.P., J. Rose; & K.L. Bristow (1991). Perspicacity, precision and pragmatism in modelling crop water supply. In: R.C. Muchow and J.A. Bellamy (Eds). Climatic Risk in Crop Production: Models and Management for the Semi-Arid Tropics and Sub-Tropics, CAB International. p73-96.

Wisiol, K. & J.D. Hesketh (Eds) (1987). Plant Growth Modeling for Resource Management. Volume 1 and 2. CRC Press, Boca Raton.

Woldemariam, D. (1989). Food Policy Objectives in the Ten Year perspective Plan. In: Towards a Food and Nutrition Strategy for Ethiopia, Proceedings of the National Workshop on Food Strategies for Ethiopia. Office of the National Committee for Central Planning. p9-25.

Wood, J.R.G. & A.T. Wood-Harper (1993). Information technology in support of individual-decision making. *J. Inform. Sys.* **3**: 85-101.

Woods, E.G., J.Moll, R. Coutts; C. Clarkand & Ivin (1993). Information Exchange. A report commissioned by Australia's Rural Research and Development Corporation.

Wylie, P.B. (1996). Drought management on grain farms. In: Proceedings 2nd Australian Conference on Agriculture Meteorology, Brisbane. p132-136.

Xu, Y. & G.J.V. Tonder (2001). Estimation of recharge using a revised CRD method. *Water SA*. **27**(3): 341-344

Yehualawork, Y. (1989). Agricultural credit and rural financial markets in Ethiopia. In: Towards a Food and Nutrition Strategy for Ethiopia, Proceedings National Workshop on Food Strategies for Ethiopia. Office of the National Committee for Central Planning. p383-406.

Yeshanew, A. (2003). Mechanism and Teleconnections of Climate Variability in Tropical North Africa. PhD thesis, University of Zululand, KwaZuluNatal, South Africa. pp546.

Zere, T.B. (2003). Evaluating Maize Production Potential of Selected Semi-Arid Ecotopes using a Water Balance Model. MSc thesis (Soil Science). University of the Free State, Bloemfontien, South Africa. pp102.

Appendices

Appendix A Weighted Average WRSI of a 120-day sorghum cultivar grown in May at Miesso, CRV of Ethiopia

Year	Observed grain yield (kg/ha)	WRSI at various growth stages				Weighted WRSI (composite from different growth stages)										
		Initial stage	Development stage	Mid season	End of season	1111	1121	1131	1141	1232	1242	1244	1344	1444	2444	3444
1990	605.6	28.0	51.5	90.8	100.0	67.6	72.2	75.3	77.5	75.4	77.1	81.3	78.8	76.7	73.2	70.2
1993	605.6	6.0	33.9	58.5	100.0	49.6	51.4	52.5	53.4	56.2	56.4	64.3	61.8	59.7	55.8	52.5
1994	1429.8	0	100	84.5	100	67.5	70.9	73.2	74.8	81.7	78.8	82.7	82.9	83.1	77.2	72.0
1996	4187.9	100.0	100.0	95.6	97.8	98.3	97.8	97.4	97.1	97.8	97.5	97.6	97.8	97.9	98.1	98.2
1997	622.2	54.1	75.5	55.6	27.3	53.1	53.6	54.0	54.2	53.3	53.6	48.8	51.0	52.9	53.0	53.1
1998	2323.2	57.5	51.3	100.0	100.0	77.2	81.8	84.8	87.0	82.5	84.4	87.3	84.3	81.7	80.0	78.5
1999	3153.9	46.1	89.8	100.0	100.0	84.0	87.2	89.3	90.9	90.7	91.8	93.3	93.0	92.7	89.4	86.5
2000	2629.2	86.9	79.6	100.0	100.0	91.6	93.3	94.4	95.2	93.3	94.0	95.1	93.8	92.7	92.3	91.9
r^2						0.757	0.681	0.775	0.744	0.756	0.756	0.648	0.704	0.742	0.81	0.748

Appendix B Weighted average WRSI and their correlation with the grain yield of a 120-day sorghum grown In June at Melkassa Research Centre, CRV of Ethiopia

Year	Observed grain yield (kg/ha)	WRSI at various growth stages				Weighted average WRSI									
		Initial stage	Development stage	Mid season	End of season	**1111**	**1121**	**1131**	**1141**	**1232**	**1242**	**1244**	**1344**	**1444**	**2444**
1983	1471.1	64.6	83.0	95.5	86.3	82.3	85.0	86.7	88.0	86.2	87.2	87.1	86.7	86.4	84.9
1984	1190.5	100.0	100.0	55.5	90.2	86.4	80.2	76.1	73.2	80.9	78.0	80.3	81.9	83.3	84.5
1985	1977.8	58.6	77.5	100	77.2	78.3	82.7	85.5	87.6	83.5	85.3	83.9	83.3	82.9	81.1
1987	4070.4	100	100.0	100	78.4	94.6	95.7	96.4	96.9	94.6	95.2	92.1	92.8	93.3	93.8
1988	977.8	0	61.8	100	100.0	65.4	72.4	77.0	80.3	77.9	80.4	84.0	82.1	80.5	74.8
1989	325.3	27.5	88.0	100.0	23.1	59.6	67.7	73.1	76.9	68.7	72.2	63.3	65.3	67.1	64.2
1990	4238.2	100	100	100	100	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
1992	2601.0	95.0	100.0	98.8	64.2	89.5	91.4	92.6	93.5	90.0	91.0	86.1	87.3	88.2	88.7
1993	3044.4	100.0	97.5	100.0	100.0	99.4	99.5	99.6	99.6	99.4	99.5	99.6	99.4	99.2	99.3
1994	4940.8	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
1995	3666.1	95.0	100.0	97.0	100.0	98.0	97.8	97.7	97.6	98.3	98.1	98.5	98.6	98.7	98.4
1996	3303.1	100.0	84.8	100.0	100.0	96.2	97.0	97.5	97.8	96.2	96.6	97.2	96.2	95.3	95.7
1997	2873.8	100.0	99.0	88.4	62.6	87.5	87.7	87.8	87.9	86.1	86.3	82.0	83.4	84.6	85.7
1998	2666.7	100	100	87.1	42.8	82.5	83.4	84.0	84.5	80.9	81.6	74.5	76.6	78.4	80.0
1999	604.4	34.8	42.3	89.1	53.3	54.9	61.7	66.3	69.5	61.6	64.7	62.6	60.9	59.5	57.7
2000	2045.3	19.5	100.0	100.0	100.0	79.9	83.9	86.6	88.5	89.9	91.1	92.7	93.3	93.8	88.5
r^2						**0.784**	**0.83**	**0.834**	**0.792**	**0.772**	**0.769**	**0.637**	**0.667**	**0.681**	**0.753**

