Strategies to adapt to climate change in the Central Rift Valley of Ethiopia: landscape impact assessment for on-farm adaptation

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Table of contents

Chapter 1

Introduction

Introduction

1.1 Food security at risk?

The Central Rift Valley (CRV) is a food producing area in Ethiopia with an average rainfall of 881 mm per year divided over two rainy seasons. Food security is low and poverty is widespread in the region, because of low and variable crop productivity. There are several reasons for this; large rainfall variability is one of these. Long dry spells during critical crop development stages causes yield reductions and sometimes total crop failure.

Decades of publications about climate change has created fear that future changes in rainfall may worsen food security in this already critical area. And, will further reduce options for investments in agricultural intensification. However, a problem is that current models predicting climate change do not have the right scale to predict what may occur in the CRV. Hence, details of possible changes in rainfall are lacking. Is it total rainfall or is it rainfall in the *Belg* season or in the *Kiremt* season that will change? Is it rainfall intensity increasing the risk of water erosion or are dry spells becoming longer? This uncertainty implies also uncertainty about those measures that will reduce the impact of projected climate change.

Hence, there is a need to downscale climate change models, to analyze details of changes in rainfall and compare these with current rainfall variability, to determine the impact of these changes in relation to possible other crop production limiting factors and to develop options for crop intensification that reduce the impact of climate change and increase food security in the CRV.

Though most studies conducted in Ethiopia indicate that climate change is likely to affect crop yields negatively (e.g., Deressa, 2007; Deressa and Hassan, 2009), there is little quantitative evidence about effective climate change adaptation options to improve food security (Bryan et al., 2009; Di Falco et al., 2011*;* Conway et al., 2011). Quantitative assessment of climate change impact adaptation strategies at micro or farm level is important, since "effective adaptation measures are highly dependent on specific, geographical and climate risk factors among other things" (IPCC, 2007).

Ethiopia's rain-fed agriculture based economy is highly sensitive to climate fluctuations. Rainfall is the most important determinant of Ethiopia's economic success or failure from year to year (Devereux, 2000). Variations in average rainfall of preceding year are directly proportional to growth/decline in GDP of current year in Ethiopia (World Bank, 2006; Thornton et al., 2006; Yeshanew and Jury, 2006). Rainfall shock in one year has a lingering effect on households` welfare for many years to come. For instance, Dercon (2004) indicated that a 10% rainfall decrease in one year has an impact of 1 % on the growth rates of about 4 to 5 years to come. Similarly, a 10% decrease in seasonal rainfall from the long-term average generally translates into a 4.4% decrease in the country's food production (von Braun, 1991).

In Ethiopia only about 2% of the country's arable land is irrigated (FAO, 2006), food grain production is almost entirely dependent on rainfall, with generally low yield levels and large on-farm water losses during occasional periods of heavy rainfall (Georgis et al., 2001; Westgate, 1994). Production of major cereals (teff, barley, wheat, maize, sorghum and millet) showed statistically significant correlations with seasonal rainfall variability in the north-western part of Ethiopia during 1994-2003 (Bewket, 2009). Similarly, anomalously short *Belg* rainy seasons during 2000–2004 have led to food shortages in southern Ethiopia (Verdin et al., 2005). Despite more than a decade of policies placing high priority on cereal intensification, food production, a key element in food security, is hardly improving and poverty and food insecurity are persistent phenomena (Ramakrishna and Demeke, 2002; Kassie et al, 2009).

Generally, Ethiopia faces daunting challenges from high poverty levels, rapid population growth, over-reliance on rain-fed agriculture, high levels of environmental degradation, chronic food insecurity, and frequent natural drought cycles and low level of adaptive capacity to climate variability and change (Kidanu et al., 2009). Thus, Ethiopia continues to be one of the largest recipients of food aid in the world (Byerlee et al., 2007), more than 7 million people required assistance during 1991–1992, 7–11 million similarly were affected in 1999–2000, and in 2003 the number exceeded 13 million (Segele and Lamb, 2005). Overall, about 10% of the population continuously requires food aid assistance annually (Conway and Schipper, 2011).

A recent study by Robinson et al. (2013) indicated that climate change scenario by 2050 could cause Ethiopian GDP to be 8-10 % smaller than under a no-climate change baseline. Therefore, climate variability and change poses an increasing risk to hold back some of the progress made over recent years in overcoming hunger and poverty reduction and could even reverse the gains made in Ethiopia’s development and could exacerbate poverty (Eshetu et al., 2014).

The CRV is one of the most drought prone areas in Ethiopia. Like most parts of Ethiopia, food security situation of households in the CRV region of the country is greatly influenced by the performance of rain-fed cropping systems. Interannual variability of seasonal rain fall in terms of dry spells, late onset, early cessation of rainfall and total lack of rainfall are the major causes of crop failure in Ethiopia, including the CRV (Segele and Lamb, 2005; Araya and Stroosnijder, 2011; Biazin and Sterk, 2012). In the CRV, farmers also believe that a decrease in rainfall and a change in its distribution as the main cause of yield reduction (Kassie et al. 2013; Adimassu et al., 2014).

The dryland part of the CRV has semi-arid and dry sub-humid climate, with an aridity index of 0.50-0.65 computed as the ratio of mean annual precipitation to mean annual reference evapo-transpiration (ET_O). There are two rainy seasons: *Belg* and *Kiremt.* The small rainy season (*Belg)* is during March-May and the main rainy season (*Kiremt*) is during June-September. The mean annual rainfall varies between 685 and 1118 mm with a mean of 881 mm for the past 40 years (1970-2009).

Maize is one of the most important food crops for household food security in the CRV. Nationally, maize plays a critical role in smallholder food security. Among the major cereal crops in the country, it ranks first both in production and productivity and second after teff in area coverage. Maize is a long cycle crop sown during the *Belg* season (March - May) and harvested at the end of the *Kiremt* between September and December (Figure 1.3). Dry spells during the *Belg* create serious moisture stress at critical stages of crop growth, because dry-spells are longer during ‘*Belg*’ than *Kiremt* season.

A related problem is that, due to the potential risk of crop failure from periodic water scarcity, small-holder farmers are not willing to invest in fertilizer and other inputs. This can be attributed to farmers’ aversion to risk. Smallholder farmers show rationally reluctance to invest in soil fertility, improved crop varieties and other yield enhancing inputs (Hilhost and Muchena, 2000; Rockström et al., 2002**),** when the returns to investment appear so unpredictable due to the risk associated with climate variability, mostly crop failure due to dry spells and drought (Cooper, et al., 2008). Thus, this lack of investment in productive inputs means that even in a year where rainfall is favourable, the yield is not as large as it should be. Therefore, uncertain rainfall and very low levels of irrigation make intensive cultivation with improved seeds and fertilizer risky (McCann 1995). Actual farmers’ maize yield in the CRV is about 2.3 t ha^{-1} which is only 28–30% of simulated yield attainable underwater-limited conditions, which indicate the large potential to increase yields with improved agricultural inputs, especially nitrogen fertilizer (Kassie et al., 2014).

1.2 Hypotheses

In our wish to downscale climate change models, to analyze details of changes in rainfall and compare these with current rainfall variability, to determine the impact of these changes in relation to possible other crop production limiting factors and to develop options for crop intensification that reduce the impact of climate change and increase food security in the CRV we start with a number of hypotheses.

1 The first hypothesis relates to climate change models. We assume that we can find methods that can downscale reputed models to the regional scale of the CRV in Ethiopia.
2 The second hypothesis is that due to current rainfall variability crop production is limited by drought stress, notably by long dry spells in critical crop growth stages.
3 The third hypothesis is that the effect of climate change on crop production can only be studied if we can obtain insight in the details of changes in rainfall characteristics and in the prediction of the occurrence of extreme events like long dry spells.
4 The fourth hypothesis is that we can use a crop growth model and long term rainfall data to predict effects in a statistically sound way.
5 The fifth hypothesis is that adaptation measures must aim at improving the water supply to the crop so that investments in crop intensification are worth the effort.
6 The sixth hypothesis is that crop intensification is only worth the effort if not only the water supply is improved but also other production limiting factors, such as fertility, are improved.
7 The seventh hypothesis is that farmers are right in their idea that small scale forest have a beneficial effect of rainfall and one of the recommended impact reducing strategies therefore is the protection and plantation of small forests.

1.3 State of the art

Downscaling (hypothesis 1)

GCMs are the most widely used tools used to project future climate change under different scenarios (IPCC, 2007). However, GCMs are not very reliable when simulating atmospheric dynamics associated with landscape variability (Boko et al. 2007; Moore et al. 2012) - especially when the terrain is extremely complex as in Ethiopia. Furthermore, effective climate change adaptation requires spatially and temporally downscaled climate change projections. Therefore, to assess local scale potential impacts of climate change and adaptation planning the existing GCM outputs are too coarse in their spatial and temporal resolutions and unable to capture the required details. Hence, projected changes from GCMs need to be downscaled to provide fine-resolution or point-scale information required for impact models.

The method used to convert GCM outputs into locally relevant climate data required for impact models are usually referred to as 'downscaling' techniques. There are two kinds of commonly used downscaling methods, namely, dynamic downscaling and empirical (statistical) downscaling. Dynamic downscaling approach is a method of extracting local-scale information by developing regional climate models (RCMs) with the coarse GCM data used as boundary conditions. Statistical downscaling, on the other hand, starts with the premise that the regional climate is the result of interplay of large-scale climatic/atmospheric features (global, hemispheric, continental, regional) and local conditions (topography, water bodies, land surface properties) (von Storch et al., 2000). Statistical downscaling is an easy-to-apply and much more rapid method for developing high-resolution climate change surfaces for high resolution regional climate change impact assessment studies. The fundamental assumption of downscaling methods is that the statistical relationships will continue to be valid in the future under conditions of climate change (Karamouz et al, 2010).

Current rainfall variability (hypothesis 2)

Many studies have been conducted during the last decades in Ethiopia to assess the spatial and temporal patterns of rainfall in different parts of the country (Conway, 2000; Conway et al*.,* 2004; Seleshi and Zanke, 2004; Bewket and Conway, 2007; McSweeney et al. 2008; Cheung et al., 2008). However, the existing studies usually disagree on the magnitude and pattern of change. Ethiopia`s geography is diverse, with a wide range of climatic variations, spatial and temporal aggregation over such diverse climates and seasons within the country are mostly sources of disagreement (Easterling *et al*., 2000; Seleshi and Zanke, 2004).

Given Ethiopian extensive geographical diversity, the climatological variation of rainfall is large, both in total rainfall amounts and in the seasonality of the rainfall (Figures 1.1 & 1.2). The arid area of eastern and north eastern borders of the country gets <320 mm while most areas in the south western highlands get >1189 mm. Overall, Ethiopia receives one of the highest levels of rainfall in eastern Africa (Dalelo, 2012). Therefore, Ethiopia does not face a catastrophic national failure of rainfall, but rather regional hot spots with a tendency towards more frequent droughts (Funk et al., 2012).

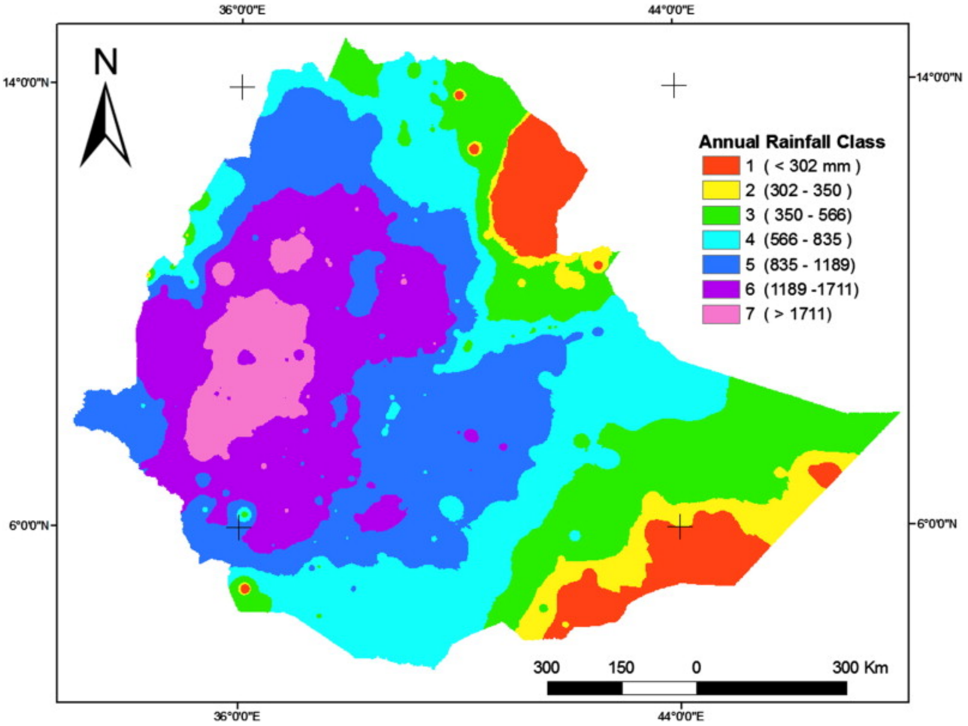
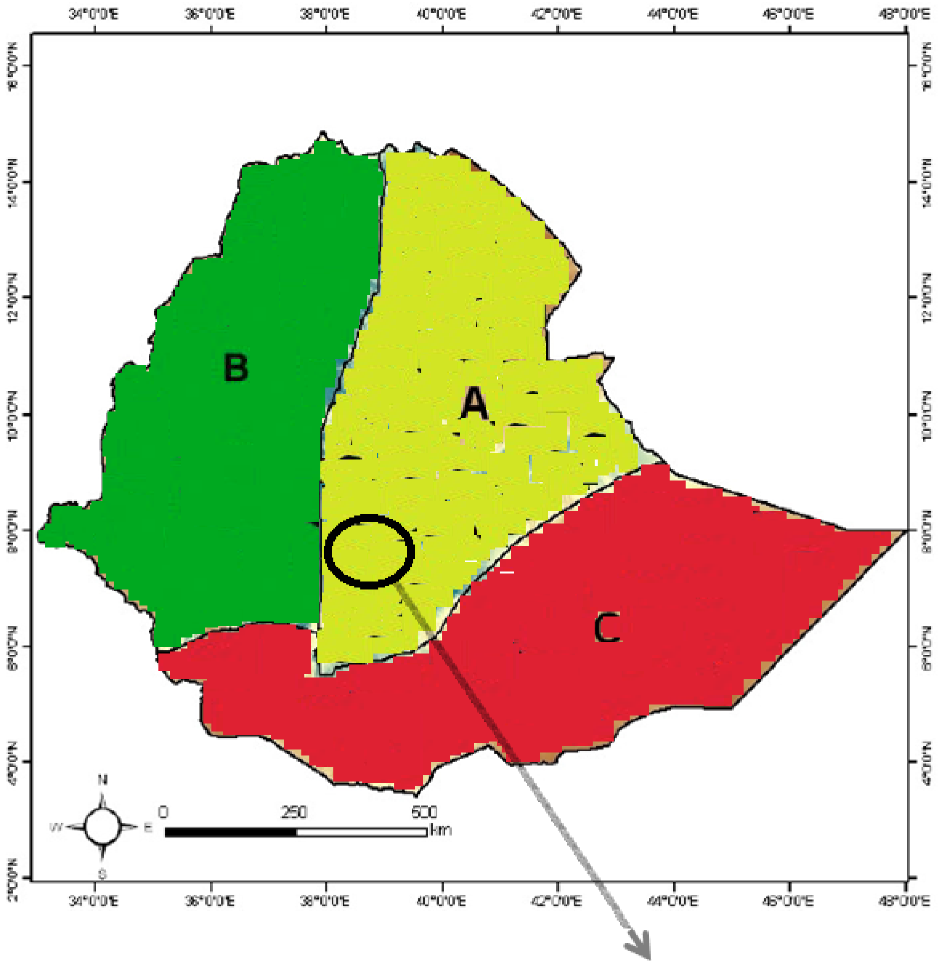


Figure 1.1 the spatial patterns of mean annual rainfall in Ethiopia (Berhanu et al., 2013)

The country has also three rainfall regimes as shown in Figure 1.2, (i) Regime A comprises the central, eastern and north-eastern part of the country and has a bi-modal rain which is the *Kiremt* and *Belg* rains, (ii) Regime B has a Mono-modal rainfall pattern, which includes the south-western, western and north-western parts of the country and are under their wet season during February/March to October/November, April/May to October/November and June to September, respectively, (iii) Regime C comprises the south and south-eastern part of Ethiopia which is characterized by two distinct rainfall peaks with dry season in between, with a main rainy season in March to May and short rains of October-November.



Central Rift Valley

Figure 1.2 Rainfall regimes of Ethiopia (containing regions with similar annual rainfall cycles)

Detailed rainfall characteristics (hypothesis 3)

The main effects of climate change on crop production will be changes in regular crop planting times, length of growing season, and shifts in suitable crop types or cultivars (Mahoo et al., 2013). For example, in semi-arid rainfed agriculture the onset of the rainy season often determines the length of the growing period and thereby suitable combination of crops (Mugalavai et al., 2008). Due to the delays in onset and early cessation of rains farmers miss the optimum planting time and fail to plant long-season crops in dryland areas.

There is evidence that the change in growing season rainfall characteristics such as dry spells, onset, cessation, duration of the growing season and seasonal rainfall variability are affecting crop growth and final yields in Ethiopia (Segele and Lamb 2005; Yengoh, 2010; Araya and Stroosnijder, 2011; Biazin and Sterk, 2013).

But, the possible direction and magnitude of change and potential impact in the future is yet unknown. To predict effects of climate change at farm level in the CRV in Ethiopia, the expected change of these growing-season rainfall characteristics need to be known and their impacts need to be examined. This helps to support farmers in making informed decisions regarding their farming strategies. For example, identification of the most reliable onset will enable farmers to improve rainwater use and to reduce false start risks and to obtain better crop yield (Mugalava *et al*., 2008). A lesson from this is that we need better climatological information on spatial organization of rainfall at different time scales and tools adapted for using the space-time information

Ethiopia is also often associated with the risk of climate extremes, such as droughts and occasionally floods and intense rainfall which can cause devastating damage to crops. It is not, however, known whether the extreme events including drought are becoming more frequent and intense in the face of assumed global warming (Seleshi and Camberlin, 2006) and how the direction and magnitude of change varies with location and seasons. In order to understand rainfall behaviour of climate extremes, particularly as an indicator of climate change, daily rainfall series must be analysed (Jones *et al*., 1999; Brunetti *et al*., 2001a). But, very few such studies exist in Ethiopia (Seleshi and Zanke, 2004; Seleshi and Camberlin, 2006; Bewket and Conway, 2007). There are few studies that reported some isolated incidence of climate extremes, manifested in the form of drought and recent flooding. For example, in Ethiopia, 2009 was the second driest year known on record, surpassed only by the catastrophic 1984 drought (Viste *et al*. 2012). Both 2002 and 2003 were also extremely dry years in the CRV of Ethiopia (Ayenew, 2004). At the other extreme, there have been extreme wet conditions in Ethiopia. For instance, the October to February season in 1997-98 (normally considered dry season) was the wettest on record over much of Ethiopia (Conway, 2000). Overall in 1998 annual rainfall in some parts of Ethiopia was up to ten times higher than the long-term average, and there was heavy flooding in many parts of the country in 2007 as well that affected thousands of people (Spinage, 2012). These are isolated rainfall and flood incidents which did not indicate the general trend of different rainfall extremes at different seasons in different areas.

Crop growth models (hypothesis 4)

There are many crop growth models that can be used to find long-term trends in crop production. However, some are very complex and need excessive amount of input data. AquaCrop, developed by FAO, has been parameterized and tested under a wide range of environmental conditions for different crops in Ethiopia (Araya et al. 2010, Erkossa et al. 2011; Biazin and Stroosnijder 2012; Abrha et al. 2012) and elsewhere (Heng et al. 2009; Hsiao et al. 2009; Andarzian et al. 2011; Salemi et al. 2011; Mhizha et al. 2014). AquaCrop is designed to be widely applicable under different climate and soil conditions, without the need for local calibration, once it has been properly parameterized for a particular crop species (Hsiao et al. 2012).

The FAO's AquaCrop model is a dynamic crop-growth model developed to simulate attainable crop yield in response to water, particularly suited to address conditions where water is a key limiting factor in crop production (Hsiao et al. 2009; Raes et al. 2009; Steduto et al. 2009). Hsiao et al. (2009) revealed that AquaCrop was able to simulate the canopy cover, biomass development and grain yield of maize cultivars over six different cropping seasons that differed in plant density, planting date and evaporative demands.

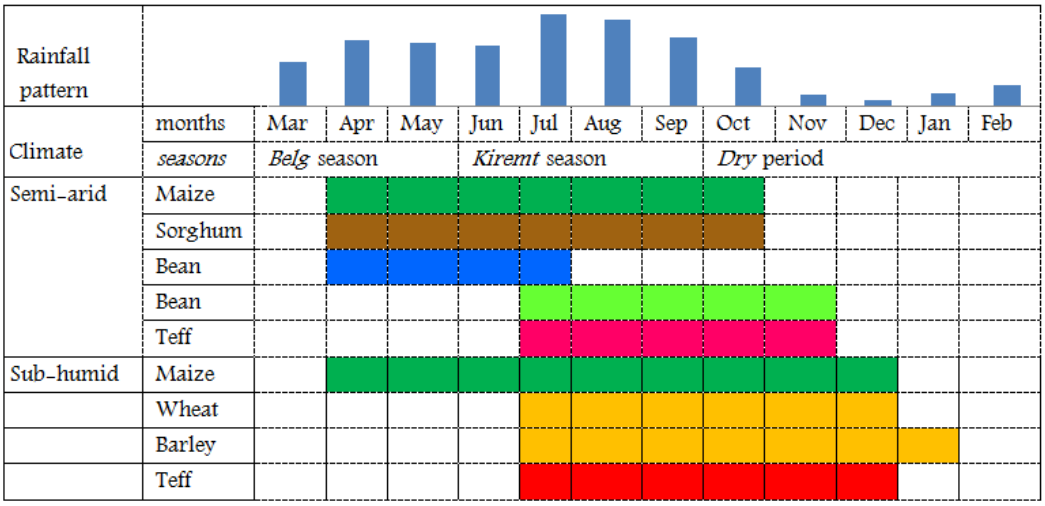
The input parameters of the AquaCrop model encompass and organizes (i) the soil, with its water balance; (ii) the crop, with its growth, development and yield processes; and (iii) the atmosphere, with its thermal regime, rainfall, evaporative demand, and carbon dioxide concentration and (iv) the management which includes major agronomic practices such as planting dates, fertilizer application and irrigation (Raes et al. 2009; Steduto et al. 2009).

Water and crop production (hypothesis 5)

The timing, variability, and quantity of seasonal and annual rainfall are important factors in the relationship between climate and cultivation (Cheung et al., 2008). The seasonality and cropping of rainfall varies in different areas of Ethiopia. Agricultural calendars in Ethiopia are closely tied to the timing of local rainfall (Riddle and Cook, 2008). These are very important early indicators of the quality of the agricultural season and hence expected agricultural production (Tadesse et al. 2008). The short cycle crops (e.g. wheat, teff, barley) that are cultivated during the *Belg* and *Kiremt* seasons constitute 5–10% and 40–45% of national crop production, respectively (Verdin *et al*., 2005). Many farmers plant slowly maturing but high yielding 'long cycle' crops that grow during both the *Belg* and *Kiremt* seasons. These are long cycle crops, such as maize and sorghum, which are grown during the entire *Belg* and *Kiremt* seasons, and are responsible for 50% of national production (Verdin *et al*., 2005).

The CRV has a bimodal rainfall pattern under regime A (Figure 1.2) which gets the *Kiremt* and *Belg* rains. Both the *Kiremt* and *Belg* are important in the central and north-eastern regions – the most drought prone regions of Ethiopia (Region A). Farmers make agricultural decisions based on the timing of rainfall. For instance, in the semi-arid part of the CRV, if the rains come during March/April (*Belg*) then long cycle maize and sorghum and short duration beans can be planted during April and until the end of May. If the rains are delayed and adequate rains are only received later, then only teff and beans can be planted during June until the end of July (Figure 1.3). For the sub-humid part of the CRV, similarly maize can be planted during *Belg* season mostly during April and May but if the onset of the rains is delayed then the cash crops such as potatoes, onion and tomatoes could be planted during June and July. When the rain starts late, farmers can also cultivate early-maturing maize varieties during the *Kiremt* season, usually in early June. Now the question is could these cropping systems stay same in the face of future climate change scenarios?

In the CRV, areas used for growing chick pea, peas and long maturing sorghum varieties are now growing medium or early maturing varieties of other crops (ICRA, 1999). In recent times, due to the shifting seasons, farmers have started to use the *Kiremt* season for most of the crops (Sime and Aune, 2014**)**. Generally, replacement of maize and sorghum over time by teff owing to early maturity, late planting and lower total water consumption has been observed in most of the semi-arid regions (Mahoo et al., 2013). Thus, as indicated by Cooper *et al.* (2008) an understanding of the farmers' options for coping better with current variation is a necessary preparation for adaptation to future climate change.



Climate	months	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb
	seasons	*Belg* season			*Kiremt* season				*Dry* period				
Semi-arid	Maize		🟩	🟩	🟩	🟩	🟩	🟩	🟩				
	Sorghum		🟫	🟫	🟫	🟫	🟫	🟫	🟫				
	Bean		🟦	🟦	🟦	🟦							
	Bean					🟩	🟩	🟩	🟩	🟩			
	Teff					🟪	🟪	🟪	🟪	🟪			
Sub-humid	Maize		🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩		
	Wheat					🟧	🟧	🟧	🟧	🟧	🟧		
	Barley					🟧	🟧	🟧	🟧	🟧	🟧	🟧	
	Teff					🟥	🟥	🟥	🟥	🟥	🟥		

Figure 1.3 Major cropping systems and rainfall patterns in the CRV, Ethiopia.

Crop intensification (hypothesis 6)

African farmers have developed several adaptation options to cope with past climate variability (Adger et al., 2007; Boko et al., 2007; UNFCCC Secretariat, 2008) such as by adopting new crops or varieties or by altering the timing of planting and other agronomic practices (Burk et al. 2009). But existing coping mechanisms may not be up to the challenges that are likely to be faced in the future (Ziervogel et al, 2008).

In Ethiopia, major adaptation strategies used by farm households include, for example, changing crop varieties, adoption of soil and water conservation measures, and tree planting, water harvesting, is considered as a better strategy for coping climate change impact (Bryan et al., 2009; Di Falco et al., 2011; Birhanu and Sterk, 2013). The productivity of rainfed agriculture can be improved through a combination of rain water harvesting (RWH), improved soil fertility, supplementary irrigation using low cost micro irrigation technologies, higher cropping intensity and improved varieties can lead to a doubling of rainfed yields(Awulachew et al., 2005). However, the combined (synergetic) effect of these factors has been rarely studied on maize.

Effect of forests (hypothesis 7)

Local people in the CRV and elsewhere believe that the presence of forests attracts rain (Sheil & Murdiyarso, 2009; Stroosnijder, 2012), whereas most climate experts would disagree mainly at local and meso-scales. Many also believe that frequent droughts and floods in eastern Africa can partly be blamed on widespread deforestation in the region (Sarkar et al., 2014). In Thailand, Tangkitjavisuth (1979) has indicated that forest clearing as the cause of drought. Similarly, Nicholson et al. (1998) reported that the loss of vegetation in tropical humid and dry regions to increase drought in regions such as the Sahel (Nicholson et al. 1998). Forests could also help combat drought by influencing rainfall patterns. For instance, in Indonesia and Madagascar tropical forest protection has been shown to generate drought mitigation and flood mitigation benefits (Pattanayak and Kramer, 2000; Kramer et al., 1997).

1.4 Objectives and research questions

Ethiopia faces daunting challenges from climate change if this does increase climate variability due to a large dependence on rainfed agriculture, low levels of development and adaptive capacity to existing climate variability. Where are the areas that are most likely to experience more food insecurity due to climate change? In many of the sub-Saharan African countries (including Ethiopia) there are 'hotspots' that are most likely to experience more food insecurity due to climate change unless urgent steps are taken to adapt to predicted climate changes (Liu et al. 2008).

In Ethiopia, ecologically arid, semi-arid and dry sub-humid parts of the country are most vulnerable to drought (Tadeg, 2007). The risks may be exacerbated by the projected climate change in the semi-arid and dry sub-humid areas of the CRV of Ethiopia, because, in areas where crop cultivation is already on the threshold, small variations will be more noticeable (Tadross et al. 2009). The rainfall in the CRV of Ethiopia is already highly unpredictable and variable with higher risks of crop failure and low productivity due to inter-annual and intra-seasonal rainfall variability and less water availability during the growing seasons (Tesfaye and Walker, 2004; Tilahun, 2006; Kassie et al. 2013) which contribute to extreme poverty and food insecurity. That is why understanding the existing and future climate pattern, its impact and potential adaptation options in the region seem to be critical.

Therefore, the general objective of this study was to assess the impact of predicted changes in rainfall and develop appropriate adaptation options for the CRV of Ethiopia. The following research questions were addressed in this study:

1. Do extreme rainfall events changed over the past 40 years (1970-2009) annually and seasonally in the Ethiopian CRV? (Chapter 2)
2. How are growing season rainfall characteristics likely to change during *Belg* and *Kirem*t seasons in the semi-arid and sub-humid/humid part of the CRV? (Chapter 3)
3. How will the projected changes in climate and elevated CO_2 affect maize and wheat yields in the CRV ? (Chapter 3)
4. Is maize intensification using supplemental irrigation and optimum plant density under optimum fertilizer a viable option for bridging dry spells in the Ethiopia's CRV? (Chapter 4)
5. Is maize intensification through supplemental irrigation, optimum plant density and adjusting sowing date under optimum fertilizer a viable option for adaptation to climate change in the Ethiopia's CRV? (Chapter 5)
6. Do forests affect rainfall and what other local factors affect rainfall distribution in the CRV of Ethiopia? (Chapter 6)
7. Do deforestation induce temperature increase? (Chapter 6)

1.5 Research methodologies

A number of different approaches such as downscaling methods, statistical models, field experiments and dynamic crop growth simulation have been used to assess the changes and impacts of climate variability and change on crops and for devising adaptation options.

Downscaling climate data

In our study the MarkSimGCM which is an updated version of MarkSim model that stochastically generates daily weather data including maximum and minimum temperatures and rainfall for a future time period (Jones and Thornton, 2000; Jones and Thornton, 2013) were used to downscale GCM data. MarkSimGCM generates downscaled projections by spatially downscaling GCM output using the delta method; stochastically generating daily series based on a previously performed calibration procedure that involved clustering observations from more than 10,000 stations worldwide and selecting an analogue among the clusters that best matches values generated by the GCMs (Jones and Thornton, 2013). MarkSimGCM has been specifically designed for tropical countries and it has been widely used in East Africa and reportedly provides a realistic simulation of daily precipitation and temperature distributions (Thornton et al., 2009; Lobell and Burke, 2010; Thornton et al., 2011; Dixit et al., 2011; Farrow et al., 2011). The advantage of MarkSimGCM is also it gives projected climate data at station level which can be used for local level climate study.

The downscaled data were used to analyse *Belg* and *Kiremt* seasons rainfall at the semi-arid, sub-humid and humid agro-climatic zones/landscape units of the CRV. The growing season rainfall characteristics such as onset, cessation and dry spells were analysed using the Instat" Climatic Statistical Software (Stern *et al.,* 2006) which has a built-in facilities for analysis of events of agricultural significance in daily rainfall records. To assess the impact of climate change on maize and wheat crops in the CRV, the FAOs AquaCrop model were used.

Statistical methods

The CRV consists of three landscape units: the valley floor, the escarpments, and the highlands all of which are considered in our data analysis. These landscape units are also equivalent in agro-climatic zones as semi-arid, sub-humid and humid zones. The rainfall analysis was categorized in to these landscape units. Therefore, local-scale investigations into trends of daily rainfall and extreme rainfall events have important practical implications.

Extreme rainfall analysis was analysed using different statistical methods. This study investigates trends in 10 extreme rainfall indices over a period of 40 years (1970-2009) in the CRV using 14 meteorological stations to detect any changes in the rainfall behaviour. For data quality and homogeneity test, the dataset were thoroughly checked for outliers, negative values and discontinuities. The data quality was checked by the RClimDex software developed by the Expert Team on Climate Change Detection, Monitoring and Indices (ETCCDMI) and detecting discontinuities and making adjustments in the daily rainfall data series were conducted using the RHtests-dlyPrcp software package. Finally, trends in the time series of the rainfall indices were detected using the Mann-Kendall non-parametric test.

The analysis on the effect of forests and deforestation on climate in the environmentally hotspot area of the CRV of Ethiopia was conducted using, the Mann-Kendall test and stepwise multiple regression statistical methods.

Forest experimentation

Since the time for a PhD thesis does not allow planting a forest and measuring its effect, we took a situation with existing forests. We installed a closely spaced network of 15 Watchdog Tipping Bucket rain gauges equipped with automatic data loggers adjusted to record on hourly basis. The installation of Watchdog Tipping Bucket rain gauges was along a 60 km transects line that traverses forest areas and open areas (Figure 1.4). The distance between the subsequent watchdog rain gauges was within 5 km, as it was suggested by Hubbard (1994), for rain gauges to explain at least 90% of the variation between sites. It is also obvious that the best method to improve quality of spatial rainfall estimation is to increase density of the monitoring network. In addition to the two years observational data from installed rain gages, long term daily rainfall dataset (1970-2009) from 16 meteorological stations over the CRV was used to assess effects of deforestation on long term rainfall pattern and temperature.

Crop intensification

An experiment was conducted at three farmers' fields with terraces and farm ponds during two cropping seasons 2012 and 2013. The experiment was laid in Randomized Complete Block Design (RCBD) with combined treatments of supplemental irrigation and plant density. The four different levels of plant density and supplemental irrigation combinations were used together with optimum fertilizer level. For the supplemental irrigation of the three farms, the experiment used two household water harvesting farm ponds that existed already in the two farms. The supplemental irrigation treatments were SI1, SI2, SI3 and SI4 where SI1 is only rainfed without supplemental irrigation. The supplemental irrigations treatments were tested with a combination of four different plant densities: D1, D2, D3 and D4, where D1 is a density of 30,000 plants ha^{-1}, D2 is 45,000 plants ha^{-1}, D3 is 60000 plants ha^{-1} and D4 is 75000 plants ha^{-1}.

Crop modelling

Experiments, despite their role in testing hypothesis and calibrating and validating models, they are limited in their scope in time and space for conducting the long term effect and future scenarios. Therefore modeling is important in this case. Assessments of the effect of climate change on agriculture focus on either crop yield or crop variability. Different methods are used to evaluate the effect of climate change on yields. The two main techniques are (i) crop growth models and (ii) regression analyses.

Many climate change studies use crop growth models to quantify the response of crops to changes in weather conditions. Bio-physical crop growth models have more advantages compared to regression analyses (Sonka and Lamb, 1987), because bio-physical crop growth models enable estimation of the effect of changes in management strategies (Nix, 1985) and, they can explicitly capture the effect of weather and its variability since they use daily climatic data (Blanc, 2011). AquaCrop model has already been calibrated for maize and validated under a wide range of environmental conditions in Ethiopia (Erkossa et al. 2011; Biazin and Stroosnijder 2012) and elsewhere (Heng et al., 2009; Hsiao et al., 2009; Mhizha, 2010; Salemi et al., 2014). Therefore, due to its simplicity, accuracy, and robustness, AquaCrop is becoming a widely used crop model for estimating crop yield for climate change scenarios and to test different adaptation options (Mainuddin et al., 2011; Mainuddin et al., 2013; Soddu et al., 2013; Abedinpour et al., 2014; Deb et al., 2014; Shrestha et al., 2014a.; Shrestha et al., 2014b; Vanuytrecht et al., 2014b). In this study AquaCrop was used for simulations of crop yields under the baseline climate for 30 years (1966-1995) and under the climate change scenarios for the two future periods: 2020–2049 and 2066–2095.

Study area description

The CRV of Ethiopia is located at approximately 38^{o} 00' - 39^{o} 30`E and 7$^{o}$ 00` - 8^{o} 30`N in the Ziway–Shala lake basin (Figure 1.2). The CRV of Ethiopia is part of the Great East African Rift Valley and covers the major dry land portion of the country. The Great Rift Valley highlights the complex topography found within Ethiopia, and splits the center of the country in the northeast and southwest direction by the divergence of tectonic plates (Figure 1.4). This prominent feature produces the Ethiopian Highlands, which are found on either side of the Great Rift Valley.

The climate of the Ethiopian Rift Valley is diverse and ranges from humid to sub-humid in the highlands to semi-arid in the rift floor. The climate of the CRV varies markedly over quite short distances. It is mainly characterized by alternating wet and dry seasons following the annual movements of the Inter-tropical Convergence Zone (ITCZ) which separates the air streams of the northeast and southeast monsoons (Nicholson, 1996). Highlands bordering the rift valley intercept most of the monsoonal rainfall in the region, resulting in a strong moisture deficit in the rift valley floor. The mean annual rainfall and mean annual temperature range from 685 mm to 1118 mm and 15C to 20C, respectively. Evaporation ranges from more than 2500 mm on the rift valley floor to less than 1000 mm in the highlands.

The vegetation ranges from open woodland to bushed grassland on the rift floor. Rift shoulders are characterized by bushed grassland, then remnants of dry, montane forest and, from 3200 to 3500 m, ericaceous scrub and Afroalpine moorland (Makin et al., 1975). The soils of the CRV range from sandy loams to clay loams with varying levels of fertility and degradation status.

Rainfed agriculture is the most important livelihood source for people in the CRV of Ethiopia. Although there are a large variety of crops grown in the CRV, wheat and maize together cover more than 50% of cultivated areas (wheat accounting for about 32% and maize for about 23%) (Scholten, 2007).

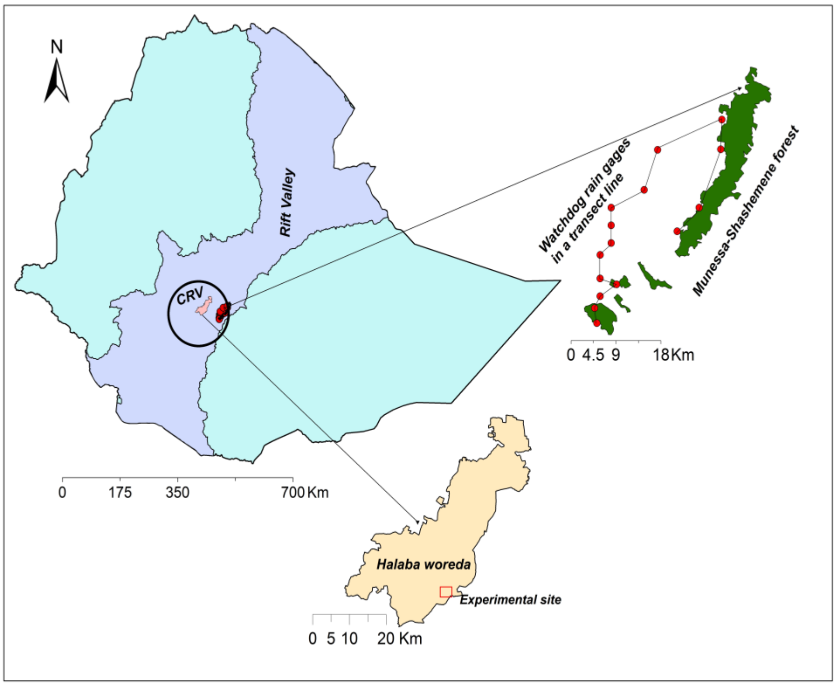


Figure 1.4 The study area and the two experimental sites in the Central Rift Valley, Ethiopia

1.6 Thesis outline

This thesis consists of seven chapters. The first chapter (Chapter 1) describes the general part of the whole thesis, such as problem statement, objectives, description of the study areas and methodologies. The research objectives formulated in section 1.4 are addressed in chapters 2 to 6 all of which are independently addressing each of the objectives and stand-alone. Chapter 2 looks in to evidences of long term changes in extreme rainfall indices in the CRV of Ethiopia. The response of local climates to climate change could be different in physiographic complex regions like Ethiopia. The Rift Valley highlights the complex topography found within Ethiopia with abrupt changes in rainfall. Therefore, this chapter investigates changes in daily rainfall and extreme events at the landscape and seasonal scales in the CRV of Ethiopia.

In Chapter 3, first, how the climate change scenario can affect the growing season rainfall during *Belg* and *Kiremt* at different landscape units in the CRV was assessed. Second, the potential impacts of those changes on yields of maize and wheat crops in the CRV of Ethiopia were investigated.

Chapter 4 explores experimentally the hypothesis that supplemental irrigation in combination with increased plant density and optimum fertilizer would greatly increase grain yield. This explains how maize cropping intensification using supplemental irrigation, optimum plant density and optimum fertilizer in terraced farms can significantly improve crop yield and water productivity in Ethiopia's CRV. It further assesses farmers own practice maize yield with that of on-farm experiments**.**

Chapter 5 assesses the hypothesis in chapter 4, using AquaCrop yield simulation model, those possible adaptation strategies for their capability to overcome or reduce the adverse effects of climate variability and climate change to improve food security. It further testes the hypothesis in chapter 4 for current long term climate conditions and climate change scenarios using the FAO AquaCrop model. After validation based on field experimental data, the possibility of three adaptations options were examined.

Chapter 6 assesses whether local isolated forests affect local rainfall distribution and how long term deforestation affects rainfall and temperature of the CRV. It also looks in to the effects of topographical factors such as elevation, slope and slope aspect on rainfall.

The last chapter (Chapter 7) presents a synthesis on the major findings of this study while answering all the objectives mentioned in section 1.4. This chapter also presents implications and recommendations of the study.

Chapter 2

Searching for evidence of changes in extreme rainfall indices in the Central Rift Valley of Ethiopia

Abstract

Changes in magnitude and frequency of extreme rainfall events have serious implications for economic sectors with a close link to climate such as agriculture and food security. This holds true in the Central Rift Valley (CRV) of Ethiopia where communities rely on small scale, subsistence and rainfed agriculture for livelihoods. This study investigates trends in 10 extreme rainfall indices over a period of 40 years (1970-2009) in the CRV using 14 meteorological stations to detect any changes in the rainfall behavior. The CRV consists of three landscape units: the valley floor, the escarpments, and the highlands all of which are considered in our data analysis. The analysis also considered the different seasons in the study area: the *Belg* (March-May) and *Kiremt* (June-September) seasons. Trends in the time series of the rainfall indices were detected using the Mann-Kendall non-parametric test. The key findings are the following. At the annual time scale, more than half (57%) of the stations showed significant trends in total wet-day precipitation (PRCPTOT) and heavy precipitation days (R10mm). Only 7-35% of stations showed significant trends, for the other rainfall indices. Spatially, the rift valley floor received increasing annual rainfall while the escarpments and the highlands received decreasing annual rainfall over the last 40 years. At the scale of the two seasons, 50% of the stations showed significant increases in the maximum number of consecutive dry days (CDD) during *Belg* in all parts of the CRV. Overall, our analysis of the many indices, during the last 40 years, indicates that in both *Belg* and *Kiremt* no significant change in extreme rainfall indices has occurred at the majority of stations at the escarpment and highlands. However, during *Belg* there was significant change in CDD in all parts of the CRV. The significant increase in CDD combined with the tendency towards decrease in annual rainfall during *Belg* has implications for future *Belg* season crop production in the CRV. Insights into the spatial (landscape) and temporal (cropping season) differences as demonstrated in this paper can assist farmers to make informed decisions for adaptation to climate variability and climate change.

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Searching for evidence of changes in extreme rainfall indices in the Central Rift Valley of Ethiopia

2.1 Introduction

Changes in extreme weather and climate events are among the most serious challenges to society in coping with the changing climate (CCSP 2008). The impacts of climate extremes and weather events may threaten human security at the local level (Cutter et al. 2012). The increase in the magnitude and frequency of extreme climate events is mostly felt through the impacts of the extremes (Kharin and Zwiers 2005). Extreme events will have greater impacts on issues with a close link to climate, such as agriculture and food security (Handmer *et al.* 2012). The CRV represents major cereal based farming systems of the semi-arid environment of Ethiopia and are hot spots for climate induced risks such as droughts and floods. The inhabitants are dependent on rainfed agriculture for their livelihood and are poor and vulnerable communities under stress that are feeling this challenge and the related factors even now.

Most food crops are sensitive to direct effects of high temperatures, decreased precipitation, and flooding (Rosenzweig *et al*. 2001). For example, extreme events may lower long-term yields by directly damaging crops at specific developmental stages, such as temperature thresholds during flowering (Porter and Semenov 2005). Heavy flooding from extreme rainfall will have serious effects on agriculture, such as erosion of topsoil and leaching of nutrients (WWF 2006) which affect future crop productivity. According to Easterling *et al*. (2007) "Projected changes in extreme climate events will have serious negative consequences for food and water security, than will changes in the projected means of precipitation". Thus, considerations of the potential impacts of climate change on agriculture should be based not only on the mean values of expected climatic parameters but also on the probability, frequency and severity of possible extreme events (Rosenzweig *et al*. 2001).

Based on observed changes since the beginning of the twentieth century, Donat *et al*. (2013) found more areas of the globe with significant increasing trends in extreme precipitation amounts than decreasing trends. Rosenzweig *et al.* (2001) note that under an enhanced greenhouse effect, change can occur in both mean climate parameters and the frequency of extreme climate events. However, Global Climate Models (GCMs) project more/greater increases in extreme precipitation events than changes in the mean precipitation amounts (Karl and Trenberth 2003). A warming climate has been shown to increase intense precipitation events (Easterling *et al*. 2000) since the water holding capacity of the atmosphere increases by about 7% per 1°C warming, which increases water vapor in the atmosphere and subsequent thunderstorm activity (Trenberth *et al*., 2011).

In most regions of eastern Africa, climate extremes such as droughts and floods have increased over the past several decades causing significant social and economic damage (Cheung *et al*. 2008). For example, the extreme drought and famine that occurred in 2006 in northern Uganda, northern Kenya, Somalia and the Horn of Africa was considered to be more severe than droughts in 1984, 1999, and 2000 in the east African region (Spinage 2012), and the year leading up to June 2011 was the driest in 60 years in some regions of southern Ethiopia, Somalia and northern Kenya (USAID/FEWS 2011). In Ethiopia, 2009 was the second driest year known on record, surpassed only by the catastrophic 1984 drought (Viste *et al*. 2012). Both 2002 and 2003 were also extremely dry years in the CRV of Ethiopia (Ayenew, 2004). At the other extreme, there have been extreme wet conditions in the east African countries including Ethiopia. For instance, the October to February season in 1997-98 (normally considered dry season) was the wettest on record over much of Ethiopia (Conway 2000). Overall in 1998 annual rainfall in some parts of Ethiopia was up to ten times higher than the long-term average, and there was heavy flooding in many parts of the country in 2007 as well that affected thousands of people (Spinage 2012). Clearly there is a need to find ways to better understand or anticipate these climate extremes in order to develop adaptation measures and strengthen resilience to changing climate conditions.

Future climate projections indicate continued increases in extreme precipitation events over east Africa as well as an increase in consecutive dry days and soil moisture droughts (Shongwe *et al*. 2011). Over the Ethiopian Highlands, the number of extreme wet days is predicted to increase by 50%-90% by the mid-21st century (Vizy and Cook 2012). Similarly, in the upper parts of the Nile river basin extreme precipitation events are expected to increase (Ogiramoi *et al*. 2011). Generally, a more intense wet season is projected in most east African countries (Shongwe *et al*., 2011). The driving mechanism of these extreme events in east Africa, and mainly in Ethiopia, is attributed to the warming of the Indian Ocean (Webster *et al*. 1999; Saji *et al*. 1999; Verdin et al. 2005).

To develop climate change adaptation measures from the food security perspective it is important to consider regional landscape heterogeneity factors that impact crop yields (Moore et al. 2012). Thornton et al. (2009) argue strongly against using large spatially contiguous domains, such as those at national scales, to develop adaptation options in regions with large variations in topography, because that approach overlooks effects of local features that contribute to high local variability in the climate. East Africa's varied topography (e.g., mountain ranges and rift valleys); expansive inland lakes (Anyah et al. 2006; Shongwe *et al*. 2011) and different seasons are prime examples of such features.

Rainfall in Ethiopia is already known for its high variability both in amount and distribution across regions and seasons due to different global and regional rain-bearing factors and Ethiopia's geographical location and topographic variations. While many studies of mean rainfall patterns have been conducted in Ethiopia at various spatial (e.g. national and sub-national) and temporal (e.g. annual, seasonal, monthly) scales (e.g. Conway 2000; Seleshi and Zanke 2004; Bewket and Conway 2007; Cheung *et al*. 2008; Araya et al. 2010), there has been little work on extreme rainfall events at the national level (Easterling *et al*. 2000; Seleshi and Camberlin 2006; Shang *et al*. 2010; Mekasha *et al*. 2013) or at local scale (Bewket and Conway 2007; Degefu and Bewket 2014). Studies on trends in daily rainfall extremes at small spatial and temporal scales are important; as local and regional scale factors also play important roles in the production of extreme events (Trenberth 2005). Also, impacts of most extremes are typically felt at local or regional scale as a result of interactions between large-scale forcings and local terrain and land surface (IPCC 2007). That is, response of local climates to climate change could be different in regions with physiographic diversity like Ethiopia. Therefore, local-scale investigations into trends of daily rainfall and extreme rainfall events have important practical implications.

The objective of this study was to detect changes in daily rainfall and extreme events at the landscape and seasonal scales in the CRV of Ethiopia for the period 1970-2009. This was carried out by calculating a number of rainfall indices, based on the recommendations by the ETCCDMI (Expert Team on Climate Change Detection, Monitoring and Indices) of the CLIVAR (Climate variability and predictability) project of UNWMO's World Climate Research Programme. The study focuses on the CRV area where daily rainfall data are available from a relatively dense network of stations beginning from the 1970s. The results of this study will contribute to understanding local-scale consequences of climate change and thereby to the design of locally-specific adaptation interventions.

2.2 Materials and methods

Description of the study area

The study covers the CRV of Ethiopia which is located at approximately 38^o00` - $39^o30$` E and 7^o00` - $8^o30$` N (Figure 2.1). The CRV, covering an area of about 16,352 km^2, is one of the most environmentally vulnerable areas of Ethiopia. It is part of the Great East African Rift Valley and covers the major dry land portions of the country. The CRV has three physiographic regions/landscape units: the rift valleyfloor, escarpments and the surrounding highlands. Altitude ranges from about 2000 m to 3200 m a.s.l in the eastern and western highlands to 1600 m a.s.l around the lakes in the rift valley floor. There are four major lakes namely; Ziway (440 km^2), Abiyata (180 km^2), Langano (230 km^2), and Shala (370 km^2) (Ayenew 2003).

The climate of the CRV is classified as semi-arid, dry sub-humid and humid. In eastern Africa, several major convergence zones are superimposed upon regional factors associated with influences of lakes and topography, resulting in markedly complex climatic patterns that change rapidly over short distances (Nicholson 1996; Shang *et al*. 2010). Due to the intense heating of the high plateau land, the convergence of the wet monsoonal currents from the southern Indian and Atlantic Oceans brings much rain to the region (Griffiths 1972). Mean annual precipitation and mean annual temperature range from 685 - 1118 mm and 15 – 20 C, respectively. The pattern of precipitation in the rift floor is more of stormy type with relatively high intensities (up to 100 mm/hr) compared to the highlands with only 60–70 mm/hr intensity (Makin et al. 1975).