Appendix C Weighted Average WRSI of a 180-day sorghum cultivar grown in May at Arsi Negele, CRV of Ethiopia

Year	Observed grain yield (kg ha^{-1})	WRSI of various growth stages				Weighted Average WRSI										
		Initial stage	Development stage	Mid season	End of season	1111	1121	1131	1141	1232	1242	1244	1344	1444	2444	3444
1988	4550.6	100	100	91.5	100	97.9	96.6	95.8	95.2	96.8	96.2	96.9	97.2	97.4	90.4	97.7
1989	2677.8	100	71.2	80.4	69.2	80.2	80.3	80.3	80.3	77.8	78.1	76.4	76.0	75.6	70.2	78.9
1990	3433.3	100	100	88.8	28.5	79.3	81.2	82.5	83.4	77.9	79.1	69.9	72.4	74.6	69.2	78.0
1992	8392.6	100	100	100.0	86.3	99.6	97.3	97.7	98.0	96.6	97.0	95.0	95.4	95.8	89.0	96.4
1993	8466.5	100	100	100.0	98.2	98.3	99.6	99.7	99.7	99.6	99.6	99.4	99.4	99.5	92.4	99.5
1994	6214.3	100	100	93.0	100.0	90.8	97.2	96.5	96.0	97.4	96.9	97.5	97.7	97.9	90.9	98.1
1995	4790.5	63.3	100	100.0	100.0	89.7	92.7	93.9	94.8	95.4	95.9	96.7	96.9	97.2	90.2	92.7
1996	4073.0	100.0	100	100.0	58.9	93.8	91.8	93.2	94.1	89.7	90.9	85.1	86.3	87.4	81.1	89.0
1999	4370.4	100.0	100.0	75.2	100.0	80.1	90.1	87.6	85.9	90.7	89.0	91.0	91.7	92.4	85.8	93.4
2000	3612.7	100.0	74.4	100.0	46.0	?	84.1	86.7	88.6	80.1	82.3	75.7	75.6	75.5	70.1	78.8
r^2						**0.598**	**0.689**	**0.699**	**0.657**	**0.609**	**0.635**	**0.520**	**0.530**	**0.530**	**0.535**	**0.584**

Appendix D User Manual for ABBABOKA 1.0 Decision support tool (DST)

To obtain decisions regarding plant varieties to be planted and the technology thereby employed, data for four important facets concerning the area under consideration need to be provided. These are: specific zone in which the area is situated, soil-water data, Meteorological information and (target) planting date. If any of this data is not supplied, the model will not be able to provide any decision aid. Should any data be omitted the system will request the user to supply (fill-in) all the required data by displaying a message box.

Having provided all the necessary data, pressing the "show decision" button will reveal a recommendable decision, i.e., either to "keep on fallowing" or to "go ahead and plant". If the recommended decision is "keep on fallowing", the program will display a very brief message box stating the decision. If the recommended decision is to "go ahead and plant", the most suitable planting specifications as well as other planting options (if applicable) will be displayed in another ensuing form. The most suitable planting option will be displayed on the top of the form and the remaining option(s) will be enumerated below. Clicking the radio buttons showing the enumerated options will reveal the planting technology that goes with it.

In cases where the required data is not provided on the entry field/s the program will display a message box requesting the missing entry/ies/ to be displayed. Furthermore, the model assumes a limited planting time for the area under consideration and thereby provides a decision support system for the months between March and September, on monthly time interval basis. If the target month lies out of this range, the system will display a message box letting the user know that it is only designed for this specific planting season.

To quit the program click on the "File" menu and choose "Exit".

Computations

In the main menu, "Computations" provides the user with opportunity to calculate PAWC, DUL, LL and PAW, given some soil values. The user is required to fill-in all the soil related values and then press the button to display the result. The system provides

some default values on the entry points just to show the user what kind of data is required to enter.

Maps

Choosing "Maps" from the main menu will enable the user to see the general map and seasonal water requirement satisfaction index (WRSI) maps of the area under study, by clicking on one of the sub menus. Once the "Maps" form appears on the screen, the user can switch from general map to the seasonal ones by clicking on the "Switch to" menu. The seasonal WRSI maps provide radio buttons to enable the user to choose a specific cultivar and time. The maps can be further magnified by double clicking on the map.