The region is characterized by three main seasons. The dry period (locally known as *Bega*) extends between October and February having occasional rains which account for about 10-20% of the annual total; the small rainy season (locally known as *Belg*) occurs from March to May contributing 20-30% of the annual rainfall; and the long rainy season (locally known as *Kiremt*) is from June to September during which 50-70% of the mean annual total rainfall is received. Occurrence of rainfall in Ethiopia is mostly controlled by the seasonal migration of the inter-tropical convergence zone (ITCZ). The dry season occurs when the ITCZ lies south of Ethiopia, the rainfall belts shift south and the area is influenced by dry northeastern trade winds originating in Arabia and northeast Africa (Muchane 1996). As the Arabian high moves towards the Indian Ocean and decreases, warm, moist air with a southerly component begins to flow over most of the country coinciding with *Belg*, the small rainy season (Griffiths 1972).

The soils of the Rift Valley are largely derived from recent volcanic rock. The main parent materials are: basalt, ignimbrites, lava, gneiss, volcanic ash, alluvium and pumice. Some of the soil problems include, low phosphorus levels, micronutrient imbalances and, in some cases, poor physical structure (Makin et al. 1975).

The distribution of plants in the study area is highly influenced by elevation which also impacts the rainfall pattern (Musein 2006). The rift valley floor is largely dominated by deciduous *Acacia* woodland and wooded-grasslands that are increasingly becoming more open (Feoli and Zerihun 2000), whereas deciduous woodlands (*Olea europaea*, *Celtis*, *Dodonaea viscosa* and *Euclea*) occupy the escarpments (Mohammed and Bonnefille 1991). The montane forest exists between 2000 and 3000 m on the eastern Ethiopian plateaus bordering the rift and is dominated by *Podocarpus gracilior* (Friis 1986).

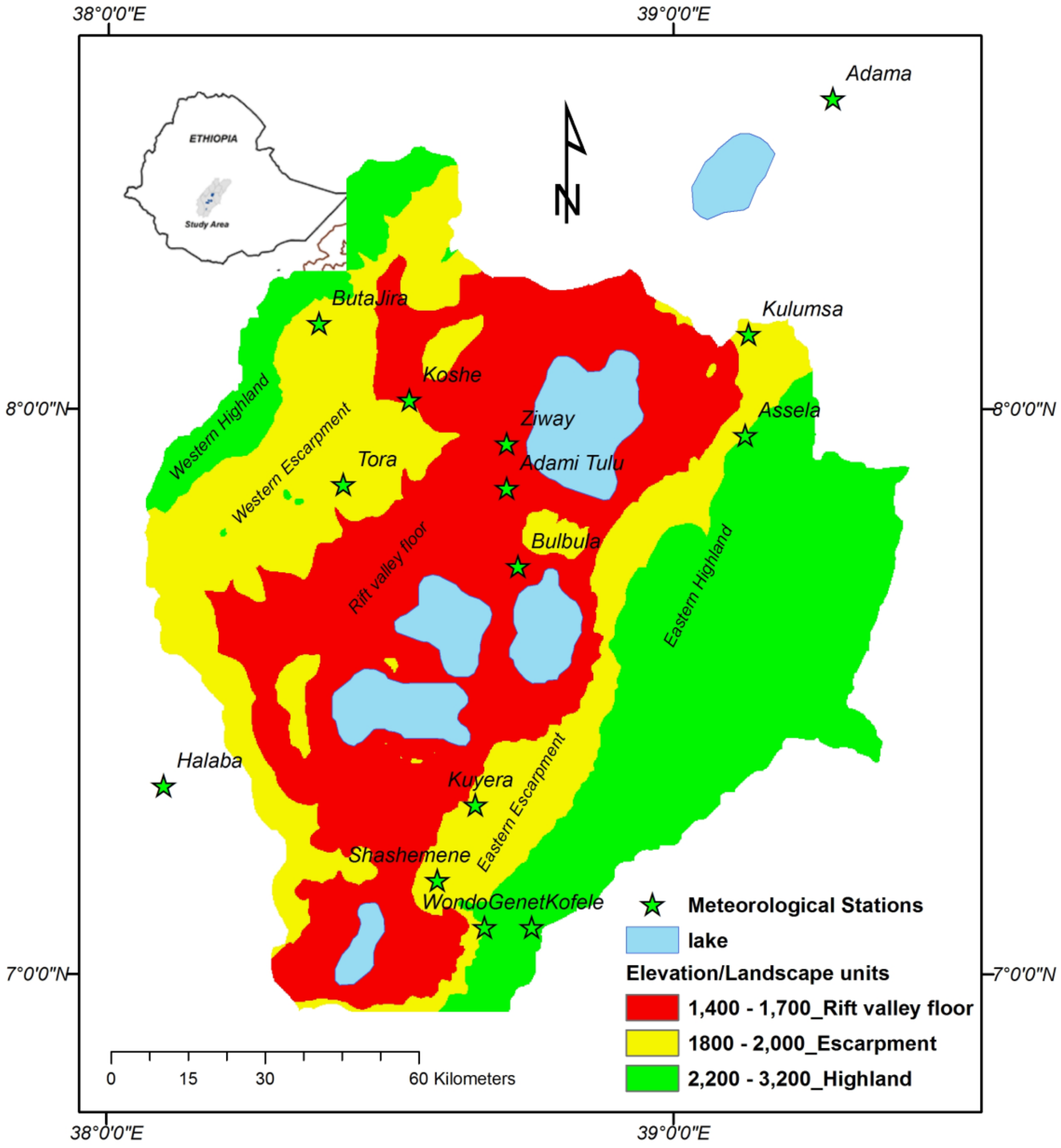


Figure 2.1 The study area with the landscape units and distribution of meteorological stations in the CRV, Ethiopia

Rainfall data description

We found 25 meteorological stations covering the CRV from the National Meteorological Agency of Ethiopia, 18 of which had long records (covering a common period of 40 years; 1970-2009) with good quality data (less than 10% missing values). The remaining 7 stations had records for only a short period or had many missing values. The 14 stations with the best quality daily rainfall data were eventually selected for use in the final analysis (Table 2.1). This selection was made after conducting a thorough assessment of inhomogeneities which further excluded 4 stations with major discontinuities (Table 2.2). The 14 selected stations are spatially well distributed across the three landscape units (physiographic regions) of the study area (Figure 2.1) with four of the stations (Adami

Tulu, Ziway, Adama and Bulbula) located in the rift valley floor (the semi-arid eco-climatic zone) seven stations (Halaba, Wondo Genet, Koshe, Kuyera, Shashemene, Tora and Butajira) located in the eastern and western escarpments (the sub-humid eco-climatic zone) and the remaining three stations (Kulumsa, Assela and Kofele) located in the eastern highlands (the humid eco-climatic zone). Ziway, in the rift valley floor, had only 29 years of data (1981-2009) but was included to improve station density in this area, where fewer stations existed.

Table 2.1 Description of the meteorological stations used for the study

Landscape	Station	Northing(m)	Easting(m)	Elevation(m)	Mean annual rainfall(mm)	CV	Period
Rift valley floor	Adami Tulu	467545	868876	1636	703.40	0.30	1970-2009
	Ziway	467545	877624	1640	727.23	0.20	1981-2009
	Adama	531119	945113	1643	831.71	0.18	1970-2009
	Bulbula	469732	853566	1700	684.00	0.23	1970-2009
Mean				**1655**	**736.59**		
Escarpments	Halaba	400662	810697	1750	910.48	0.16	1970-2009
	Wondo Genet	463190	782974	1880	1107.70	0.18	1970-2009
	Koshe	448575	886170	1910	918.02	0.25	1970-2009
	Kuyera	806928	461367	1932	904.26	0.15	1970-2009
	Shashemene	453994	792195	1933	876.38	0.24	1970-2009
	Tora	435696	869603	1998	922.77	0.20	1970-2009
	Butajira	430910	901136	2000	1090.59	0.18	1970-2009
Mean				**1922**	**961.46**		
Highlands	Kulumsa	514688	899040	2202	810.57	0.12	1970-2009
	Assela	514021	879265	2390	1118.00	0.16	1970-2009
	Kofele	472392	782968	2620	918.02	0.25	1970-2009
Mean				**2404**	**948.86**		

Data quality and homogeneity

We checked the dataset thoroughly for outliers, negative values and discontinuities. The RClimDex software developed by the Expert Team on Climate Change Detection, Monitoring and Indices (ETCCDMI) was used first to identify unreasonable values (like negative precipitation values); we then visually inspected plots of the data to detect outliers. Finally, we checked the temporal homogeneity of the data series since detection of changes in daily rainfall characteristics requires the time-series to be homogenous (e.g. Peterson *et al*. 1998). This allowed us to identify effects due to artificial discontinuities, for example, those caused by changes in observation instruments (or observers), location, environment, and observation practices/procedures taking place over the period of data collection. If inhomogeneities are not accounted for properly, it can distort, or hide, actual climate variability, and trends in extremes.

After identifying all of the significant change points, the daily rainfall data series were adjusted using the quintile matching (QM) algorithm (Wang *et al*. 2010). This method homogenizes the data by adjusting the series in such a way that the empirical distributions of all segments of the detrended series match each other. The data series were detrended by subtracting the estimated linear trend component from the series. This detrended series is then used to develop empirical cumulative distribution functions (ECDF) for each segment of the base series, and to define the adjustments needed to make the base series homogeneous.

Discontinuities from daily rainfall could exist in both the frequency and amount of rainfall measured. In observation practices discontinuities often exist in the frequency of measured small rainfall amounts (Wang *et al*. 2010), mostly thresholds lower than 1 mm introduce trends in the number of wet days, associated with measurement errors introduced by the observers/ instrument inaccuracies (Haylock and Nicholls 2000; Haylock and Goodess 2004). Therefore, the frequency discontinuities in small rainfall amounts were identified using the “go around” approach (Wang *et al*. 2010). This approach involves testing the series of daily precipitation amounts that are larger than a small threshold value (> 0), varying the threshold over a set of small values that reflect changes in measuring precision over time, and then homogenizing the series of greater than the threshold daily rainfall data that were found to be free of frequency discontinuities. Finally, use only the homogenized series of greater than the threshold daily rainfall amounts for indices calculation. Usually, calculation of rainfall indices does not include small daily amounts, e.g. < 1.0 mm, because rainfall amounts below this value are not absorbed by soils and, instead, are evaporated directly (Ceballos *et al*. 2004). Thus, the frequency discontinuities were assessed by testing the rainfall data series using threshold values of 0.0, 0.2 and 0.99 mm to confirm whether or not the detected discontinuity was a frequency discontinuity. As shown in Table 2.2, most discontinuities were observed from the rainfall series of less than 0.99 mm (threshold value). Accordingly, in our change point detection analysis, we set the minimum threshold daily rainfall value at 0.99 mm. By using 0.99 mm as the threshold value we avoided the frequency discontinuities that could arise from measured values of less than 1.0 mm.

Lastly, after performing the necessary homogeneity testing, adjustments were made for discontinuities and comparisons were made for statistical significance in the trend and its slope sign for each rainfall index before and after significance adjustments. There was not much difference in the significance and sign of the linear slope before and after adjustment for stations with less than three discontinuities but stations with more than three inhomogeneities showed some difference in statistical significance before and after adjustments. Therefore, the four stations with more than three inhomogeneities were removed from the subsequent analysis of the rainfall indices, especially as there was no metadata support to use adjustments for such large discontinuities. The stations with less than three discontinuities were used without adjustment (Table 2.2).

Both detecting discontinuities and making adjustments in the daily rainfall data series were conducted using the RHtests-dlyPrcp software package, (Figure 2.2, example Meki station) which was developed at the Climate Research Branch of Meteorological Services of Canada (available from http://cccma.seos.uvic.ca/ETCCDI) (Wang *et al.* 2010).

The rainfall indices

After the quality control and homogeneity assessments, 10 commonly used rainfall indices developed by ETCCDI (available from http://cccma.seos.uvic.ca/ETCCDI) were selected and used (Table 2.3). The indices were calculated using the RClimDex software.

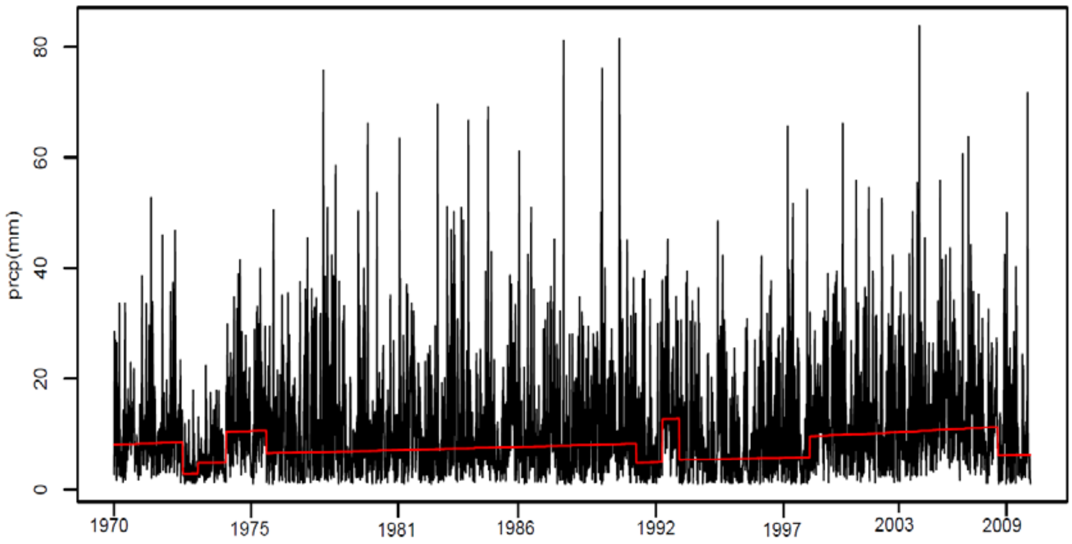
Table 2.2. Detected change points at different precipitation thresholds (P_{thr}) at 5% significance level.

No	Station	Change points at P>0.0P_{thr}	Change points at P>0.2P_{thr}	Change points at P>0.99P_{thr}
1	**Langano**	**8**	**10**	**4**
2	Adami Tulu	8	5	2
3	Ziway	1	1	0
4	Adama	2	2	2
5	**Meki**	**4**	**6**	**9**
6	Bulbula	8	4	3
7	Halaba	3	3	2
8	Koshe	3	3	3
9	Wondo Genet	9	4	0
10	Kuyera	1	5	1
11	Shashemene	15	6	2
12	Tora	1	1	1
13	Butajira	2	1	0
14	**Degaga**	**9**	**5**	**7**
15	Kulumsa	1	0	0
16	Assela	4	5	1
17	**Sagure**	**6**	**7**	**5**
18	Kofele	8	4	1

Bolded Stations are with more than three inhomogeneities which were removed from the subsequent analysis

Table 2.3 Rainfall indices used for the study and their description

Index	Indicator name	Description	Units
PRCPTOT	Annual total wet-day precipitation	PRCPTOT in wet days (rainfall ≥1.00 mm)	mm
RX1day	Maximum 1-day precipitation	Maximum precipitation received in 1-day	mm
RX5day	Maximum 5-day precipitation	Maximum precipitation received in a consecutive 5-day period	mm
SDII	Simple daily intensity index	Annual total wet-day precipitation divided by the total number of wet days in the year	$mmday^{-1}$
R10mm	Number of heavy precipitation days	Annual count of precipitation days when rainfall was ≥10 mm	days
R20mm	Number of very heavy precipitation days	Annual count of precipitation days when rainfall was ≥20 mm	days
CDD	Consecutive dry days	Maximum number of consecutive days with rainfall <1.00 mm	days
CWD	Consecutive wet days	Maximum number of consecutive days with rainfall ≥1.00 mm	days
R95p	Very wet days	Annual total precipitation when precipitation >95th percentile	mm
R99p	Extremely wet days	Annual total precipitation when precipitation >99th percentile	mm



b. QM-adjusted daily rainfall series

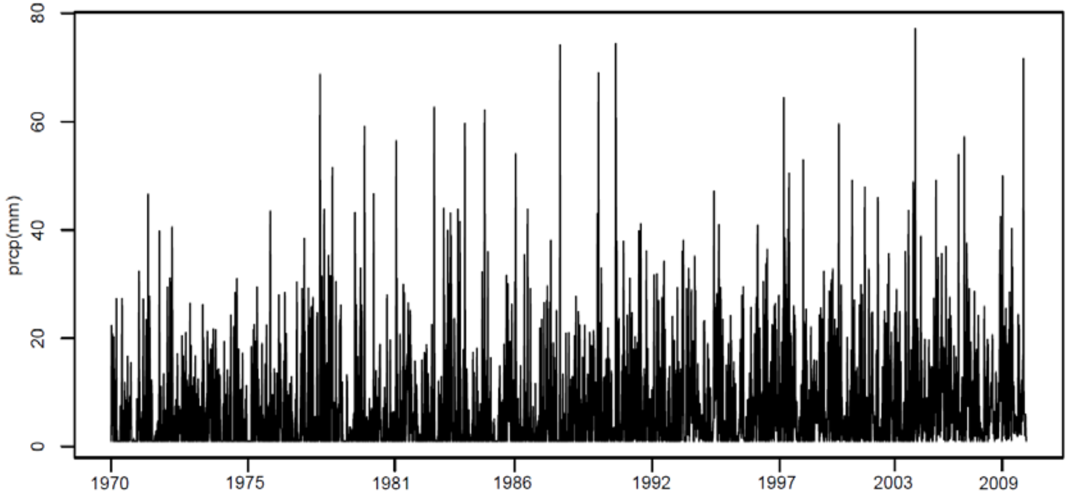


Figure 2.2 (a) Example of detected inhomogeneities during 1973, 1975, 1990, 1992, 1998 and 2008 years using the RHtests dlyPrcp homogeneity testing software from $P>0.99P_{thr}$ daily rainfall series at Meki meteorological station, the red hrizontal line shows the break points(discontinuities) (b) Quantile-Matching (QM) adjusted $P>0.99P_{thr}$ daily rainfall series**.**

Trend calculation

The Mann-Kendall test for trends and Sen`s slope estimator to detect and estimate trends in annual and seasonal rainfall series were used (Mann 1945; Kendall 1975; Sen 1968) This estimator is not affected by outliers in the series, and has been widely used to compute trends in hydro-meteorological series (e.g., Wang and Swail 2001; Zhang *et al*. 2000). The significance of the trends is determined by using Kendall's test, because this test does not have assumptions about the underlying probability distribution of the data series. In this study, the 5% probability level was used to determine the statistical significance of trends.

2.3 Results

2.3.1 Trends in rainfall indices on an annual basis

Annual total wet day precipitation (PRCPTOT) and simple daily intensity index (SDII)

Table 2.4 presents the trends per decade for each of the 10 rainfall indices at each of the 14 stations on the basis of the full year. For annual total wet day precipitation (PRCPTOT) 57% of the stations (8 stations) showed significant trends, with 36% (5 stations) showing a decreasing trend and 21% (3 stations) showing an increasing trend (Figure 2.3). Decreasing trend values ranged from 58.3 mm/decade at Assela to 76.9 mm/decade at Shashemene, while increasing trend values ranged from 48.9 mm/decade at Bulbula to 109.6 mm/decade at Adami Tulu. From the 43% (6 stations) of the stations that showed non-significant trends, 29% showed increasing trends, and 14% showed decreasing trend. When we consider both significant and non-significant trends, half of the stations showed an increasing trend and half showed a decreasing trend. The trend pattern exhibits a spatial pattern such that all stations in the rift floor (in the semi-arid eco-climatic zone) showing an increasing PRCPTOT while most stations in the escarpment and highlands (sub-humid and humid eco-climatic zone) showing a decreasing trend.

Table 2.4 Trends of 10 indices (unit/decade) for 14 stations in the CRV (Ethiopia) using daily data for all months of the year

Index*	PRCPTOT	RX1day	RX5day	SDII	R10mm	R20mm	CDD	CWD	R95P	R99P
Unit	mm	mm	mm	mm/day	days	days	days	days	mm	mm
Station										
Adami Tulu	**109.6**	**4.7**	**9.7**	**1.2**	**3.9**	**2.7**	0	-0.1	**52.3**	**20.9**
Ziway	26.7	-1.2	1.6	-0.4	0.5	0.8	-10.5	0.5	16.7	5.4
Adama	32.2	**8.2**	**10.7**	**1.1**	0.1	**2.2**	0.1	**-0.9**	**77.3**	**37.5**
Bulbula	**68.9**	**5.8**	**13**	-0.1	**6.3**	**1.4**	**-26.2**	**1.8**	**27.1**	11.4
Rift valley floor	**59.4**	**4.4**	**8.8**	**0.5**	**2.7**	**1.1**	**-9.2**	**0.3**	**43.4**	**18.8**
Halaba	13.1	-3.3	-5	**-0.8**	0.4	-0.3	-9	-0.2	**-26.8**	-13.7
Koshe	**-70.8**	0.3	-7.2	-0.2	**-4.9**	0	3.1	**-1.2**	11.9	4.6
Wondo Genet	-32.4	-3.6	-0.2	-0.1	-0.6	-0.6	8.3	-0.3	-23.4	-12.4
kuyera	**-35.0**	-0.7	-0.9	-0.1	**-1.6**	-0.2	4.4	-0.4	-1.3	1.0
Shashemene	**-76.9**	**-4.7**	**-7.9**	**-0.7**	**-5.8**	**-1.3**	0.4	0.8	-25.8	-12.6
Tora	**-48.3**	-0.9	-5.3	0.1	**-2.8**	-0.3	2.9	**-1**	-1.1	-2.5
Butajira	**62.3**	0.6	2.9	-0.1	**3.1**	0.9	0.1	0.5	-1.6	6.6
Escarpment	**-26.9**	**-1.8**	**-3.4**	**-0.3**	**-1.7**	**-0.3**	**1.5**	**-0.3**	**-9.7**	**-4.1**
Kulumsa	-12.9	-0.9	0.9	-0.1	-0.8	0.1	-1.7	-0.4	-12.8	-10.4
Assela	**-58.3**	0.1	0.3	-0.1	**-2.3**	**-1.3**	-0.8	-1.4	-18.6	2.8
Kofele	19.3	-1.4	-0.4	-0.1	0.1	0	-0.9	0.4	-4.6	-6.1
Highland	**-17.3**	**-0.7**	**0.3**	**-0.1**	**-1**	**-0.4**	**-1.1**	**-0.5**	**-12**	**-4.6**

Values significant at 5% level are red. *See Table 3 for definition of the indices.
Bold values in front of the respective landscape units are the average values of the stations in each landscape units.

Regarding the simple daily intensity index (SDII), only 29% of the stations (4 stations) showed a significant trend, two stations (Adami Tulu and Adama) showed an increasing trend, Halaba and Shashemene showed a decreasing trend (Table 2.4; Figure 2.4).

Maximum 1-day and 5-day precipitation amounts (RX1day, RX5day)

For the maximum 1-day and 5-day precipitation amounts (RX1day, RX5day), only 29% of the stations showed significant trends; the stations were the same for both indices. Of these, three stations (Adama, Adami Tulu and Bulbula) located in the rift valley floor showed increasing trends, one station (Shashemene) showed a decreasing trend (Figure 2.5, e.g. for RX5day). The remaining 10 stations did not show significant trends, but most of the stations located in the escarpment and highland (sub-humid and humid eco-climatic zones) showed small negative changes indicating tendencies towards a decreasing trend for both 1-day and 5-day maximum rainfall extremes (Table 2.4).

Most increasing and decreasing trends in RX1day and RX5day follow similar trends to that of PRCPTOT, as indicated by the significant correlations for both RX1day and RX5day with the PRCPTOT (Table 2.5).

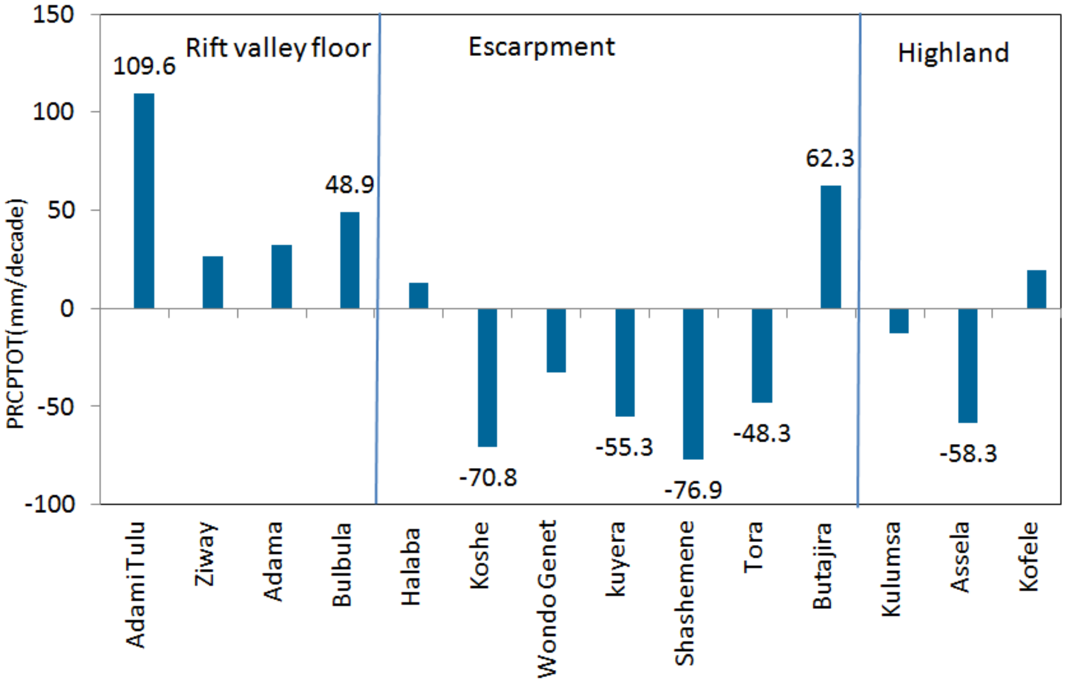


Figure 2.3 Trends in PRCPTOT (mm/decade) for 1970–2009 at the three landscape units (Rift valley floor, Escarpment and Highland) for the 14 stations in the CRV, Ethiopia. The bars with values on top are stations with significant trends at 5% significance level.

Heavy and very heavy precipitation days (R10mm and R20mm)

As shown in Table 2.4, 57% of the stations (8 stations) showed significant trends in the occurrence of heavy (R10 mm) precipitation events; half of these stations (Adami Tulu, Bulbula, Butajira and Kofele) showed increasing trends, while the other half (Koshe, Kuyera, Shashemene and Tora) showed a decreasing trend. For the occurrence of very heavy precipitation (R20mm) events 36% of the stations (Adami Tulu, Adama, Bulbula, Shashemene and Assela) showed significant trends (Table 2.4). Of these 5 stations, Shashemene and Assela, located in the escarpment and highland(sub-humid and humid eco-climatic zones), showed decreasing trends while the other three stations, Adami Tulu, Adama, and Bulbula, located in the rift valley floor(semi-arid eco-climatic zone) showed increasing trends.

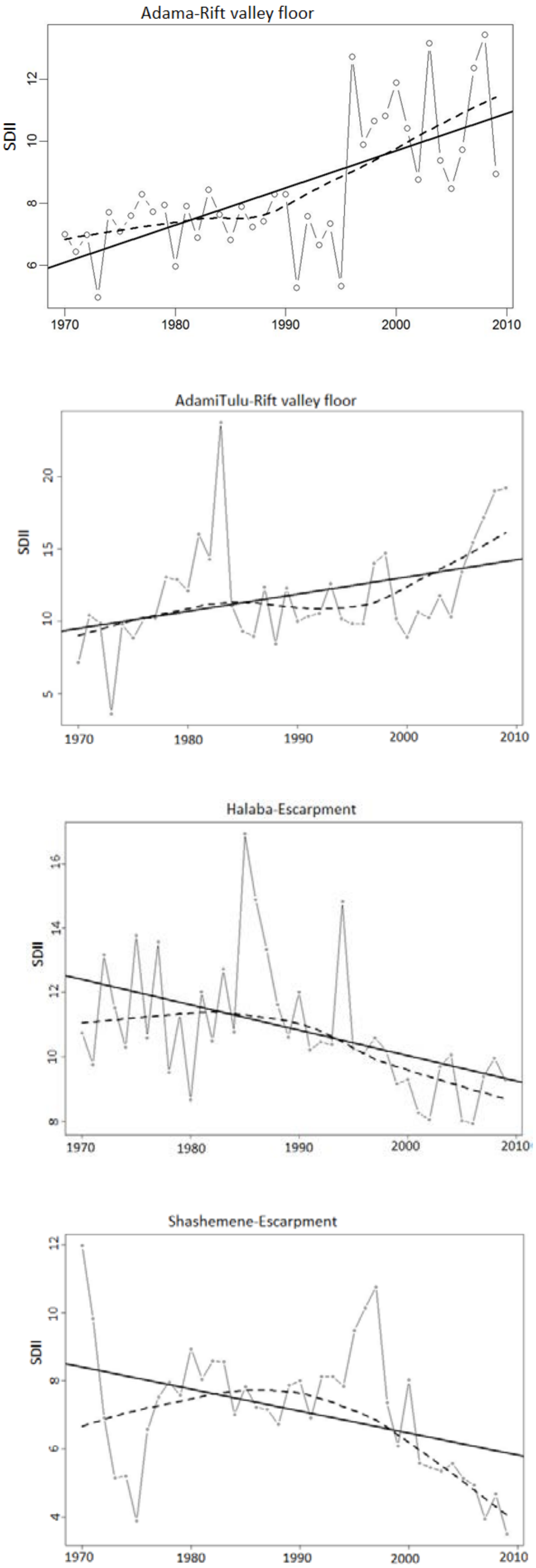


Figure 2.4 Trends in simple daily intensity index (SDII) for the stations with significant trends (at 5% significance level) in the CRV, Ethiopia. The solid lines represent linear trends over the period 1970–2009 and the dashed lines indicate the local trends.

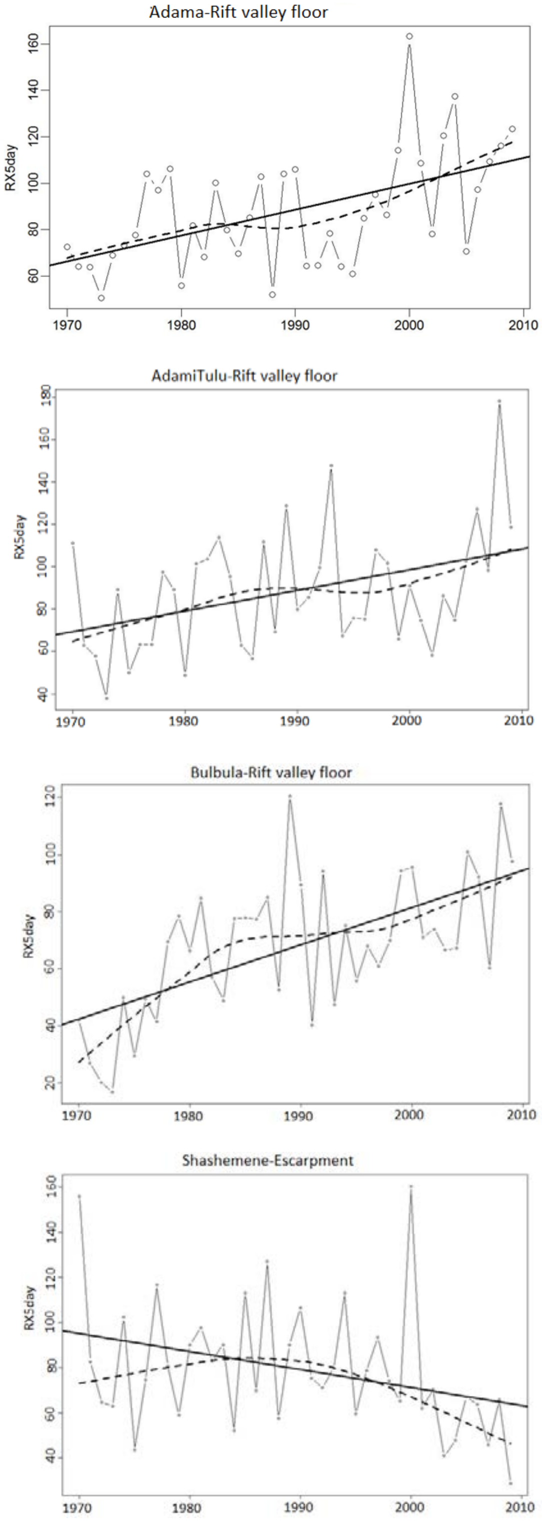


Figure 2.5 Trends in maximum 5-day precipitation amounts (RX5day) for the stations with significant trends (at 5% significance level) in the CRV, Ethiopia. The solid lines represent linear trends over the period 1970–2009 and the dashed lines indicate the local trends

The trends in the occurrence of R10mm and R20mm precipitation events follow similar patterns to that of total precipitation, as can be seen in the strong correlation between total precipitation and both heavy and very heavy precipitation days (Table 2.5).

Consecutive dry and wet days (CDD and CWD)

A significant trend in consecutive dry days (CDD) was found at only the Bulbula station, where CDD showed a decreasing trend (Table 2.4). Though not significant, the overall trend in the humid eastern highlands (Kulumsa, Assela and Kofele) was slightly decreasing while in the semi-arid rift valley floor it showed either a clear tendency towards a decrease (Ziway and Bulbula) or no change (Adami Tulu and Adama). The correlation between CDD and PRCPTOT on the basis of annual rainfall was significant and opposite (Table 2.5) implying that total precipitation decreases as CDD increases**.**

For the Consecutive Wet Days (CWD), 9 stations (64%) showed slightly (insignificant) decreasing CWD, of which 3 stations (Adama, Koshe and Tora) showed a significantly decreasing trend. Also from the 5 stations that showed a slightly increasing CWD trend, only the Bulbula station showed a significant increasing trend for CWD (Table 2.4).

Total precipitation on very wet and extreme wet days (R95p and R99p)

As shown in Table 2.4, there were significant trends in very wet days (R95p) at four stations (29%) and in extreme wet days (R99p) at 2 stations (14%). Stations in the rift valley floor (Adami Tulu, Adama, and Bulbula) showed a significant increasing trend in R95p and only one station (Halaba) from the escarpment of the CRV showed a significant decreasing trend. The 2 stations (Adami Tulu and Adama) that showed a significant increasing trend for R99p are from the rift valley floor.

Correlation analysis of the ten precipitation indices for the 14 stations to reveal relationships among the different precipitation indices is presented in Table 2.5. It can be seen that PRCPTOT is strongly correlated with RX1day, RX5day, R10mm and R20mm, indicating that annual total precipitation is strongly correlated with heavy precipitation events while it is not significantly correlated with precipitation indices of SDII, CWD, R95P and R99P. Particularly, the lack of strong correlation between PRCPTOT and R95P and R99P suggests that the contribution of precipitation from very wet and extreme wet days to the annual total wet day precipitation is not significant. Based on this total year analysis, the precipitation indices of CDD and CWD are not correlated with most of the other indices, indicating that CDD and CWD could provide information that is essentially different from the other indices. However, it is important to note that the correlations between CDD and other precipitation indices, except SDII, showed negative signs.

Table2.5 Correlation coefficients of precipitation indices during 1970–2009 in the CRV, Ethiopia (full year)

	PRCPTOT	RX1day	RX5day	SDII	R10mm	R20mm	CDD	CWD	R95P	R99P
PRCPTOT	1									
RX1day	0.58*	1								
RX5day	0.84**	0.85**	1							
SDII	0.52	0.76**	0.72**	1						
R10mm	0.99**	0.55*	0.81**	0.53*	1					
R20mm	0.67**	0.84**	0.83**	0.75**	0.64*	1				
CDD	-0.61*	-0.34	-0.45	0.14	-0.53	-0.29	1			
CWD	0.48	0.05	0.32	-0.31	0.44	0.24	-0.66**	1		
R95P	0.49	0.92**	0.76**	0.80**	0.47	0.88**	-0.19	-0.019	1	
R99P	0.42	0.93**	0.74**	0.76**	0.40	0.80**	-0.14	-0.102	0.94**	1

** Significant at the 0.01 level, * significant at the 0.05 level

Based on simple linear trend analysis, regression coefficients that show the strength and direction of trends were calculated for each of the 10 rainfall indices at the 14 meteorological stations. The 140 regression coefficients, from the matrix of 10 rainfall indices by 14 stations are plotted by frequency distribution in Figure 2.6, which shows the regional trend of the rainfall indices. Of these 140 regression coefficients, 96 (69%) exhibit non-significant trends while 44 (32%) show significant trends. Among the 44 statistically significant regression coefficients, 21 show decreasing trends and 23 show increasing trends.

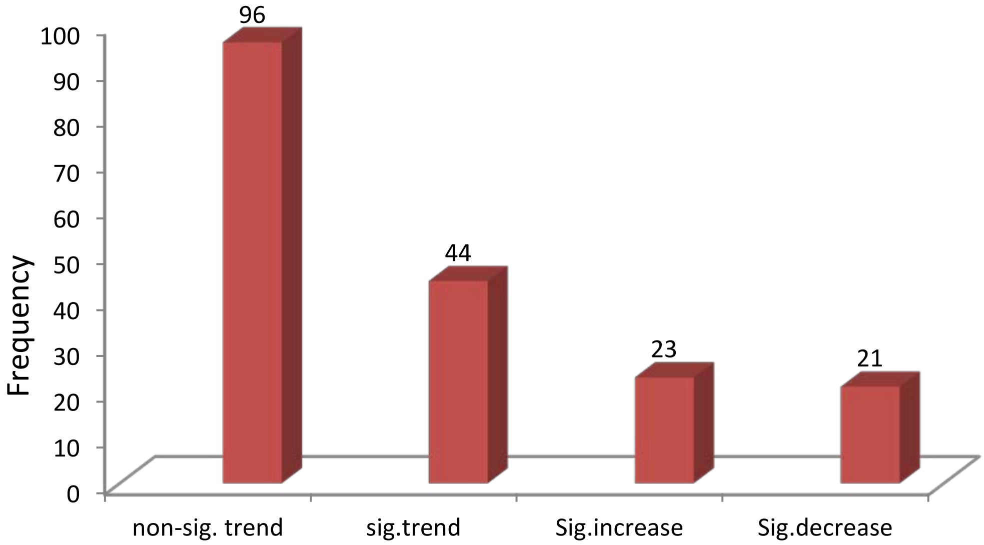


Figure 2.6 Frequency distribution of the linear regression coefficients showing non-significant (non-sig) and significant (sig) trends and significantly increasing and decreasing trends. The values on top of each bar.

2.3.2 Trends in rainfall indices during *Belg* and *Kiremt*

Looking at changes in rainfall on an annual basis often masks significant inter-seasonal variations (Garnaut 2008), so rainfall indices were also analyzed for the two wet seasons in the region, *Belg* (March - May) and *Kiremt* (June-September) separately. Tables 2.6a and 2.6b show *Belg* and *Kiremt* seasonal trends, respectively, for the 10 rainfall indices at the 14 stations.

During the *Belg* season, PRCPTOT showed a slightly decreasing trend from 64% of stations (9 stations) and an increasing trend from 36% of stations (5 stations), 2 of which showed a significant trend. RX1day and RX5day showed no significant trends except at Bulbula where an increasing trend for RX5day was indicated. Similarly, rainfall indices R95p and R99p showed no significant trends except at Adama which showed an increasing trend for R99p. During the *Belg*, two of the stations (Adama and Ziway) showed a slightly decreasing trend for PRCPTOT, RX5day and R10mm rainfall indices while the other two stations (Adami Tulu and Bulbula) showed a slightly increasing trend on most rainfall indices. However, based on the mean of stations from the rift valley floor landscape unit, the rift valley floor showed a tendency toward increasing trends on all rainfall indices (Table 2.6a).

The result for CDD during *Belg* was striking because all stations with the exception of Bulbula showed an increasing trend, with the trend being significant for 7 stations (50%). Meanwhile, CWD showed significant trends at 4 stations (29%), 2 being decreasing and 2 being increasing.

For the *Kiremt* season, 6 stations (AdamaTulu, Adama, Bulbula, Halaba, Shashemene and Assela) showed significant trends in PRCPTOT (Table 2.6b). Similarly, these stations showed significant trends in R10mm and R20mm indices. From these, three stations (Adami Tulu, Adama and Bulbula) showed increasing trends, and the remaining (Halaba, Shashemene and Assela) located in the escarpment and highland parts showed decreasing PRCPTOT trends. For *Kiremt*, almost all 10 rainfall indices at almost all stations in the rift valley floor (taking into account both significant and non-significant trends) showed an increasing trend and all stations in the escarpment and highlands, except Butajira, showed a decreasing PRCPTOT trend. CDD showed an increasing trend except at Bulbula and Halaba where there are slight decreasing trends. On the other hand, CWD showed a tendency towards decrease, with about 10 stations (71%) showing a negative sign of which 4 stations showed a significant decreasing trend.

The percentage of stations that showed significant trends for annual, *Belg* and *Kiremt* time series is presented in Table 2.7. For the annual time series, the stations that showed significant trends ranged from 7-57%, from which CDD had only 7% of stations with significant trend while PRCPTOT and R10mm showed 57% stations with significant trend.

For the *Belg* season, none of the stations showed significant trend for RX1day and R95p rainfall indices. For RX5day, R20mm and R99p, 7% of the stations and for PRCPTOT, 14% of the stations showed significant trends, all increasing. Similarly, R10mm 21% of the stations showed significant trend with 14% increasing trend. Most striking is that 50% of the stations showed a significant trend for CDD all increasing. From the 29% of the stations that showed significant trends for CWD, 14% showed significant decreasing trend and 14% showed an increasing trend. Though not significant, the CWD during *Kiremt* showed a tendency towards decreasing.

For the *Kiremt* season, 14-43% of the stations showed significant trend for all 10 rainfall indices. For PRCPTOT and R20mm, 43% of the stations showed significant trends with 21% increasing trend.

2.4. Discussion and conclusions

In this study we investigated changes in daily rainfall and extreme rainfall events at the landscape and seasonal scales for the last 40 years (1970-2009) in the CRV. In such a diverse and heterogeneous region, knowing the spatial and temporal distribution of daily rainfall and extreme events and observing its trends is important for planning food security and sustainable agricultural production.

In the annual time series analysis, most of the stations in the rift valley floor showed increasing trends in total precipitation (PRCPTOT) and extreme rainfall indices. For example, Adami Tulu has experienced an increase of about 438 mm rainfall over the last four decades (1970-2009) and also showed similar significant increases in all of the extreme rainfall indices. The CDD and CWD remained almost unchanged. On the other hand, the Shashemene station, which is located in the escarpment, has experienced a decrease of rainfall of about 308 mm over the period studied. Similarly, most rainfall extremes there showed decreasing trends.

Table 2.6a Trends of 10 indices (unit/decade) for 14 stations in the CRV (Ethiopia) for the *Belg* season (March-May) of the year.

Index	PRCPTOT	RX1day	RX5day	SDII	R10mm	R20mm	CDD	CWD	R95P	R99P
Unit	mm	mm	mm	mm/day	days	days	days	days	mm	mm
Station										
AdamaTulu	20.7	4.4	4.6	0.8	0.7	0.5	11	0.3	10.7	-0.2
Ziway	-13.3	-2.7	-3.4	-0.6	-0.4	-0.2	16.4	0.2	-0.3	-5.7
Adama	-19.5	4.3	-0.5	0.9	-0.8	0	13.9	-1	10	9.1
Bulbula	30.6	5.1	11.8	-0.1	1.1	0.2	-2.1	1	6.3	3.2
Rift valley floor	**4.6**	**2.8**	**3.1**	**0.3**	**0.2**	**0.1**	**9.8**	**0.1**	**6.7**	**1.6**
Halaba	39.6	1.6	5.8	-0.3	1.4	0.7	5.6	0.6	5.4	-3.7
Koshe	-32.3	1.4	-4.3	0.8	-1.4	-0.1	11.5	-0.8	0.7	8.6
Wondo Genet	-0.8	-3.4	-1.6	0	0.4	-0.1	10.9	0.3	-5.2	-7.4
kuyera	-10.2	-2.7	-2.9	-0.2	-0.7	-0.2	10.4	-0.5	-1.5	-2.7
Shashemene	-10.1	-2.9	-3.7	-0.7	-1.3	-0.3	7.5	1.3	-4.7	-2.1
Tora	-31.4	-0.1	-4.5	0.6	-1.1	-0.4	10.6	-1	-1	-2.7
Butajira	28.7	1.3	9.3	0.4	1.5	0.7	8.9	0.4	8.2	-2.7
Escarpment	**-2.4**	**-0.7**	**-0.3**	**0.1**	**-0.2**	**0.1**	**9.3**	**0.1**	**0.3**	**-1.8**
Kulumsa	-3.8	-2.7	-2.5	0	0.2	0.2	11.3	-0.3	-10.6	-7.8
Assela	-13.4	-1.3	-2.3	0	-0.4	-0.4	9.4	0.1	-7.9	1.8
Kofele	17.7	-0.1	4	0.1	0.3	0.2	8.3	0.6	2	0.2
Highland	**0.2**	**-1.4**	**-0.3**	**0**	**0**	**0**	**9.7**	**0.2**	**-5.5**	**-1.9**

Table 2.6b Trends of 10 indices (unit/decade) for 14 stations in the CRV (Ethiopia) for the *Kiremt* months (June-September) of the year

Index	PRCPTOT	RX1day	RX5day	SDII	R10mm	R20mm	CDD	CWD	R95P	R99P
Unit	mm	mm	mm	mm/day	days	days	days	days	mm	mm
Station										
AdamaTulu	85.1	4.8	12.2	1.4	3.0	2.2	2.3	-0.2	36.5	20.1
Ziway	30.7	1.1	6.7	-0.4	0.7	0.8	4.1	0.6	10.0	6.4
Adama	34.5	7.0	11.1	1.3	1.2	2.0	5.0	-0.9	59.0	25.5
Bulbula	37.4	4.2	10.8	-0.1	4.1	0.7	-4.8	1.9	13.3	1.7
Rift valley floor	**46.9**	**4.3**	**10.2**	**0.5**	**2.2**	**1.4**	**1.6**	**0.4**	**29.7**	**13.4**
Halaba	-64.1	-6.4	-12.6	-1.4	-2.3	-1.4	-0.1	-0.7	-41	-14.7
Koshe	-22.8	1.4	-1.1	0.0	-0.6	-0.1	5.0	-1.2	7.0	-0.5
Wondo Genet	-36.4	-7.1	-4.3	-0.1	-1.0	-0.4	14??	-1.0	-17	-10.3
kuyera	-5.9	1.0	-1.2	-0.1	-0.2	-0.2	3.5	-0.1	-5.5	1.1
Shashemene	-48.0	-3.9	-8.8	-0.8	-3.2	-0.8	3.3	-0.3	-30	-12.7
Tora	-21.1	-1.4	-2.6	0.2	-0.7	0.3	2.8	-1.1	1.0	-6.7
Butajira	27.5	0.2	2.4	-0.3	1.4	0.0	1.5	0.3	0.0	-1.7
Escarpment	**-24.4**	**-2.3**	**-4.0**	**-0.4**	**-0.9**	**-0.4**	**4.3**	**-0.6**	**-12**	**-6.5**
Kulumsa	-8.6	-0.9	0.9	-0.1	-0.8	0.1	2.9	-0.4	0.1	-2.8
Assela	-54.8	-0.4	-4.2	-0.3	-2.0	-1.2	3.7	-1.5	-23.0	-5.4
Kofele	-5.7	-0.9	-0.8	-0.2	-0.7	-0.2	2.0	0.0	-5.9	-7.7
Highland	**-23.0**	**-0.8**	**-1.4**	**-0.2**	**-1.2**	**-0.4**	**2.9**	**-0.6**	**-9.6**	**-5.3**

Values significant at 5% level are red.

Table 2.7 Stations (%) with significant trends at the 14 stations for annual, *Belg* and *Kiremt* at CRV, Ethiopia

	PRCPTOT	RX1day	RX5day	SDII	R10mm	R20mm	CDD	CWD	R95p	R99p
Annual	57	29*	29	29	57	36*	7	29	29	14
Positives (↑)	21	21	21	14	14	21	0	7	21	14
Negatives (↓)	36	7	7	14	43	14	7	21	7	0
Belg	14	0	7	14	21	7	50	29	0	7
Positives (↑)	14	0	7	7	14	7	50	14	0	7
Negatives (↓)	0	0	0	7	7	0	0	14	0	0
Kiremt	43*	28	36	28	36	43	14	36	36	21
Positives (↑)	21	14	21	14	14	21	14	7	14	14
Negatives (↓)	21	14	14	14	21	21	0	29	21	7

*Due to rounding of digits to full numbers, some values do not exactly add up to exact values.

For the *Belg* season, changes in total rainfall and extreme rainfall indices showed a general tendency towards decreasing trend across the stations, with more than half of the stations showing negative trends (though mostly not statistically significant) for all rainfall indices with the notable exception of CDD. PRCPTOT showed a slightly decreasing trend from most of the stations (64%; 9 stations). Other rainfall indices that showed strong correlation with PRCPTOT also showed similar decreasing trend across the stations in all landscape units. Even, the rift valley floor that showed a general increasing trend on annual time series and during *Kiremt*, exhibited a mixed tendency during *Belg* where two stations showed decreasing tendency and the other two showing an increasing tendency, though the mean of the stations in this landscape unit showed increasing trend. The *Belg* season analysis showed consistent increases in the maximum number of consecutive dry days (CDD) from 1970-2009 at almost all stations in the whole of the CRV, with 50% of them significantly increasing and none with a decreasing trend. The increases ranged from ≈14 days/decade at Adama to ≈9 days/decade at Assela (Table 2.6a). According to IPCC (2007) in a warmer future climate dry extremes are projected to become more severe in areas where mean precipitation is projected to decrease.

The *Kiremt* season also showed a significant change in PRCPTOT, increasing in the rift valley floor and decreasing in the escarpment and highlands. Similarly, the trend at the two sample stations, Adami Tulu and Shashemene, showed similar trends during *Kiremt* to that of the annual series, but the rate of change during *Kiremt* is less than that of the annual time series. Though only 14% (2 stations) were significantly increasing in statistical terms, the CDD during *Kiremt* showed consistent increases across the stations. On the contrary, the CWD during *Kiremt* showed consistent decreases across the stations. This opposite trend between CDD and CWD during *Kiremt* is consistent with their strong opposite relationships which is shown in Table 2.5.

The difference in results obtained from daily rainfall and extreme rainfall events for landscape units and seasons indicates the importance of climate assessment at the local and seasonal scales. In terms of annual and seasonal differences of daily rainfall and extreme rainfall events; for example, the annual time series and *Kiremt* season analysis of the annual total rainfall showed more significant trends (57% and 43% respectively) than the *Belg* season which showed almost no significant trend at all stations except at two stations where it showed increasing trend. Similarly, the annual time series and *Kiremt* season analysis of the CDD showed significantly increasing trend only at one and two stations respectively, while the *Belg* showed significantly increasing trend from half of the stations (7 stations). Where annual time series and *Kiremt* season analysis showed close results, the *Belg* season analysis showed quite different results from both Annual and *Kiremt* in many of the rainfall indices (Tables 2.4, 2.6a and 2.6b). The knowledge of such seasonal differences in the rainfall indices can help farmers to devise different adaptation strategies for each season.

Spatially, different results at each landscape unit were found. At the rift valley floor, all rainfall indices showed a tendency towards increase, while at the escarpment and the highland, it showed decreasing tendency. This difference in a landscape unit is more evident for the *Kiremt*, the most important crop production season, where the total rainfall and extreme rainfall indices showed consistent tendency towards increase at the rift valley floor and decreasing trend at the escarpment and the highland except the CDD where there is an increasing tendency in all landscape units. The difference in results obtained for total rainfall and extreme rainfall indices for landscape units demonstrates the importance of considering rainfall analysis at a finer spatial scale, in a spatially heterogeneous region like in the CRV. Previous studies covering different parts of Ethiopia reported absence of significant trends in most rainfall indices; for example, Degefu and Bewket (2013) and Mekasha *et al*. (2013) reported absence of any trend in CWD, CDD and SDII rainfall indices. Similarly, Seleshi and Camberlin (2006) found no significant trend in CDD and R95P. Since most of these studies were conducted at the national and sub-national levels, i.e., large spatial units in which topographic influences are ignored, the information they generated could be less relevant for farm level decision making.

Based on the relationships between the Indian Ocean cyclone and precipitation in Ethiopia, *Belg* rainfall is much more affected by cyclonic activity than *Kiremt* since the *Kiremt* season is outside the cyclonic season of the southeast Indian Ocean (Shanko and Camberlin 1998).

Thus, the generally declining *Belg* rainfall which is already occurring in the CRV is likely to continue to decrease during the rest of this century due to increasing Indian Ocean Sea Surface Temperature (Lyon and DeWitt 2012). This, in combination with the increasing CDD, will present challenges for future *Belg* crop production (Muluneh et al., 2015). The same study (ibid), also found that the cessation date of *Kiremt* rainfall is likely to be extended in the future, which could help farmers grow long cycle crops like maize by adjusting their cropping calendars.

The increasing trend for annual rainfall and extreme rainfall events in the rift valley floor and the tendency towards decrease (though not significant statistically) in the western and eastern escarpments suggest differences in local and regional scale rain-forming factors in the region. However, this requires a further study, which should consider how local factors (topography, forest, land cover change, water bodies etc.) affect rainfall amounts in the region.

The spatial and temporal distribution of the *Belg* season rainfall is very important and has wider implications for food security in two ways: 1) during *Belg* land is prepared and locally important short cycle food crops are planted, and 2) *Belg* is also the sowing time for important long maturing crops such as Maize and Sorghum which are harvested in October-December. Thus, the detected consistent increase in CDD and the decreasing tendency of total rainfall during *Belg* can affect crop production. The *Kiremt* season also showed statistically non-significant but consistent increasing tendency of CDD and decreasing tendency of CWD particularly in the escarpment and highland parts of the CRV.

Local climate studies - such as the present study - are useful to provide fine scale climate information for impact assessment and adaptation purposes because climate impacts occur locally and can take many different forms in different places (Elasha et al. 2006). The result of our long term seasonal rainfall and extreme event analysis provides useful insights into the long-term changes in rainfall characteristics at the local scale and this is important to design appropriate climate risk management strategies at the community scale. Particularly the spatial (landscape level) and temporal (cropping seasons level) downscaling of our analysis and the insight gained from that provides valuable information that could be used to assist local farmers to adapt to the changing climate through different strategies such as adoption of new agricultural technologies or farm management practices.

Chapter 3

Impact of predicted changes in rainfall and atmospheric carbon dioxide on maize and wheat yields in the Central Rift Valley of Ethiopia

Abstract

This study assesses potential impacts of climate change on maize and wheat yields in the Central Rift Valley (CRV) of Ethiopia. We considered effects of elevated atmospheric carbon dioxide (CO_2) and changes in rainfall during the main (*Kiremt*) and the short (*Belg*) rainfall cropping seasons during the two future periods (2020–2049 and 2066–2095). The MarkSimGCM daily weather generator was used to generate projected rainfall and temperature data using the outputs from ECHAM5 general circulation model and ensemble mean of six models under A2 (high) and B1 (low) emission scenarios. Crop yield simulations were made with the FAO's AquaCrop model. The projected rainfall during *Kiremt* increases by 12–69 % while rainfall during *Belg* decreases by 20–68 %. The combined effect of elevated CO_2 and projected climate factors increases maize yield by up to 59 % in sub-humid/humid areas of the CRV, but could result in a decrease of up to 46 % in the semiarid areas under ECHAM5 model. However, the maize yield increases in all parts of the CRV under the ensemble mean of models. Wheat yield shows no significant response to the projected rainfall changes, but increases by up to 40 % due to elevated CO_2. Our results generally suggest that climate change will increase crop yields in the sub-humid/humid regions of the CRV. However, in the semi-arid parts the overall projected climate change will affect crop yields negatively.

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Impact of predicted changes in rainfall and atmospheric carbon dioxide on maize and wheat yields in the Central Rift Valley of Ethiopia

3.1 Introduction

Climate change poses a serious threat to agricultural production and food security in many African countries. The effects of reduced crop-water availability, drought, increased temperatures and elevated carbon dioxide (CO_2) are expected to cause significant changes in crop yields, cropping systems, and scheduling of field operations (Chiotti and Johnston 1995). However, the direction and magnitude of long-term impacts of these changes on crop production remain uncertain.

Different studies conducted on rainfall changes over the past decades in Ethiopia have reported mixed patterns and trends of rainfall change. For instance, there are several studies that showed absence of clear trend in the annual and June–September (*Kiremt*, long rainy season) rainfall total or number of rainy days between the 1960s and 2000s (Seleshi and Zanke 2004; Seleshi and Camberlin 2006; Bewket and Conway 2007). However, Cheung et al., (2008) and Williams et al., (2012) reported a significant decline of the *Kiremt* rainfall between 1960s and 2000s in some parts of the country. Williams and Funk (2011) have also found a sharp decline in the March–May (*Belg*, short rainy season) rainfall since 1980s for the entire country. There could be several reasons for such contradictory results, such as, the use of different periods for analyses and station densities (Bewket and Conway 2007; Rosell 2011), and mixing up of study units having different physical characteristics and quality of data used (Seleshi and Zanke 2004).

Much uncertainty remains in projecting future rainfall in the East African region. One reason for this is that global circulation models (GCMs) with their coarse resolution are not very reliable when simulating atmospheric dynamics associated with landscape variability (Moore et al., 2012)—especially when the terrain is extremely complex as in East Africa. Most GCMs have projected general annual rainfall increase due to expected warming in the region (McHugh 2005; Doherty et al., 2010; Shongwe et al., 2011). However, Williams and Funk (2011) and Lyon and DeWitt (2012) argued strongly against the future rainfall increase predicted by GCMs for East Africa and, rather, indicated a likely decline in rainfall for the region, particularly during the March–June period due to increasing Indian Ocean sea surface temperature (SST).

Lack of rains or successive dry spell occurrences during critical crop growing seasons leads to severe yield reductions (cf. Araya et al., 2011, 2012). The most damaging effect of dry spells is manifested during sensitive stages of crop development such as flowering and grain filling (mainly 60–90 days after sowing) and during establishment of seedlings (mainly during the first 30 days after sowing) (Stern and Coe 1984). A 10-day dry spell causes water deficit to crops that can lead to crop failure in East Africa (Barron et al., 2003; Segele and Lamb 2005).

The effect of climate change on agricultural production is expected to vary by region and crop with both gains and losses commonly predicted (Chiotti and Johnston 1995; Moore et al., 2012). For example, crop yields are expected to increase in the East African region, such as the southern Ethiopian highlands, central and western highlands of Kenya and the African Great Lakes region, whereas most African countries are expected to face yield declines (Jones and Thornton 2003; Thornton et al., 2009, 2011; Doherty et al., 2010). Elevated CO_2 tends to increase yield of most agricultural plants as a result of high rates of photosynthesis and low rates of water loss that improve water-use efficiency (Parry et al., 2004; Vanuytrecht et al., 2011). Hence, a better understanding of future crop production potentials requires consideration of both climatic change and elevated CO_2 concentration effects (Parry et al., 2004).

Previous studies on potential agricultural impacts of climate change in Ethiopia were either at the national or even East African regional level (Jones and Thornton 2003; Deressa and Hassan 2009; Thornton et al., 2009). Very few studies at sub-national and local levels within Ethiopia exist (e.g., Di Falco et al., 2011). Given Ethiopia's very complex topography and climate, the impact of climate change on crops needs to be assessed at sub-national and local scales to be of practical value (cf. Araya et al., 2010). This study sets out with two interrelated objectives: (1) to assess how growing season rainfall is likely to change in the future, (2) to assess potential impacts of changes in rainfall characteristics and elevated CO_2 on yields of maize and wheat—the two most important crops—in the Central Rift Valley (CRV) of Ethiopia.

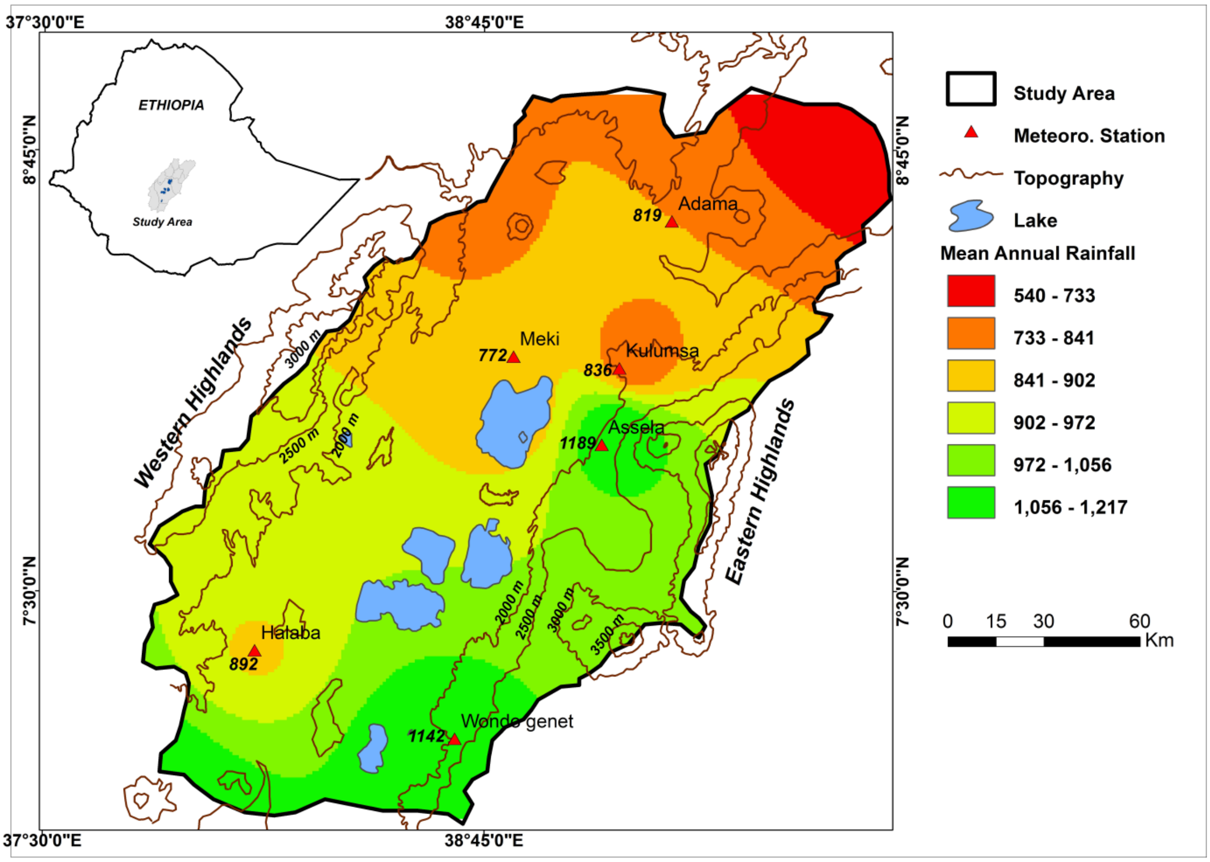


Figure 3.1 The study area showing the meteorological stations, the 30 year annual rainfall pattern, the topographic lines and lakes in the CRV of Ethiopia.

3.2 Materials and methods

Description of the study area

The study was conducted in the central part of the Ethiopian rift valley, located approximately between 38° 00" and 39° 30" E and 7° 00" and 8° 30" N (Figure 3.1). The Ethiopian rift valley is part of the Great East African Rift Valley. In the CRV, altitude ranges from about 1643 m to 2390 m above mean sea level (msl) (Table 3.1). Corresponding with the altitudinal variation, the climate of the CRV ranges from humid to sub-humid in the highlands to semi-arid in the rift floor.

Two of the meteorological stations (Adama and Meki) used in this study are in the semi-arid zone, two others (Halaba and Wondo Genet) fall in the sub-humid zone, and two others (Assela and Kulumsa) are in the humid zone. Mean annual rainfall and temperature range from 685 - 1118 mm, and 15 - 20^{o}C, respectively. The region is characterized by three main seasons: *Kiremt,* Bega and *Belg.* The main rainy season (*Kiremt*) extends from June to September and accounts for 50 to70% of the mean annual rainfall. The dry period (Bega) extends from October to February and experiences occasional rains which account for only about 10 to 20% of the annual total. The small rainy season (*Belg*) extends from March to May and delivers some 20 to 30% of the annual rainfall.

The soils of the CRV vary from sandy loams to clay loams with varying levels of fertility and degradation status. According to the National Soil Laboratory of Ethiopia, soils around our study stations have sandy loam texture except Assela and Meki with a clay loam texture. In this study we have used texture to evaluate soil hydraulic properties using Pedotransfer functions.

Major crops in the study area

Rainfed wheat and maize crops cover more than 50% of cultivated areas in the CRV.

Maize is a long-cycle crop which is planted during the *Belg* season between March and April and harvested between September and December. In this study, the BH-660 maize cultivar which adapts well in areas with altitudes ranging from 1600 to 2400 m was used for the Assela and Kulumsa areas and the BH-540 cultivar, which adapts for areas with altitudes varying from 1000 to 2000 m, was used for the Wondo Genet, Halaba and Adama areas.

Wheat is a short-cycle crop sown around June and July and harvested between September and December. Assela **l**ocated in one of the major wheat producing areas was used for wheat (*Kiremt* season crop) analysis using the wide ranging wheat cultivar Pavon 760.

Baseline climate data

An available 30 year data set of daily rainfall and temperature for the period 1966-1995 was used to represent the *baseline climate* of the study area. The data were from six meteorological stations and were obtained from the Ethiopian National Meteorological Agency (Table 3.1). To estimate reference evapotranspiration (ET_O) no data was available on relative humidity, actual vapor pressure, net radiation and wind speed. Hence, values for these variables were estimated based on the missing climatic data estimation procedures recommended by Allen et al (1998) using the ETo calculator (FAO 2009).

Table 3.1 Meteorological stations used for the study in the CRV of Ethiopia

Station	Latitude	Longitude	Elevation(m)	Observation Period
Adama	8° 33' 0"	39° 16' 58"	1643	1966-1995
Assela	7° 57' 0"	39° 7' 48"	2390	1966-1995
Halaba	7° 18' 46"	38° 5' 24"	1782	1966-1995
Kulumsa	8° 0' 35"	39° 9' 18"	2202	1966-1995
Meki	8° 9' 0"	38° 49' 1"	1664	1966-1995
Wondo Genet	7° 2' 52"	38° 36' 54"	1736	1966-1995

Climate change data

For this study, we used the ECHAM5 GCM (Roeckner et al., 2003) and ensemble mean of six GCMs under A2 (high) and B1 (low) emission scenarios. The future climate data generated and used were for two different time periods: 2020-2049 and 2066-2095 with the baseline period (1966-1995). The ECHAM5 model is known for its good performance in east Africa on estimating average annual rainfall rates (McHugh 2005) and abrupt declines of March-April-May (*Belg*) rainfall due to changes in SST (Lyon and DeWitt 2012). On the other hand, multi-model ensemble means are believed to be better reliable in climate projections (Semenov and Stratonovitch 2010), and Giorgi and Coppola (2010) suggest a minimum of four to five models to obtain robust regional precipitation change estimates. In this study, ensemble mean of six GCMs was used. GCMs included in the average of the six models are: BCCR_BCM2.0 (Bjerknes Centre for Climate Research ,University of Bergen, Norway, $1.9^o \times 1.9^o$), CNRM-CM3(Météo-France/Centre National de Recherches Météorologiques, France, $1.9^o \times 1.9^o$), CSIRO-Mk3.5 (Commonwealth Scientific and Industrial Research Organization Atmospheric Research, Australia, $1.9^o \times 1.9^o$), ECHam5 (Max Planck Institute for Meteorology, Germany, $1.9^o \times 1.9^o$), INM-CM3_0(Institute for Numerical Mathematics, Moscow, Russia, $4.0^o \times 5.0^o$) and MIROC3.2 (Center for Climate System Research, National Institute for Environmental Studies, and Frontier Research Center for Global Change, University of Tokyo, Japan, $2.8^o \times 2.8^o$).

Climate change impact studies usually require information at finer spatial and temporal scales than the typical GCM grid resolutions. To generate daily rainfall and temperature (maximum and minimum) data, the web-based MarkSimGCM module with a user interface in Google Earth was used (Jones and Thornton 2013). It is an updated version of the MarkSim model (Jones and Thornton 2000). MarkSim, a third-order markov rainfall generator, is a generalized downscaling and data generation method used as GCM downscaler by using both stochastic downscaling and climate typing. MarkSim takes the outputs of the original resolution of each GCM and interpolates to 0.5^o latitude–longitudes. Generally, the model uses a mixture of methods, including simple interpolation, climate typing and weather generation to generate daily weather data that are to some extent characteristics of this future climatology. A detailed description of the MarkSim model can be found in Jones and Thornton (2000). To make a globally valid model that does not need recalibration every time that it is used, the developers of the model calibrated MarkSim using over 10,000 stations worldwide with more than 10 years of continuous data, which were clustered into 702 climate clusters of monthly precipitation and monthly maximum and minimum temperatures. Accordingly, MarkSim has been widely used in East Africa and reportedly provides a realistic simulation of daily precipitation and temperature distributions (Thornton et al., 2009; Lobell and Burke 2010; Thornton et al., 2011). Dixit et al., (2011) and Farrow et al., (2011) have demonstrated that MarkSim can generate synthetic time series that show patterns of rainfall variability over East Africa with acceptable accuracy (without statistically significant difference between observed and MarkSim generated data) for applications in agriculture.

Though MarkSim has been extensively tested (Jones and Thornton 1993; Jones and Thornton 1997; Jones and Thornton 2013), in this study, we made a comparison of MarkSimGCM simulations with historical data from 6 rainfall stations. For each station, a MarkSimGCM was run for current climate to produce 30 years of simulated daily data, and monthly mean rainfall, annual totals, and variances. Overall, the MarkSimGCM simulated monthly and annual means adequately close to the historical values on most stations in the CRV. Hence, MarkSimGCM is capable of capturing seasonal rainfall by slightly overestimating rainfall in July and August. The result is shown in Table 3.2.

Table 3.2 Comparison of MarkSimGCM simulations with historical data from 6 rainfall stations in the CRV, Ethiopia

	J	F	M	A	M	J	J	A	S	O	N	D	Annual
Adama													
Hist.Ẋ	20	49	71	72	76	84	154	146	98	31	10	7	819
Var	878	2794	3474	2015	2278	1668	1693	1343	680	2322	819	251	15106
Mark.Ẋ	18	42	64	70	71	80	158	159.4*	90	22	13	7	815
Var	742	2154	2504	3412	2209	1666	1435	3681.3*	2734	569	374	148	18023
Assela													
Hist.Ẋ	16	49	95	119	119	128	202	215	167	48	18	13	1189
Var	520	2084	3455	6617	5332	1636	3417	3721	3655	2144	700	433	43342
Mark.Ẋ	20	54	102	110	109	118	210	221	154	52	17	17	1190
Var	480	1756	3487	3579	2735	1970	8338	5916	4570	1924	351	330	41132
Halaba													
Hist.Ẋ	14	40	51	72	69	72	214	206	105	29	13	7	892
Var	695	1796	2268	3354	3728	2781	9599	4568	2149	1593	489	185	22936
Mark.Ẋ	17	45	59	79	80	90	200	194	111	37	21*	15*	948
Var	397	1389	1870	2291	3248	2718	7168	5218	4026	1540	455	255	27016
Kulumsa													
Hist.Ẋ	22	53	84	83	83	84	129	136	107	33	13	11	836
Var	1146	2485	5103	2851	2348	1034	733	1040	615	1125	446	220	12320
Mark.Ẋ	22	59	81	98	96	88	172*	166*	115	43	17	10	981*
Var	676	1752	2514	4060	3775	2482	5219*	5125*	4270	1508	268	117	51423*
Meki													
Hist.Ẋ	18	45	56	59	66	81	171	149	87	29	7	4	772
Var	879	3586	2814	1824	3073	3420	4967	3746	1429	1867	501	150	30203
Mark.Ẋ	21	53	53	69	73	79	182	153	97	31	10*	4	825
Var	587	1083	3058	1680	2675	1775	11382	6166	4325	1456	186	48	28885
Wondo Genet													
Hist.Ẋ	26	56	111	140	121	104	157	145	142	91	32	18	1142
Var	867	2258	2671	4251	3372	2373	4640	2281	1032	3771	1226	372	18031
Mark.Ẋ	25	52	103	127	111	97	160	158	136	80	36	14	1097
Var	557	1886	2351	3844	4420	1863	6810	5705	5557	3353	703	127	28093

Hist.Ẋ = historical mean rainfall (mm); Mark.Ẋ =MarkSimGCM generated mean rainfall (mm); Var=variance (mm). Significant statistical differences at the 5% level between the simulated and the historical values are marked with an asterisk.

Analysis of rainfall characteristics

The rainfall analysis started with calculating changes in seasonal rainfall both for *Kiremt* and *Belg* followed by comparing the values of March-September monthly average rainfall to the baseline and projected climates.

To define successful planting dates, the onset for maize and wheat crops was determined by combining the start of rain and dry spell data. Hence, onset was defined as the date when accumulated precipitation over 3 days was at least 20 mm and no dry spell longer than 10 days appeared within the subsequent 30 days (Sivakumar 1988). Later, the onset was processed starting from 1st March for maize and 1st June for wheat based on the assumed starting dates of the *Belg* and *Kiremt* rainy seasons, respectively.

For defining the end of the growing season (cessation) soil water balance was determined from daily ET_O and total available water estimated from soil texture values for each meteorological station. Cessation of the growing season for this study is any day after 1 October when the soil water balance reaches zero. In the end, the Length of the Growing Period (LGP) was obtained by subtracting the onset from the cessation.

The analysis of seasonal dry spells was carried out using the statistical package Instat+3.36 (Stern et al., 2006). A dry spell was defined previously in Africa as a continuous period of “no rainfall” (< 0.85 $mmday^{-1}$) during a rainfall season after sowing dates (Rockström et al., 2003). Maximum dry spells for successive 30 day periods after sowing and until the end of the growing season were determined.

Though the pattern of rainfall changes during both *Belg* and *Kiremt* were similar at most stations (Table 3.3), there were differences in onset, cessation, LGP, dry spell and crop yield , mostly between semi-arid and sub-humid/humid areas of the CRV (results not shown). Therefore, we present the results of Adama as representative of the semi-arid parts and Assela as representative of the sub-humid/humid parts of the CRV region.

Crop yield simulation

The AquaCrop model was used to simulate attainable crop yields in response to water through its soil-crop-atmosphere components (Raes et al., 2009; Steduto et al., 2009). The growth engine of AquaCrop is water-driven*,* in that transpiration is calculated first and then translated into biomass using a conservative, crop-specific parameter: the biomass water productivity, normalized for atmospheric evaporative demand and CO_2 concentration. Thus, the total biomass (B) is estimated by Eq. 3.1 (Steduto et al., 2009):

$$B = WP^* \sum Tr \qquad (Eq. 3.1)$$

Where WP* is the normalized water productivity parameter in units of kg (biomass) m^{-2} (land area) mm^{-1} (mm of accumulated water transpired over the time period in which the biomass is produced) and Tr is crop transpiration (mm).

The harvestable yield (Y) is expressed as a function of total biomass (B) using a harvest index (HI) and distinguishes between environmental stress effects on B from those on HI (Eq. 3.2).

$$Y = B \times HI \qquad (Eq. 3.2)$$

There are five input parameter files for the model simulation: climate, crop, soil, management and initial soil water content.

The climate file includes user-specific daily values of (i) minimum and maximum air temperatures, (ii) ET_O and (iii) rainfall from both the baseline data and the projected climate change scenarios. The soil texture and hydraulic properties mentioned in section 2.1 were used. The runoff was described with a curve number (CN) which is automatically adjusted by AquaCrop based on the saturated hydraulic conductivity (K_{sat}) of the soil. Optimal soil fertility level under rainfed conditions was considered as management input. Initial soil water content was fixed at 75% of the field capacity following a similar approach for simulations in the CRV of Ethiopia (Biazin and Stroosnijder 2012). In this study, parameterized and tested crop input files were adopted from a previous simulation and validation by Biazin and Stroosnijder (2012) in the same study area (CRV). AquaCrop model responds to changes in CO_2 concentration by adjusting the CO_2 concentration when it differs from its reference value (369 ppm) (Raes et al., 2009; Vanuytrecht et al., 2011). AquaCrop makes a distinction between C3 and C4 crops. Because for C4 plants, photosynthesis is considered to be almost CO_2 saturated at present levels of ambient CO_2. Therefore, elevated CO_2 is not expected to have a strong direct impact on the photosynthesis process of C4 plants. But for both, a C3 and C4 crop, an increase in atmospheric CO_2 level causes partial closure of stomata, which reduces water loss by transpiration and thereby improves water use efficiency. Therefore, the WP* response to elevated CO_2 is smaller for C4 crops (with a typical WP* of 30–35 g m^{-2}) than for C3 crops (with a typical WP* of 15–20 g m^{-2}). For more details the reader is referred to Vanuytrecht et al., (2011). The mean annual CO_2 input for AquaCrop during the baseline climate was the reference value taken from the Mauna Loa Observatory for the year 2000 while the future period was obtained from the projected SRES B1 and A2 scenarios (Houghton et al., 2001). Under the A2-scenario, during the periods 2020-2049 and 2066-2095, the CO_2 level increased from 369 ppm (baseline) to 559 ppm and 779 ppm, respectively. Under the B1 scenario, during the periods 2020-2049 and 2066-2095, the CO_2 level increased from the 369 ppm (baseline) to 468 and 560 ppm, respectively.

AquaCrop has been well tested for maize and wheat crops under a wide range of environmental conditions in Ethiopia (Erkossa et al., 2011; Biazin and Stroosnijder 2012) and elsewhere (Heng et al., 2009; Hsiao et al., 2009; Salemi et al., 2011). However, this study has undertaken a re-validation using 10 years (2000-2010) of maize yield data obtained from Ziway Woreda (district) agricultural office.

The result showed a root-mean-square error (RMSE) of 0.39 ton ha^{-1}. At the same study area, Biazin and Stroosnijder (2012) reported a RMSE value for simulated maize yield that ranges from 0.27-0.53, with almost similar value to that of our results. The percent deviation of the simulated values from the observed values was 3.96% and the coefficient of determination was high with $R^2 = 0.91$ (Figure 3.2). Hence, AquaCrop model can be used with projections of the future.

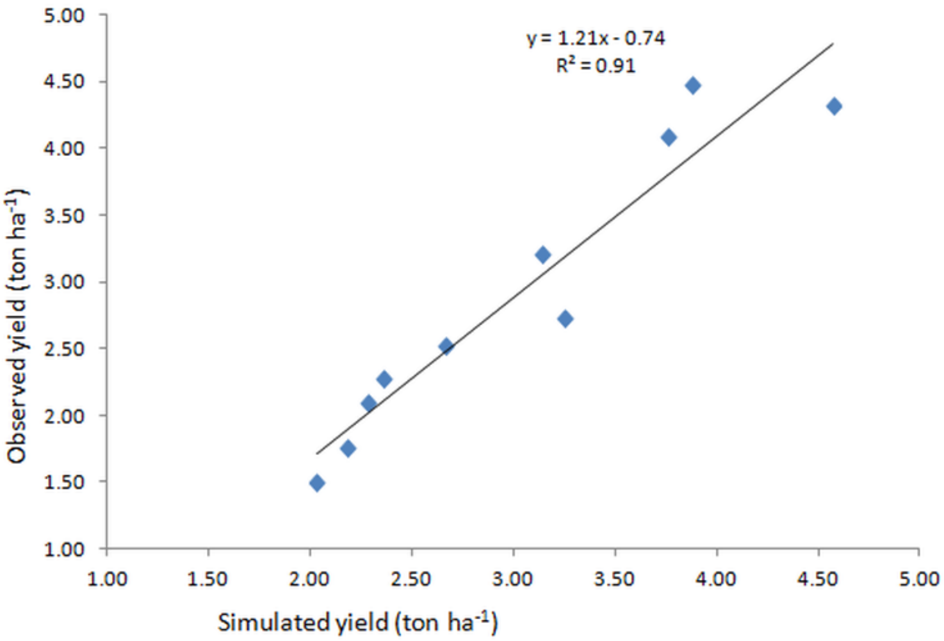


Figure 3.2 Observed versus simulated maize yield using the FAO's AquaCrop model in the CRV of Ethiopia

Finally, simulations of crop yields were done for the following three conditions: a) impact of projected change in rainfall alone to crop yield was obtained by subtracting the simulated yield under the baseline climate data from the simulated yield under projected rainfall alone; b) impact of elevated CO_2 alone on crop yield was calculated by subtracting simulated crop yield under the baseline climate using the reference CO_2 value from the simulated crop yield under the projected CO_2 concentration while other weather variables remain under the baseline climate conditions; c) overall climatic change impact was obtained by subtracting the baseline simulated yield from the simulated yield under the projection of climate variables and elevated CO_2.

3.3 Results and discussion

Belg and Kiremt season rainfall

Under ECHAM5 model, the *Belg* rainfall is projected to decline in all areas during the two future periods under both emission scenarios (A2 and B1), while the total rainfall during the *Kiremt* season is likely to increase under both climate change scenarios and simulation periods (Table 3.3).

The *Belg* rainfall showed a declining rate between the first period (2020-2049) and the second period (2066-2095) under both emission scenarios (A2 and B1). For instance, the *Belg* rainfall decreases by 50% in the first period and 46% in the second period for Adama under the A2 emission scenario. Similar results were observed at the rest of the stations, under both emission scenarios (Table 3.3). Each of the months of the *Belg* has shown decreasing rainfall in the future at almost all stations for both scenarios and periods (Figures 3.3a and 3.4b, only Assela and Adama shown). Several other studies conducted in the East African region, including Ethiopia, have also shown a declining *Belg* rainfall during the second half of the 20th century and projected persistence of current tendencies in the future (Funk et al., 2008; Williams and Funk 2011; Lyon and DeWitt 2012).

The projected *Kiremt* rainfall shows an increase in the CRV of Ethiopia (Table 3.3). The increase ranges between 12-32% at most stations, although a 54-69% increase was projected at Kulumsa.

Under an ensemble mean of six GCMs, the results of *Belg* and *Kiremt* rainfall for Adama and Assela stations follow the same pattern to that of ECHAM5 model, which is decreasing *Belg* rainfall and increasing *Kiremt* rainfall (Table 3.3). Both models also showed similar patterns of change from March to September at Assela and Adama (Figures 3.3 and 3.4). Generally, both ECHAM5 and ensemble mean GCMs predicted similar trends of changes in seasonal rainfall, despite some differences in the magnitude of changes. The increase in *Kiremt* rainfall agrees with the results of a previous study that was based on an ensemble of 15 GCMs and reported *Kiremt* rainfall increase in Ethiopia (Wang 2005).

Temperature

Both GCMs under the two emission scenarios suggested an increasing trend in temperature in both seasons (Table 3.4). The magnitude of temperature increase at Assela (humid area) was higher than at Adama (semi-arid area). Seasonally, the *Kiremt* is getting warmer than the *Belg.* The temperature increase under ECHAM5 was higher than under ensemble mean. For a given GCM the values under scenario B1 are generally lower than under scenario A2. The mean annual temperature projection under ensemble mean of models which increased in the range of 1.7-4.3°C during 2066-2095 is in line with the global scale projection reported by the Fourth IPCC assessment report suggested an increasing trend of temperature in the range of 1·5-4·5°C by the end of the century (Meehl et al., 2007). However, the *Kiremt* temperature projection under ECHAM5 model was overestimated. A previous study by Mariotti et al., (2011) similarly reported a temperature increase reaching a magnitude of 5°C in some areas of Africa during JJA (June-July-August) under ECHAM5 model.

Higher temperatures increase potential evapotranspiration. For example, changes in monthly potential evapotranspiration per degree of warming are on the order of 100 mm in climates typical of semi-arid Africa (Downing et al.,1997). Inevitably, these changes affect agricultural productivity with serious implications for food security.

Onset, cessation and LGP for maize and wheat crops

Table 3.5, presents the onset, cessation and LGP for maize under ECHAM5 and ensemble mean model under A2 and B1 scenarios. Both ECHAM5 and ensemble mean model revealed a similar pattern of change in the onset of rainfall for maize at Assela and Adama. The projected onset will be delayed for maize at Adama and will become earlier for maize at Assela. Thus, the difference between the two GCMs is only in the magnitude of change. Under ECHAM5 Model, the onset of the *Belg* season for maize is projected to be delayed by up to 2-9 weeks in the future compared to the baseline period. The mean onset under both A2 and B1 scenarios has been projected to be mostly around the third week of May at Assela while the mean onset for the baseline period was around the end of March (Table 3.5).

The mean cessation date for future climate scenarios will be extended by 1-2 months as compared to the mean cessation date for the baseline climate under ECHAM5 model. However, the projected onset and cessation at Adama station has shown a different onset and cessation pattern, the onset in the *Belg* season could be as late as June or July and the cessation could become as early as the first week of October (Table 3.5). The unique difference of onset and cessation exhibited at Adama station could be partly explained by its location in the dry semi-arid part of the CRV and the more erratic rainfall distribution naturally occurring here mainly during the *Belg* season.

Table 3.3 Percent change in mean rainfall during *Belg* and *Kiremt* seasons for the two future time periods using ECHAM5 and ensemble mean of six GCMs under A2 & B1 SRES scenarios against baseline.

GCM model	Season and station	Baseline period	Future rainfall simulation			
			A2 SRES Scenario		B1 SRES Scenario	
		1966-1995	2020-2049	2066-2095	2020-2049	2066-2095
		Rainfall (mm)	%Change*	%Change**	%Change	%Change
ECHAM5	***Belg* season**					
	Adama	218.3	-50.3	-45.7	-52.1	-41.2
	Assela	332.8	-61.1	-49.6	-58.1	-47.6
	Halaba	192.4	-56.4	-37	-51.8	-36.7
	Meki	181.5	-27.9	-20.4	-26.5	-19.7
	Kulumsa	249.1	-38.1	-34.2	-28	-25.9
	Wondo Genet	371.3	-68.3	-57.2	-66.4	-56.1
	***Kiremt* season**					
	Adama	482.2	31.7	22.6	15.9	146.8
	Assela	711.7	12.5	22.3	18.4	11.9
	Halaba	596.1	25.8	22.3	24.7	21
	Meki	487.6	31.9	33.1	16.3	49.8
	Kulumsa	456.6	61.5	69.4	54	56.2
	Wondo Genet	547.2	27.6	26.8	29.4	28.1
Ensemble mean	***Belg* season**					
	Adama	218.3	-21.5	-33.1	-34.6	-35.8
	Assela	332.8	-61.8	-53	-58.6	-59.9
	***Kiremt* season**					
	Adama	482.2	38.9	50.4	35.8	148.4
	Assela	711.7	18.7	35.2	15.4	23.3

- *%Change = [(Mean rainfall during 2020-2049 - Mean rainfall during 1966-1995)/Mean rainfall during 1966-1995]x100
- **%Change = [(Mean rainfall during 2066-2095 - Mean rainfall during 1966-1995)/Mean rainfall during 1966-1995]x100

The projected mean LGP for the long cycle crop (maize) will be slightly increased at Assela under both scenarios except during 2020-2049 under A2 scenario (Table 3.5). But, at Adama it was shorter under both scenarios. The LGP at Assela had ≥ 200 days while Adama showed <150 days of LGP. The LGP at Assela can support the growing of a long cycle maize variety (which takes over 150 days) and takes full advantage of the delayed cessation.

Belg is important as a pre-*Kiremt* season for planting long-cycle cereal crops like maize and sorghum (with growing cycles that extend through *Kiremt*) as well as for growing *Belg* season crops. The increasing LGP in this research is consistent with other studies in east Africa (Thornton et al., 2011; Cook and Vizy 2012)

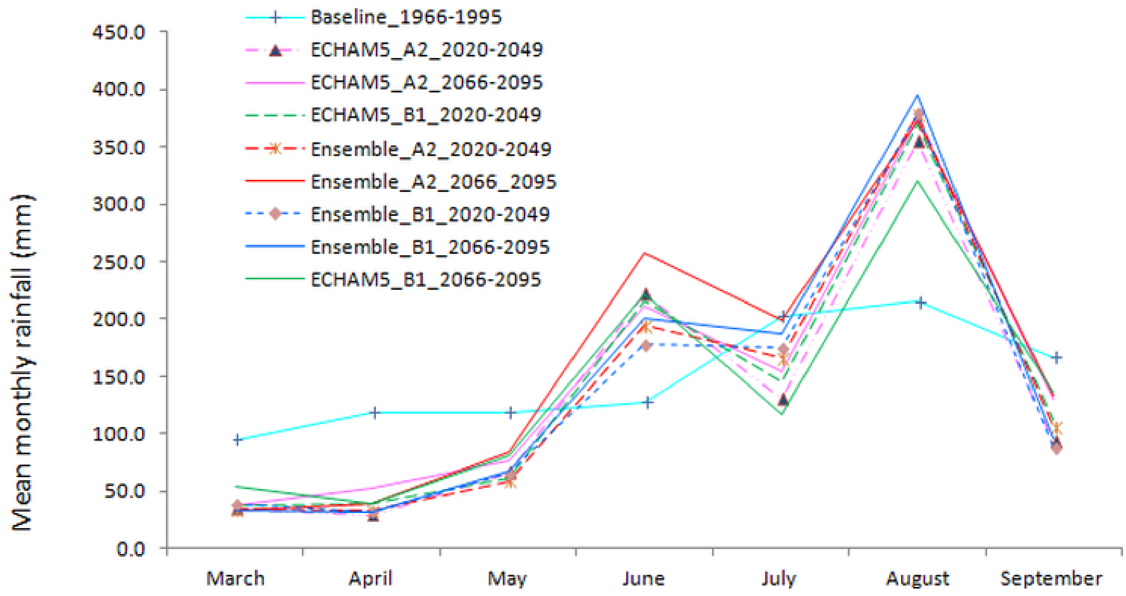
The projected mean onset for wheat at Assela is slightly earlier (2-7 June) than the baseline climate data (13 June) (Table 3.5). The projected cessation date for wheat at Assela was very late, occurring in the first week of December as compared to the baseline cessation date of 22 November

(Table 3.5). The projected LGP for wheat tends to increase for the future, under both scenarios. For the projection for the ensemble mean the onset and cessation of maize is almost similar for the Assela station, but for the Adama station the onset comes a month earlier as compared to ECHAM5 model and the cessation is almost the same for both scenarios.

Table 3.4 Change in maximum and minimum temperature (^{O}C) during *Belg* and *Kiremt* seasons and annually for the two future time periods using ECHAM5 and Ensemble mean of six GCMs under A2 & B1 SRES scenarios against baseline period, CRV, Ethiopia.

GCM	Season and station		Baseline	Future temperature simulation			
				A2 SRES Scenario		B1 SRES Scenario	
			1966-1995 Temp (^{O}C)	2020-2049	2066-2095	2020-2049	2066-2095
ECHAM5	***Belg* season**						
	Adama	Tmin	15.4	0.2	3.7	0.2	2.2
		Tmax	30.8	1.6	4.9	1.1	2.9
	Assela	Tmin	10.1	0.3	3.6	0.2	2.1
		Tmax	23.1	3.3	6.6	2.9	5.0
	Kiremt season						
	Adama	Tmin	15.8	0.7	3.8	0.5	2.4
		Tmax	27.5	2.8	6.1	2.5	4.8
	Assela	Tmin	10.1	1.9	4.9	1.6	3.5
		Tmax	20.3	4.1	7.1	3.5	5.8
	Annual						
	Adama	Tmin	14.1	3.8	0.5	0.4	2.3
		Tmax	29.7	4.5	1.4	1.1	3.0
	Assela	Tmin	8.9	1.1	4.3	1.0	2.8
		Tmax	21.6	2.5	5.6	2.1	4.2
Ensemble mean	***Belg* season**						
	Adama	Tmin	15.4	0.8	3.7	0.5	1.7
		Tmax	30.8	0.5	2.6	0.3	1.4
	Assela	Tmin	10.1	0.6	3.4	0.2	1.8
		Tmax	23.1	2.9	5.1	2.6	4.0
	***Kiremt* season**						
	Adama	Tmin	15.8	1.5	3.7	1.3	2.4
		Tmax	27.5	2.2	4.2	2.0	3.1
	Assela	Tmin	10.1	1.5	3.7	1.4	2.7
		Tmax	20.3	3.3	5.2	3.1	4.3
	Annual						
	Adama	Tmin	14.1	0.8	3.3	0.5	1.7
		Tmax	29.7	1.2	3.4	1.1	2.1
	Assela	Tmin	8.9	1.25	3.84	1.0	2.5
		Tmax	21.6	2.1	4.3	2.0	3.3

(a) Assela



(b) Adama

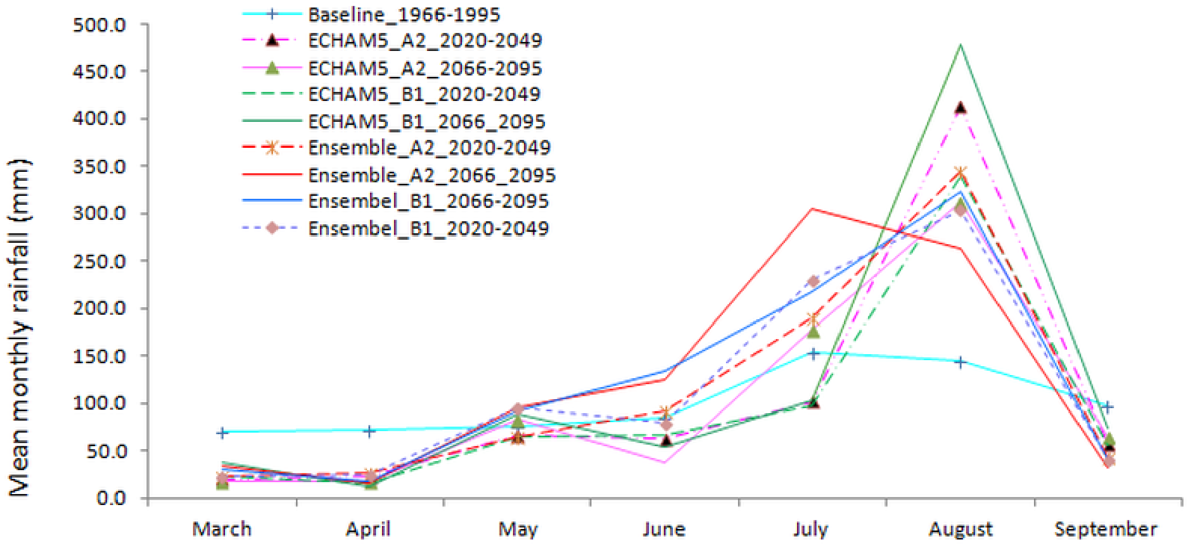


Figure 3.3 A 30-year monthly mean rainfall (mm) trend for baseline (1966-1995) and the two future climate periods (2020-2049 & 2066-2095) for ECHAM5 and ensemble mean of six GCMs under A2 & B1 SRES scenarios (a) for Assela and (b) Adama stations in the CRV of Ethiopia.

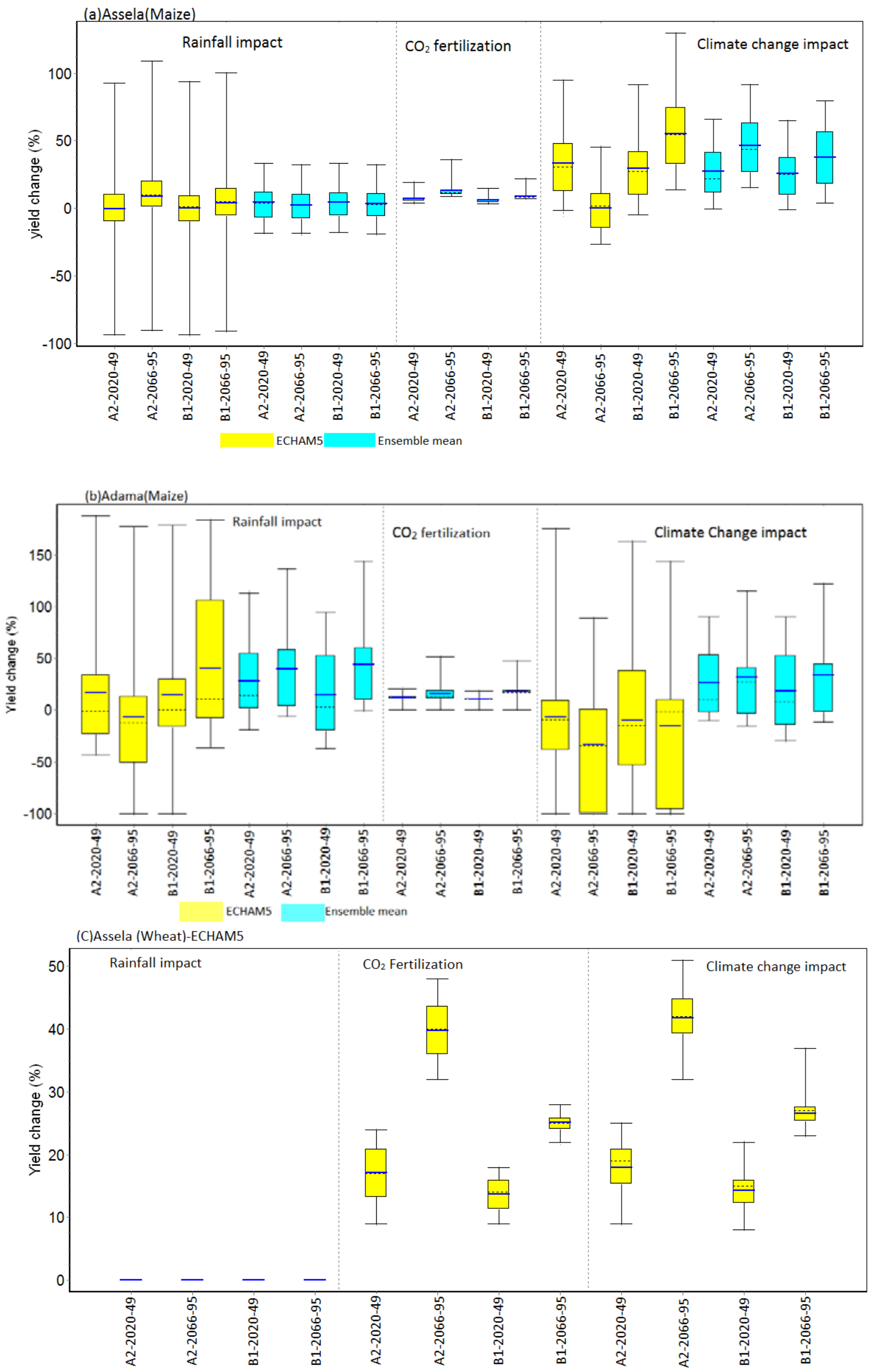


Figure 3.4 Impact of rainfall, CO_2 increase and climate change (CO_2, rainfall, temperature and ETo) on changes in maize yield (%). (a) Assela, (b) Adama under ECHAM5 and ensemble mean. (c) Assela for wheat yield (%)under ECHAM5 for two future climate periods (2020-2049 & 2066-2095) under A2 and B1 SRES scenarios against the 1966-1995 baseline period. The blue bold lines indicate the mean deviation. Boxes indicate inter-quartile ranges and error bars indicate minimum and maximum values.

Table 3.5 The mean onset and cessation dates and LGP (days) for maize (at Adama and Assela) and wheat crops (at Assela) for the baseline (1966-1995) and future climate (2020-2049 & 2066-2095) under ECHAM5 and ensemble mean based on A2 and B1 SRES scenarios, CRV, Ethiopia.

GCM model	Stations	Baseline period		Future climate							
				A2(High Emission)				B1(Low Emission)			
		1966-1995	SD	2020-2049	SD	2066-2095	SD	2020-2049	SD	2066-2095	SD
ECHAM5	**Adama(maize)**										
	Onset	7-Apr	31	13-Jul	36	14-May	26	22-Jun	36	6-Jun	30
	Cessation	9-Oct	18	8-Oct	2	4-Oct	3	6-Oct	2	8-Oct	8
	Duration	184	33	87	35	143	25	107	35	124	31
	Assela(maize)										
	Onset	29-Mar	28	19-May	2	12-May	17	18-May	1	19-May	1
	Cessation	15-Oct	14	26-Oct	16	5-Dec	8	19-Dec	8	5-Dec	1
	Duration	199	34	160	17	207	22	214	8	200	1
Ensemble mean	**Adama(maize)**										
	Onset	7-Apr	31	19-Jun	20	6-May	1	26-Jun	19	15-May	9
	Cessation	9-Oct	18	6-Oct	1	1-Oct	5	5-Oct	2	4-Oct	2
	Duration	184	33	109	20	148	1	101	19	142	9
	Assela(maize)										
	Onset	29-Mar	28	17-May	1	11-May	2	15-May	1	15-May	3
	Cessation	15-Oct	14	17-Dec	2	11-Dec	7	16-Dec	2	13-Dec	4
	Duration	199	34	214	2	214	9	215	1	212	6
ECHAM5	**Assela(wheat)**										
	Onset	13-Jun	13	2-Jun	2	7-Jun	3	5-Jun	4	3-Jun	2
	Cessation	22-Nov	14	5-Dec	7	4-Dec	8	18-Dec	8	4-Dec	3
	Duration	162	18	187	6	180	10	196	9	184	4

Dry spells

The projected changes in occurrence and length of dry spells, under ECHAM5 and ensemble mean of models, for different stages of maize growth vary by climate area. Under ECHAM5, in the sub-humid/humid areas (Assela) during flowering and grain filling stages (60-90 DAS), maize shows mean dry spell lengths of less than 10 days and a decline of up to 75% compared to the baseline dry spell. By contrast, in the semi-arid areas (Adama), maize will face mean dry spells of greater than 15 days, an increase by up to 300% compared to baseline dry spell. Generally, in the sub-humid/humid areas of the CRV during the consecutive 90 days of maize growing period it is unlikely to have dry spells lasting longer than 10 consecutive days for the two future periods under the two scenarios (e.g., Assela, Table 3.6), whereas the semi-arid areas are likely to face mean dry spells of greater than 15 days (e.g., Adama, Table 3.6). According to Biazin and Sterk (2013) the critical dry spells that cause total crop failure for maize crop in the Ethiopian CRV is greater than 30 days during the first 60 days after onset, or greater than 20 days during 60-90 days after onset, although 10-20 day dry spells during flowering can severely limit maize productivity. Therefore, under the projected climate, the humid (Assela) areas have a very low future risk of total crop failure due to dry spells, however semi-arid areas (Adama) could be at risk during the flowering and grain filling stages – if not for total crop failure, at least severe damage is likely to occur. The occurrence of dry spells on both models follow more or less the same pattern on both stations except at Adama where there was a modest decrease of dry spells mostly during the critical growth stage (60-90 DAS) under the ensemble mean of models.

For wheat, during the first 90 days of crop growth there is no continuous dry spell longer than 10 days during the baseline or future climate scenarios (Table 3.6). However, the change in length of dry spell during the projected climate scenarios shows a dramatic increase, >100% during 30-60 days after sowing (Table 3.6). Other stages of wheat growing period, 1-30 and 60-90 DAS showed either small increases or decrease or no trend (Table 3.6). Similarly, Segele and Lamb (2005) from their dry spell analyses of *Kiremt* season concluded that 3-5 continuous days of no rain are quite common over most of the *Kiremt* regions in Ethiopia. However, dry spells of greater than 10 days are limited to lowland areas of extreme western and north-eastern Ethiopia where rainfall variability is high.

Maize yield

Under ECHAM5 model, the mean simulated maize yield in response to projected rainfall changes alone shows an increase of 1-11% at Assela and 3-30% at Adama, with the exception of the A2 scenario during the 2066-2095 period in Adama which showed a 7% reduction (Figure 3.4b). The simulations suggest more impact under the conditions in Adama. Previous studies have also reported increasing yields. For example, Jones and Thornton (2003) and Thornton et al., (2009) found that maize yield can be expected to increase in the central and southern Ethiopian highlands.

The elevated CO_2 at Assela increased the mean simulated maize yield by 7% during 2020-2049 and 13% during 2066-2095 under the A2-scenario Figure 3.4a). Similarly, the mean simulated maize yield increased by 6% during 2020-2049 and 9% during 2066-2095 under the B1 scenario. At Adama, mean simulated maize yield increased in the range of 7-14% under elevated CO_2 under both scenarios.

The overall impact of climate change is quite different for the two stations. For Assela mean yield is projected to increase by 33-37% between 2020 and 2049 under both scenarios (A2 and B1). The effects under scenarios A2 and B1 for the 2066-2095 period are quite different for Assela. Under the B1 scenario, an increase of 59% between 2066 and 2095 is projected; however, the A2 scenario shows no change in yield, which could be due to enhanced ET_O resulting from the expected increase in temperature from high emissions scenario around the end of the century. At Adama, despite the generally projected increase in mean yield from rainfall change and CO_2 increase alone, the overall climate change impact is likely to show a yield decline ranging between 11% and 46%. The decrease in yield from overall climate change impact was due to increased ET_O that results from increased temperatures and also from the projected increase in dry spell duration mainly during 60-90 DAS at Adama.

Table 3.6 The mean dry spell (days) and percentage changes for future climate (2020-2049 & 2066-2095) during the first 90 days of growing season for maize under ECHAM5 and ensemble mean and wheat under ECHAM5 only under A2 and B1 SRES scenarios in the CRV of Ethiopia.

GCM model	Stations	Baseline	Future climate							
			A2(High Emission)				B1(Low Emission)			
		1966-1995	2020-2049	Change (%)	2066-2095	Change (%)	2020-2049	Change (%)	2066-2095	Change (%)
ECHAM5	**Adama(maize)**									
	1-30DAS	7	3	-58	7	0	5	-30	7	0
	31-60	12	8	-36	11	-8	10	-17	16	36
	61-90	6	24	274	15	140	17	165	18	187
	Assela(maize)									
	1-30DAS	6	8	33	9	49	8.6	49	8	37
	31-60	10	8	-20	7	-31	8.2	-21	10	0
	61-90	8	2	-80	3	-65	2.5	-80	6	-20
Ensemble mean	**Adama(maize)**									
	1-30DAS	7	6	-14	9	29	3	-57	8	14
	31-60	12	14	17	8	-33	6	-17	8	-33
	61-90	6	19	217	1	-83	19	217	2	-67
	Assela(maize)									
	1-30DAS	6	9	50	9	50	9	50	9	50
	31-60	10	8	-20	5	-50	8	-20	7	-30
	61-90	8	2	-75	3	-63	2	-75	2	-75
ECHAM5	**Assela(wheat)**									
	1-30DAS	4	4	0	3	-25	4	0	4	0
	31-60	3	8	167	6	100	8	167	10	233
	61-90	3	3	0	4	33	3	0	8	167

Under ensemble mean, more yield difference due to rainfall impact was projected at Adama during 2066-2095 for A2 as compared to ECHAM5 model. The projected increase in maize yield under ensemble mean was 39% while the projected increase in maize yield under ECHAM5 was only 7%. This yield difference between the ECHAM5 model and the ensemble mean was due to their projected rainfall and subsequent dry spell differences. Where under ECHAM5 model the *Kiremt* rainfall showed increase by only 23% while under ensemble mean the *Kiremt* rainfall showed increase by 50%. Accordingly, the projected dry spell under ensemble mean was almost non-existent during the critical growth stage of maize (60-90 DAS), whereas under ECHAM5 there was 15 days of dry spell during this growth stage. At Assela, the rainfall impact is almost the same under both models. However, the overall impact of climate change on maize yield was different under the two models. Maize yield showed a 46% increase under ensemble mean during 2066-2095 for A2, while it remains level under the ECHAM5 model. This could be because the maximum temperature during *Kiremt* under ECHAM5 (7.1°C) was higher than that under the ensemble mean model (5.2°C). This increase in temperature under ECHAM5 can increase ET_O that leads to water stress and yield decrease. Similarly, at Adama the overall impact of climate on crop yield was different for the two models, where ensemble mean projected 18-35% yield increase and ECHAM5 projected 11%-46% yield decrease. This difference between the two models could be due to their projected temperature difference during *Kiremt* which increases water stress because of ET_O increase.

Generally, both ECHAM5 and ensemble mean model projected increasing maize yield at Assela station under both A2 and B1 scenarios in response to all effects (CO_2, rainfall and combined effect). But, at Adama maize yield is projected to increase under ensemble mean for both A2 and B1 scenarios in response to all effects (CO_2, rainfall and combined climate change effect), while it is projected to decline under ECHAM5 model in response to the combined climate change effect.

Wheat yield

There is no yield difference from rainfall impact between the baseline and projected climate for wheat (Figure 3.4c). As water is not a limiting factor for wheat grown during *Kiremt* under the baseline climate, attainable yield is already obtained during the baseline climate. Even under increased ET_O in the projected climate simulations there is no water stress for wheat due to sufficient moisture during this season. Therefore, yield increase from the baseline climate shown in Figure 3.4c is obtained from projected CO_2 increase, which shows a maximum yield increase of up to 17% and 40% during 2020-2049 and 2066-2095, respectively, under A2 emission scenario. Similarly under B1 emission scenario the mean yield is projected to increase by 14% during 2020-2049 and by 25% during 2066-2095.

Hence, the simulated increase in wheat yield from the combined effect of climate change and elevated CO_2 was almost the same to that of the simulated yield obtained from CO_2 fertilization because the increment was solely from elevated CO_2. There are previous studies that obtained an increase in wheat yield by up to 30-40% when CO_2 concentration reached 700 ppm (Nonhebel 1993; Yang et al., 2013).

3.4.Conclusions

This study shows that the total rainfall during *Kiremt* is likely to increase in the future in the CRV of Ethiopia. The *Belg* rainfall which is already erratic, occurring very late or failing altogether for the current climate will continue to decrease during the rest of this century which makes future *Belg* crop production very difficult. However, for long cycle crops like maize, despite the late onset of *Belg* rainfall, the effect would be minimal because these crops could benefit from the extended cessation of the *Kiremt* rainfall. In addition, projections indicate a decrease in the occurrence of prolonged dry spells during *Kiremt* which will decrease the risk of soil moisture stress and, hence, reduced risk of crop failure. Thus, the choice of long maturing maize varieties could be considered an option for adaptation to the future climate. Long cycle crops, if sufficient agricultural inputs could be made available, are often substantially more productive than short cycle varieties planted during the *Kiremt* season (Meza et al., 2009).

Overall, the predicted changes in climate factors are expected to increase crop yields in the sub-humid/humid regions, with increased rainfall and elevated CO_2 concentration benefiting yield of long cycle maize, and elevated CO_2 benefiting *Kiremt* wheat yields. However, in semi-arid areas of the CRV, under ECHAM5 model projection, the overall projected climate change will affect the yield of long cycle crops negatively because of the prolonged dry spells and a shorter growing period due to late onset and early cessation. The projection of the ensemble mean of models indicates that the yield of maize is likely to increase due to climate change in the CRV. Although the two GCMs showed similar trends of changes in seasonal rainfall amounts and temperature in the future, they predicted different trends of changes in dry spells in some sites of the CRV. This has also caused a difference in the predicted yields of crops. Overall, this study revealed that crop yield simulations with GCMs for future climate change scenarios must be combined with detailed simulation of climate parameters like dry spells which are crucial particularly in dry land parts of the world.

Despite uncertainties with regard to the estimation of climate variables, particularly rainfall and changes in future crop yields, this study provides important insights into potential impacts of climate change on major crops at the local scale and can be used for developing local level adaptive responses.

Chapter 4

Bridging dry spells for maize cropping through supplemental irrigation in the Central Rift Valley of Ethiopia

Abstract

Maize yield in the Central Rift Valley of Ethiopia (CRV) suffers from dry spells at sensitive growth stages. Risk of crop failure makes farmers reluctant to invest in fertilizer. This makes the CRV food insecure. There are farms with well-maintained terraces and Rain Water Harvesting (RWH) systems using concrete farms ponds. We tested the hypothesis that in these farms SI with simultaneous crop intensification might boost production of a small maize area sufficient to improve food security. Intensification includes a higher plant density of a hybrid variety under optimum fertilization. First we assessed the probability of occurrence of dry spells. Then we estimated the availability of sufficient runoff in dry years. During 2012 (dry) and 2013 (wet) on-farm field research was conducted with 10 combinations of SI and plant density. The simplest was rainfed farming with 30,000 plants ha^{-1}. The most advanced was no water stress and 75,000 plants ha^{-1}. Finally we compared our on-farm yield with that of neighbouring farmers. Because 2013 was a wet year no irrigation was needed. Our long term daily rainfall (1970-2011) analysis proves the occurrence of dry spells during the onset of the maize (*Belg* months March and April). In March there is hardly enough water in the ponds. Starting from April there is more available water (runoff from a 2.2 ha catchment) than crop water requirement (for 0.5 ha maize). So, we recommend a later sowing for maize in the CRV. Significant differences between grain and total biomass yield were observed between rainfed and other irrigation levels. However, since it is not financially feasible the investment in SI during non-critical drought years is not worth the effort. A significant yield increase obtained as we increase plant density from 30,000 plants ha^{-1}to 75,000 plants ha^{-1}prompted us to advise farmers to use the highest plant density (75,000 plants ha^{-1}). The grain yield and total biomass difference between farmers own practice and our on-farm research was 101% and 84% respectively in 2012. This large increase in grain yield is contributed to the higher use of (150% recommended) of fertilizer against the current use (50% or less) by adjacent farmers. Our hypothesis was that SI in combination with increased plant density under optimum fertilizer use would bridge dry spells, reduced risk of crop failure and increase grain yield. This hypothesis could not be fully proven with our only 2 years experiment particularly in a critical drought condition.

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Bridging dry spells for maize cropping through supplemental irrigation in the Central Rift Valley of Ethiopia

4.1 Introduction

According to the Millennium Ecosystem Assessment (2005) the food security of smallholder farmers in sub-Saharan Africa (SSA) is largely constrained by water availability. However, in many sub-Saharan African countries there is sufficient average rainfall over the crop season to obtain good yields, but yields are greatly reduced by periods of > 10 consecutive dry days at critical growth stages of the crop. Water stress at flowering stage of maize, for example, reduces yields by 60%, even if water is adequate throughout the crop season (Seckler and Amarasinghe, 2000). Therefore, the key challenge is to reduce water shortage-related risks posed by high rainfall variability rather than coping with an absolute lack of water.

A related problem is that, due to the potential risk of crop failure from periodic water scarcity, small-holder farmers in the semi-arid tropics are not willing to invest in fertilizer and other inputs (Rockström et al., 2002). This can be attributed to farmers' aversion to risk. Thus, less risk of crop failure due to crop water deficits may improve farmers' willingness and ability to further invest in fertilizers and other management strategies (Barron, 2004).

Rain water harvesting (RWH) for supplemental irrigation (SI) is one of the tools for small-holder farmers to ensure crop water supply (Fox and Rockström, 2003; Falkenmark and Rockström, 2004; UNDP, 2006). RWH can increase opportunities for crop intensification and investments in smallholder farming (Pachpute et al., 2009). Posthumus and Stroosnijder (2010) argued that increased water availability from supplemental irrigation (SI) in combination with terraces, used as in situ soil and water conservation, allows higher crop densities and subsequently higher yields.

In Ethiopia rain water harvesting technologies (RWHT) were introduced and encouraged on a large scale for field crop production since early 2000s (Wakeyo and Gardebroek, 2013). However, it is mostly limited to vegetable production at home backyards (Getnet and MacAlister, 2012). Ponds are the dominant water harvesting technologies used in Ethiopia, accounting for 65% of the constructed RWHTs. The surface of ponds is often sealed with cement concrete, plastic or clay so that they can hold water for a relatively long time (Wakeyo and Gardebroek, 2013).

The Central Rift Valley (CRV) of Ethiopia is one of the most drought prone areas in Ethiopia (Biazin and Stroosnijder, 2012). Halaba *Special Woreda*, where our study was conducted, is one of the areas most affected by recurrent drought and crop failure. Hence it is known as a drought-prone and food insecure *woreda*. Farmers in this *Woreda* are constrained from using fertilizer by risk of crop failure due to high chances of a dry spell occurring in the growing season and the high level of fertilizer prices (Hulst, 2012). Surface and ground water resources are limited. In Halaba, as a means of coping with water scarcity, RWH in the form of individual farm ponds is practiced. The water of these ponds is mainly used for small-scale vegetable cropping, livestock and household.

In Halaba, maize is the staple crop grown on more than 50% of the cultivable land, while all other crops grown in the area such as tef, wheat, pepper, haricot bean, sorghum and millet account for the remaining 50% of the area. Long cycle maize (145 days) is grown with planting in the *Belg* season (March-May) and harvested at the end of the *Kiremt season* (September-December). Dry spells during the *Belg* create serious moisture stress at critical stages of crop growth causing widespread damage to the maize in Halaba in particular (Gebremichael, et al., 2014). A similar study by Muluneh et al. (2015) in the CRV showed that the effect of climate change will become more serious during the *Belg* season.

In Ethiopia, due to its high yield potential and wide adaptation, maize has been selected as one of the national commodity crops to satisfy the food self-sufficiency program of the country (Kebede et al., 1993). It is common believe that SI for staple crops is not realistic. However, we hypothesize that though intensification of maize cropping on a limited area SI may bridge dry spells, reduce risk of crop failure and increase yield that can ultimately solve very food insecure situations as in Halaba area. Under such a situation SI is a viable activity. The higher the degree of intensification, the higher the water productivity, i.e. the number of kg biomass that is produced per m^3 of water. Therefore, we include SI, optimum fertilization and plant density in our crop intensification. Conditions in Halaba seem advantageous; terraces are commonly used for a combination of soil conservation and water conservation (Hurni, 1984), and a number of RWH ponds already exists, are maintained and used.

Plant density is one of the most important cultural practices that influences maize grain yield (Sangoi, 2000). At low densities, many modern maize hybrids do not tiller effectively and quite often produce only one ear per plant (Sangoi, 2000). The introduction of hybrids with higher plant densities due to narrower spacing of rows can use available light more efficiently and also shade the surface soil more completely during the early part of the season while the soil is still moist (Bullock et al., 1998). Therefore, less water will be lost from the soil surface by soil evaporation. On the other hand, maize grain yield declines when plant density is increased beyond the optimum plant density primarily because of decline in the harvest index and increased stem lodging (Tollenaar *et al*. 1997). This is due to intense interplant competition for incident light, soil nutrients and soil water. Thus, there is an optimum population density that maximizes the utilization of available resources.

Existing studies indicate that maize plant density for maximum grain yield varies from 30000 to over 90000 plants ha^{-1}(Olson & Sanders,1988). Traditionally, farmers in the CRV use 30000-40000 plants ha^{-1} for maize. However, for most hybrid maize varieties released in Ethiopia, plant density has not been determined under different environmental conditions.

In this study we investigate whether maize intensification using SI, optimum plant density under optimum fertilizer in terraced farms is a viable option in significantly improving crop yield and water productivity in Ethiopia's CRV. The specific objectives of this study were: (i) to assess occurrence of dry spell, (ii) to evaluate the potential of RWH to irrigate maize, (iii) to identify an optimum combination of plant density and irrigation for maximum yield, and (iv) to compare yield between on-farm experiments and farmers own practices.

4.2 Materials and methods

Site description

The field experiment site is located in the CRV of Ethiopia at Halaba *Special Woreda* (district) (7°17'N and 38°06'E), which is situated 315 km south of Addis Ababa and about 85 km northwest of the regional capital, Hawassa (Figure 4.1). The *Woreda* lies at an altitude between 1554 – 2149 m.a.s.l, but most of the *woreda* is found at about 1800 m.a.s.l., with the topography ranging from flat (61.3%), rolling (21.3%) and hilly (17.4%) terrain. The experimental farms are located in the rolling terrain.

The climate of the study area is dry sub-humid, with an aridity index of 0.56 computed as the ratio of mean annual precipitation to mean annual ETo. The study area is characterized by two rainy seasons: *Belg and Kiremt.* The small rainy season (*Belg)* is during March-May and the main rainy season (*Kiremt*) is during June-September. The annual rainfall varies between 675 to 1221 mm with a mean of 922 mm for the past 42 years (1970-2011).

According to the FAO classification system, the most dominant soil of the *woreda* is Vitric Andosol (Itanna, 2005). As a result of a long history of agriculture and high population pressure in the area, vegetative cover is very low. Consequently, there is an erosion hazard in sloping areas. Gullies are common in many areas of the *Woreda*, which is aggravated by the easily detachable nature of the soil. Generally, due to intense de-vegetation taking place in the CRV the organic matter (OM) in soils declined between 59% and 70% in 25 years (1975–2000), with an average OM loss of about 2.6% a year (Itanna, 2005). A similar study in Ethiopia proved that soil fertility declines as land use changed from forest to grazing and cultivated lands (Habtamu et al**.,** 2014).

Soil physical characteristics such as bulk density, field capacity, permanent wilting point and water content at saturation were determined in the laboratory (Table 4.1).

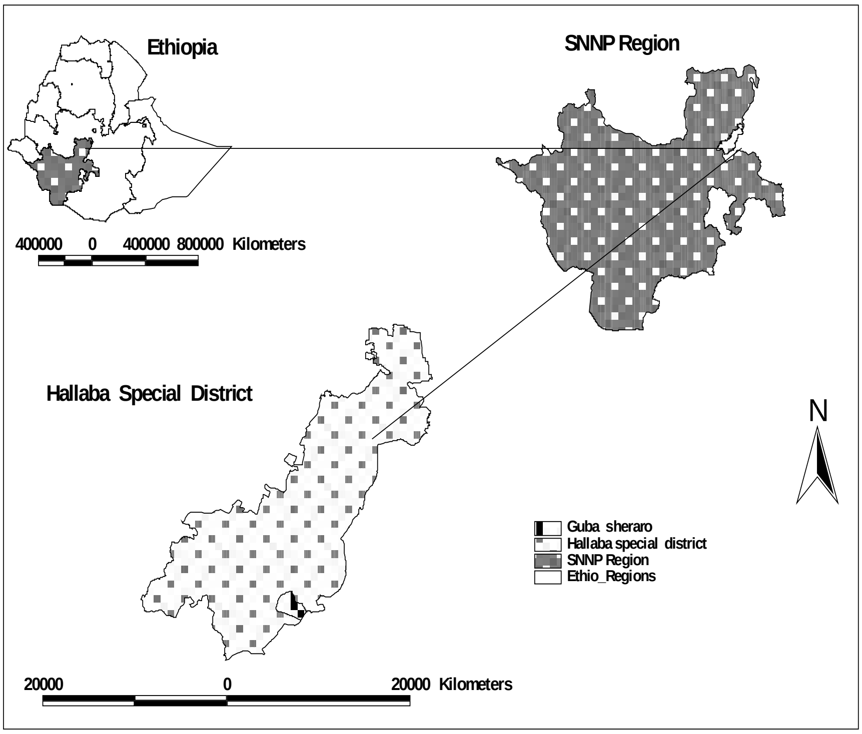

Figure 4.1 Location of the study area, Halaba *special woreda*, Central Rift valley of Ethiopia

Table 4.1 Soil physical properties of experimental fields (n=9) at the research site, Halaba *special Woreda*, CRV, Ethiopia.

	Soil water content (vol %)			
Soil layer(m)	Sat	FC	PWP	BD (gcm^{-3})
0.0-0.20	42.79(1.98)	27.71(1.07)	10.43(0.49)	1.02(0.032)
0.20-0.40	42.56(1.05)	30.99(1.40)	11.43(0.22)	0.94(0.038)
0.40-0.60	44.30(2.45)	28.13(0.77)	12.13(0.97)	0.94(0.104)

Sat, water content at saturation; FC, field capacity; PWP, permanent wilting point; BD, bulk density. Standard error of the mean in parenthesis.

Rainfall data

We used 42 years (1970-2011) of daily rainfall data from the National Meteorological Agency of Ethiopia with good quality data (less than 10% missing values) of Halaba station. This station is located in the eastern escarpment of the CRV (the dry sub-humid eco-climatic zone) and closest to our experimental site. The analysis of dry spells was carried out using the statistical package Instat+3.6 (Stern et al*.,* 2006). A dry spell was defined previously in Africa as a continuous period of "no rainfall" (< 0.85 mm day^{-1}) during the growing season after sowing (Rockström et al., 2003).

Meteorological observations were made over the entire experimental period of 2012 and 2013 using an automatic weather station (Eijkelkamp Equipment, Model 16:99 Giesbeek, the Netherlands). The data included rainfall, temperature, wind speed, sunshine hours, relative humidity and incoming radiation.

Runoff potential

The Soil Conservation Service Curve Number (SCS-CN) method was used to estimate surface runoff of daily rainfall data at Halaba *special Woreda*. The SCS-CN method, developed by the USDA-Soil Conservation Service (SCS, 1972) is widely used for the estimation of direct runoff in catchments ranging in size 0.25 ha to 1000 km^2 (Boughton, 1989). The method uses a formula where Q =f (P, Ia), where Q is amount of surface runoff (mm); P is rainfall amount (mm) and Ia is the initial abstraction, i.e. the amount of water that infiltrates before runoff occurs (mm). Estimated I_a (0.2S) by the standard SCS-CN method underestimates observed surface runoff (Shi et al., 2009).

It was Hawkins et al. (2002) who first developed a new curve number (CN) with a new value of Ia=0.05S from the previous Ia=0.2S. They determined the new relationship by converting the 0.2 based CN to 0.05 CN from model fitting results using rainfall-runoff data from 3078 watersheds (Eq. 4.1 & 4.2).

$$S_{0.05} = 0.8187 S_{0.2}^{1.15} \qquad \text{(Eq. 4.1)}$$

$$CN_{0.05} = \frac{100}{1.879\left[\frac{100}{CN_{0.2}} - 1\right]^{1.15} + 1} \qquad \text{(Eq. 4.2)}$$

Where $S_{0.05}$ and $S_{0.2}$ (mm); $S_{0.05}$ and $CN_{0.05}$ are the storage and CN values with an initial abstraction ratio (Ia/S) of 0.05Ia/S and $CN_{0.2}$ and $CN_{0.2}$ are the values with a 0.2 Ia/S ratio. The CN values ($CN_{0.2}$ and $CN_{0.05}$) were computed with the corresponding S values ($S_{0.2}$ and $S_{0.05}$) using Eq.2. The $CN_{0.2}$ and $S_{0.2}$ are derived from the original SCS-CN (SCS, 1972) equation. Therefore, we used a modified expression for Ia based on earlier studies in Ethiopia (e.g. Descheemaeker et al., 2008; Teka et al., 2013) and elsewhere (Hawkins et al., 2002; Lim et al., 2006; Shi et al., 2009; Gao et al., 2012).

The CN of a soil is a function of hydrologic soil group, slope, land use, cover and the relative wetness of the top soil (antecedent soil water conditions). The runoff harvesting catchment in our study area is a small catchment with homogenous soil, slope and land use type. The catchment area is a cropping land with slightly sloping land surface of about 5% and moderate soil water infiltration. The catchment area was estimated from empirical assessment of runoff after a rainstorm.

CN values were estimated for various Antecedent Moisture Classes (AMC) using the SCS standard Table (Table 4.5 in USDA-SCS, 1993). The 5-day rainfall prior to each event was used to estimate the relevant AMC class.

Outcome of the SCS model was validated by comparing estimated runoff with measured runoff for nine selected events in the 2012 cropping season. Runoff was measured in the collection tanks. The model efficiency was evaluated by Nash & Sutcliff (1970) equation (Eq.4.3) and the Root Mean Square Error (RMSE) (Eq.4.4):

$$ME = 1 - \frac{\sum_{i=1}^{n}(Q_{obs} - Q_{est})^2}{\sum_{i=1}^{n}(Q_{obs} - Q_{mean})^2} \qquad (Eq. 4.3)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Q_{obs} - Q_{est})^2}{n}} \qquad (Eq. 4.4)$$

Where, Q_{obs} is the observed runoff; Q_{est} is the estimated runoff. Values for ME can range between $-\infty$ to 1 and ME values closer to 1 and RMSE value closer to 0 indicates better model performance.

Water yield potential of a catchment for harvesting water is estimated from surface runoff. To estimate runoff potential, it is important to consider the probability of exceedance of a certain amount of rainfall (Ngigi et al., 2005). Therefore, we used daily rainfall events of dry years to estimate the runoff potential. The 80% dependable rainfall that could likely occur in 4 out of 5 years (characterized as a dry year) was used to calculate potential rainwater harvesting from the catchment area that feeds runoff into the water harvesting ponds. Long term seasonal rainfall probability was calculated using the following equation (Chow et. al 1988) (Eq. 4.5):

$$P(\%) = \left(\frac{M - 0.375}{N + 0.25}\right) * 10 \qquad (Eq. 4.5)$$

Where, P-rainfall probability in % of the observation of the rank 'm', m-rank of observed rainfall value (highest = 1; lowest = N); N-total number of observations.

The individual rainfall events of 80% dependable rainfall years were used to calculate runoff with the validated SCS method. Furthermore, runoff was calculated for years with longest dry spells (>20 days) that can affect crop yields significantly during the first 90 days after sowing (cf. Araya et al., 2010, 2012) and remained within the 80% dependable rainfall.

Crop water requirement

For the design of SI systems, it is necessary to assess the water requirement of the crop intended to be grown. The maximum crop water requirements of maize during the maize crop growing season (March-September) were determined based on Allen et al. (1998) (Eq. 4.6):

$$ET_c = K_c ET_o \qquad (Eq. 4.6)$$

Where *ET*c (mm day^{-1}) is the maximum crop water requirement computed for optimal conditions, *k*c is the crop coefficient where its values was taken from Table 17 of FAO-56 (Allen et al., 1998) at different crop growth stages and ET_o (mm day^{-1}) is the reference crop evapotranspiration.

ET_o was first determined using limited climate data with the daily long term temperature (1970-2011) based on FAO Penman–Monteith method and then calibrated using two years of observed full climatic data (2012 and 2013) from an automatic weather station installed at the study area and the empirical coefficients (R^2=0.88;N=188) were determined as (Eq. 4.7).

$$ET_O = 1.10ET_{O\ tmp} - 0.82 \qquad (Eq. 4.7)$$

Where $ET_{o\ tmp}$ is The ET_o determined from only long term maximum and minimum temperature.

Field experiment

An experiment was conducted on smallholder farmers' fields in three farms with terraces and farm ponds. The experiment was laid in Randomized Complete Block Design (RCBD) with combined treatments of SI and plant density. The three farms were close by each other; two of them side by side and the third about 50 meters away, which help to have more or less homogeneous slope and soil conditions.

Experimental plots are located at terraces of about 15 m wide, constructed more than a decade ago with the objective to prevent runoff and to conserve soil and water. The terraces were gradually formed behind constructed contour soil bunds. The terraces are well maintained and stabilized by plantation of terrace edges with elephant and vetiver grasses and other vegetation types. The terraces are combined with water harvesting ponds' where occasional runoff, instead of being considered as a problem, is being harvested and used for different purposes, water that otherwise gets lost and causes soil erosion.

The three farms were used as replicates, each farm having 10 treatments with a plot size of 5 m x 4m (20 m2). The combinations of plant density and SI treatments are shown in Table 4.2. The lowest irrigation treatment which is rainfed alone was combined only with the lowest plant density because having a higher planting density will not be a realistic situation.

The experiment was conducted during 2012 and 2013 growing seasons. During 2012 the sowing date was on May 2 and the harvesting on September 22 while in 2013 the sowing was on May 26 and harvesting October 17. During the experimental years (2012 and 2013), the choice of sowing dates was based on availability of sufficient water harvested in the ponds for the supplemental irrigation during the experiment. The length of growing period from sowing to harvest is 145 days based on the time it takes for full physiological maturity of BH540 maize hybrid given by the Ethiopian Institute of Agricultural Research (EIAR, 2004).

Table 4.2 Supplemental irrigation and plant density combination during the field experiment, 2012, Halaba special *Woreda*, CRV, Ethiopia

Irrigation	Density	Combination	Description
SI1	D1	SI1D1	Rainfed and 30000 plants ha^{-1}
SI2	D1	SI2D1	75% TAW depleted and 30000 plants ha^{-1}
	D2	SI2D2	75% TAW depleted and 45000 plants ha^{-1}
SI3	D1	SI3D1	60% TAW depleted and 30000 plants ha^{-1}
	D2	SI3D2	60% TAW depleted and 45000 plants ha^{-1}
	D3	SI3D3	60% TAW depleted and 60000 plants ha^{-1}
SI4	D1	SI4D1	No water stress and 30000 plants ha^{-1}
	D2	SI4D2	No water stress and 45000 plants ha^{-1}
	D3	SI4D3	No water stress and 60000 plants ha^{-1}
	D4	SI4D4	No water stress and 75000 plants ha^{-1}

Irrigation

The SI treatments were SI1, SI2, SI3 and SI4 where SI1 is only rainfed without SI. The total available water (TAW) in the root zone (60 cm) is about 105 mm. In SI2 we applied SI when the percentage of soil moisture depletion (SWD) of TAW reached 75%, i.e. when available water (AW) reached 26 mm. In SI3 we applied SI when the SWD reached 60% of TAW, i.e. when AW reached 42 mm. In treatment SI4 we kept AW as much as possible close to TAW. Since it was practically difficult to keep the moisture content all the time at field capacity, we irrigated when SWD dropped below 20%, i.e. when AW reached 84 mm.

Application of SI was done using drip irrigation, since it is a method to apply precise amounts where it is needed, while minimizing evaporation losses. As described by Polak *et al.* (1997), a low cost drip irrigation system, with no emitters but holes in the lines at every 0.30 m that uses simple containers with cloth filters for the water was used. The potential for micro irrigation such as drip irrigation is high in Ethiopia, because it is already successful at an individual level (Awulachew et al 2005).

For the SI of the three farms, the experiment used two already existed household water harvesting farm ponds located close to each other in the two farms (Figure 4.2). The total volume of water in the two farm ponds is about 345 m^3 that collects runoff from 2.2 ha catchment area.

Figure 4.2 Farm ponds in Halaba *special woreda* (Central Rift valley of Ethiopia) with sediment trap in front.

When the percentage depletion of available soil water in the root zone reaches the predefined level of depletion, the amount of water applied was calculated by the following equation (Panda et al., 2004):

$$Vd = SWD\% \, (\theta_{FC} - \theta_{PWP}) * \; D_{z\,*} A \qquad \text{(Eq. 4.8)}$$

Where Vd is the volume of SI (m^3), Dz the rooting depth (m) and A the surface area (m^2) of the irrigated plot. The rooting depth varies based on the continuous assessment of the depth of the plant root.

Cropping

A widely used maize hybrid in the CRV BH540 (Bako hybrid-540) was used for this experiment. It is highly suitable for areas with altitudes varying from 1200-1800 m.a.s.l and well suited to a climate zone with a rainfall between 979 and 1040 mm and temperature 17-23 ^{O}C. According to the EIAR (EIAR, 2004)**,** attainable yield obtained at experimental stations for maize cultivar BH540 is 8-10 t ha^{-1}.

The SIs treatments were tested with a combination of four different plant densities: D1, D2, D3 and D4, where D1 is a density of 30000 plants ha^{-1}, D2 is 45000 plants ha^{-1}, D3 is 60000 plants ha^{-1} and D4 is 75000 plants ha^{-1}.

The distance between plant rows ranges from 1.0 m for D1 to 0.45 m for D4, while we kept the distance between plants in the rows at 0.3 m for all 4 densities to coincide with drip hole distances. The recommendation from the Ethiopian Institute of Agricultural Research (EIAR) is 0.75 m between rows and 0.30 m between plants in the row.

Fertilizer was applied at 150% of the recommended amount to keep soil fertility at non-limiting level. For the CRV, the recommended fertilizer level is 100 kg of Urea and 100 kg of DAP (Debelle et al., 2001; Demeke et al., 1997). DAP was applied at planting whereas urea was side dressed at about 4 weeks after planting.

Routine farmers' practices were carried out by local farmers such as ploughing, weeding, application of insecticide*, shilshalo, etc. Shilshalo* is carried out about a month after sowing the maize which is the *s*econd ploughing of maize fields to break the superficial crust of the soil between the maize rows, which can be seen as an in-situ water harvesting technique. Stem borer infestation was controlled by application of Diazonan 60% EC insecticide.

Total above ground biomass and grain yields were determined at maturity by hand-harvesting the crop from two one square meter area in each experimental plots and farmers' own plots. The biomass and grain yields were weighed after oven drying at 70^{o}C for 48 hrs. Samples from farmers own plots were also collected from farms located at the close proximity to our on-farm experiment plots. All agricultural practices, sowing date, the slope and soil of farmers own practice plots and on farm research plots was the same. Since farmers own planting density was found to be comparable to on farm field research plant density D1, yield comparison was made between farmers own practice maize yield with on farm plant density D1 both with only rainfed.

Soil moisture and evapotranspiration

Based on periodical soil moisture measurements, the application date and quantity of SI were scheduled. Soil water content profiles were measured at soil depths of 20, 40 and 60 cm once a week with a Time-Domain-Reflectometer (TDR) (Eijkelkamp Equipment, Model 14.62, Giesbeek, Netherlands). Access tubes were installed at the center of each experimental plot. Additionally, gravimetric water content was determined during the growing season. Gravimetric values were converted to volumetric values by multiplying with the bulk density and use for calibrating the TDR (R^2 = 0.80, N = 26).

$$\text{Soil water content (vol\%)} = 1.4 \times \text{TDR reading (vol \%)} + 4.57 \qquad (\text{Eq. } 4.9)$$

The percentage depletion of the TAW in the root zone (SWD %) was estimated with the following equation (Martin et al., 1990).

$$SWD\% = \frac{(\theta_{FC} - \theta_i)}{(\theta_{FC} - \theta_{WP})}\, 100 \qquad \text{(Eq. 4.10)}$$

Where θ_{FC} is the field capacity soil water, the θ_{WP} is the water content at permanent wilting point and θ_i is the actual soil moisture measured. Actual crop evapotranspiration in 2012 and 2013 was estimated during the experiments with

a soil water balance using Eq. (4.11).

$$ET_c = P + IR + \; -DP - R \pm \Delta\theta \qquad (Eq. 4.11)$$

Where P is precipitation (mm), IR is irrigation (mm), DP deep percolation (mm), R runoff (mm) and $\Delta\theta$ is the change in soil water (mm) as measured with the TDR or gravimetrically. Runoff in the plots is insignificant since the plots were very flat. From the soil moisture measurements, deep percolation below the root zone of the crop could also be considered minimal. Therefore, Eq. (4.11) was simplified to:

$$ET_c = P + IR \pm \Delta\theta \qquad (Eq. 4.12)$$

Water productivity

The crop water productivity of maize can be expressed in terms of total dry-matter yield, WP (dry matter, or grain yield, WP (grain), per actual evapotranspiration as given by Equation 4.13.

WP (dry matter) = Y (dry matter) / ET_c and WP (grain) = Y (grain) / ET_c *(Eq. 4.13)*

Where Y (dry matter) is the total biomass yield and Y (grain) the grain yield (in kg ha^{-1}) and P is the total actual evapotranspiration (in m^3 ha^{-1}) during the maize growing season (from sowing to harvest).

Investment in farm ponds and irrigation

According to Hartog (2012), the initial investment cost for construction of a concrete RWH farm pond of ≈100 m^3 and an irrigation drip kit for 0.5 ha, is about 31500 ETB (≈1550 USD) where the details are described in Table 4.3. The annual maintenance cost of the pond, which is dredging and improvement of the cemented walls including replacement of wooden roof structures once in 4-5 years is estimated at ≈260 ETB (≈13USD) (Hartog 2012). Normally, the money (31500 ETB) will be borrowed from credit association with an interest rate of 18% (Hartog 2012). The yearly payback should be about 6000 ETB to pay all the debt in 10 years. Therefore, the annual cost of the pond will be the annual interest rate (6000 ETB) plus the annual maintenance cost (260 ETB) which is about 620 ETB. A farmer can pay 6200 ETB per year by saving money that is saved because no maize has to be bought, and money that is gained from selling surplus maize from yield increase by using SI from farm ponds (Table 4.3).

Table 4.3 Estimated cost for a household farm pond construction and drip irrigation kit and extra production needed per year to pay off investment in RWH farm ponds and irrigation system (Adapted from Hartog 2012)

<table>
<tr><td>Material</td><td>Quantity</td><td>Unit</td><td>Unit cost(ETB)</td><td>Total cost(ETB)</td></tr>
<tr><td>Cement</td><td>2100</td><td>kg</td><td>2</td><td>4200</td></tr>
<tr><td>Sand</td><td>4</td><td>truck</td><td>700</td><td>2800</td></tr>
<tr><td>Stone</td><td>6</td><td>truck</td><td>600</td><td>3600</td></tr>
<tr><td>Corrugated iron sheet</td><td>5</td><td>number</td><td>100</td><td>500</td></tr>
<tr><td>Labor</td><td>420</td><td>man-days</td><td>14</td><td>5400</td></tr>
<tr><td>Drip kit</td><td>1</td><td>set</td><td>15000</td><td>15000</td></tr>
<tr><td>Total</td><td></td><td></td><td></td><td>31500</td></tr>
<tr><td colspan="5">Revenue</td></tr>
<tr><td>Maize use</td><td colspan="2">Extra production needed per year (kg)</td><td>Unit price (ETB)</td><td>Total price (ETB)</td></tr>
<tr><td>Household consumption</td><td colspan="2">330</td><td>5.9</td><td>1947</td></tr>
<tr><td>Surplus for sale</td><td colspan="2">851</td><td>5</td><td>4253</td></tr>
<tr><td>Total</td><td colspan="2">1181</td><td></td><td>6200</td></tr>
</table>

ETB=Ethiopian currency (Birr)

4.3 Results

Dry spell occurrences

The probability of getting >10 consecutive dry days is more than 50% from March up to the mid of May and almost less than 10% during July and August (Figure 4.3). The probability of getting >15 consecutive dry days is greater than 20% from March till April. When there is sowing of maize between March and April there could be a risk of moister stress since the crop starts to experience stress when there is a dry spell longer than 10 days for the first 30 days after sowing. The probability of getting >20 consecutive dry days were less than 30% during the whole maize growing season (March-September) and non-existent during the peak rainfall months of July and August. Most of the seasonal rainfall was received in July and August which is during flowering and grain filling stage of maize crop if sowing takes place in early May.

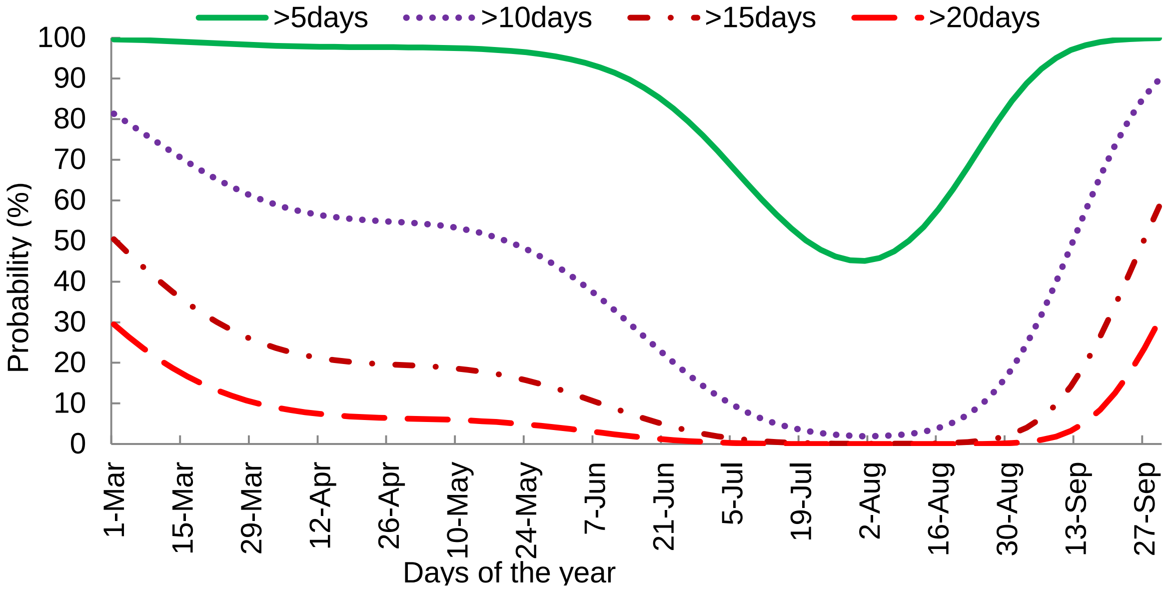

Figure 4.3 Probability of dry spells exceeding 5, 10, 15 or 20 days in Halaba, CRV of Ethiopia, during 1970-2011.

When we compare the two experimental years (2012 and 2013) with the long term (1970-2011) cropping season (March-September) mean rainfall of 786 mm, the year 2012 was having below the long term mean with 635 mm total seasonal amount, while 2013 was one of the wettest years with 983 mm seasonal rainfall. The 2013 total seasonal rainfall (983 mm) has 9% probability of occurrence which shows one of the rare seasons to occur while the 2012 total seasonal rainfall (635 mm) has 87% probability of occurrence showing that it is one of the drought years.

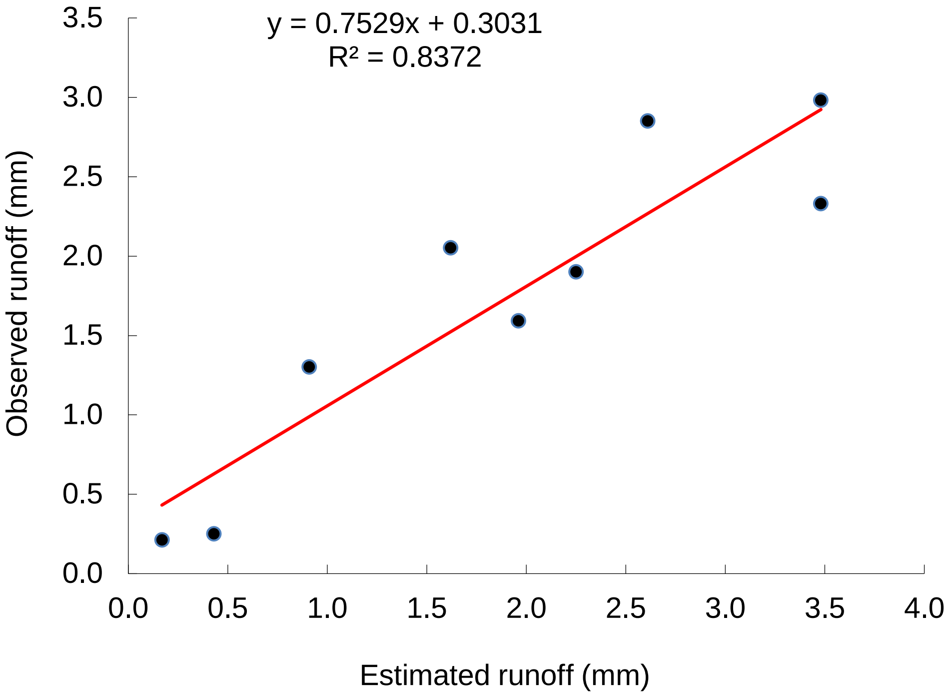

Figure 4.4 Observed versus estimated runoff during 2012 rainfall season, in Halaba special Woreda, CRV, Ethiopia

Water supply and irrigation

Figure 4.4 shows the relation between estimated and measured runoff. The ME and RMSE between predicted and observed data showed that the prediction correlated fairly well with the observed data (ME=0. 72, RMSE=0.5 and r2=0.84), (Figure 4.4). ME Values between 0 and 1 are generally viewed as acceptable levels of performance (Krause *et al.,* 2005). Therefore, we can apply the SCS model in the study area to predict runoff for water harvesting runoff estimation.

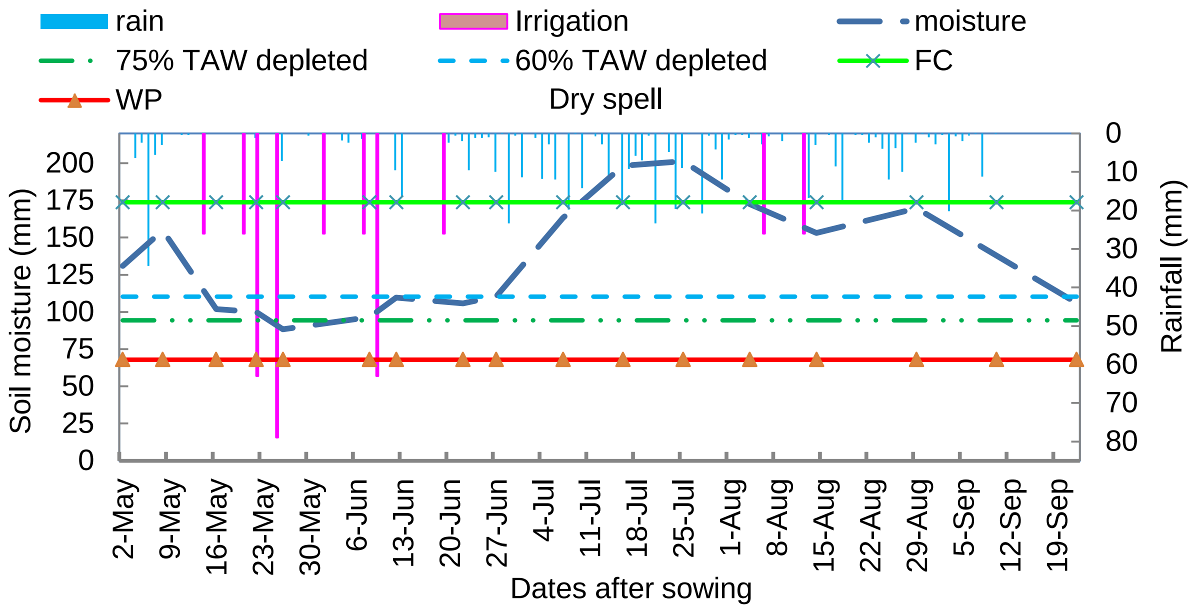

Figure 4.5 Rainfall and observed moisture change during 2012 experimental year with rainfed and with SI in Halaba, CRV, Ethiopia.

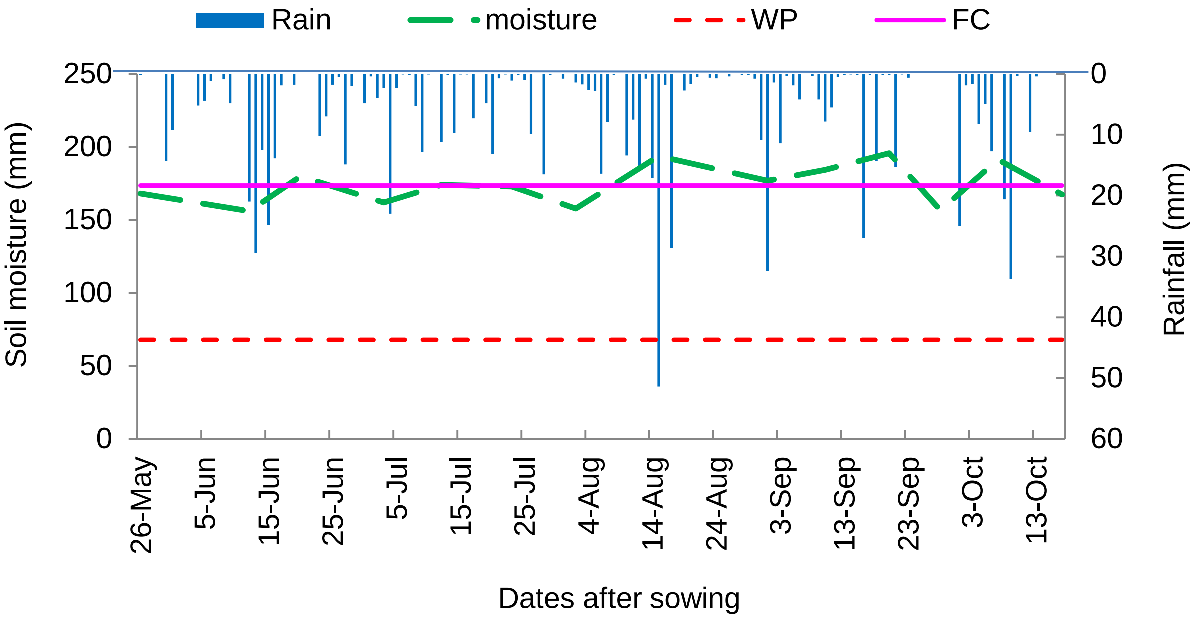

Figure 4.6 Rainfall and observed moisture change during 2013 experimental year using rainfed only in Halaba, CRV, Ethiopia

During the 2012 experiment, a few weeks after sowing and during the vegetative stage of maize (during May and June) there were two dry spell periods > 10 days where SI was triggered based on soil moisture measurements (Figure 4.5). During August there was also a short dry spell that triggered SI4 SI.

During the 2013 on-farm experiment, since the year was very wet and also the sowing of maize was late on the last week of May, there were only < 10 consecutive dry days after sowing (Figure 4.6). Therefore, there was no SI applied during the second year of our experiment (2013). The moisture content was close to the field capacity at most times of the cropping season (Figure 4.6).

Crop water requirement

Table 4.4 presents the crop water requirement, rainfall at 80% probability of occurrence, required SI and the runoff potential that can be stored in the farm ponds from the existing catchment area. Data are given per month and over the complete growing season.

Out of the 42 available years, nine years were selected with rainfall closest to the 80% dependable value. The individual rainfall events of these years were used to calculate runoff with the validated SCS method. In Table 4.4, the calculation of the volume of crop water requirement and runoff was based on 0.5 ha of maize farm and 2.2 ha catchment area respectively.

By comparing the 80% dependable rainfall with the crop water requirement, the months of March, May, June and July require 102, 43,123 and 88 m^3 respectively. The amount of runoff volume that can be harvested from the 2.2 ha catchment area during those months will be 103,156,148,487 m^3 respectively.

Table 4.4 Crop water requirement, rainfall in dry years, needed SI and runoff volume in maize growing months in Halaba special Woreda, CRV, Ethiopia

Month	Crop water requirement (mm)	Rainfall at 80% chance of occurrence (mm)	SI (mm)	SI for 0.5 ha maize farm (m^3)	Runoff (mm)	Runoff volume from 2.2 ha catchment area (m^3)
March	47	27	20	102	4.7	103
April	44	46	0	0	8.2	180
May	42	33	9	43	7.1	156
June	71	47	25	123	6.7	148
July	125	107	18	88	22.1	487
August	90	109	0	0	18.5	407
Sept.	51	59.5	0	0	8.55	188
Seasonal	469	428.5	72	356	75.91	1670

Maize yield

Figures 4.7 and 4.8 presents grain yield of different combinations of SI and plant densities for 2012 and for plant densities only for 2013 (no irrigation in 2013 because of the wet year) respectively. The highest maize yield (9.78 t ha^{-1}) was obtained from the combination of SI4D4, whereas the lowest yield (7.45 t ha^{-1}) was observed from the SI1D1 combination during the 2012 experimental year (Figure 4.7). The maize yield difference obtained between SI1D1 and SI4D4 was only 31%.

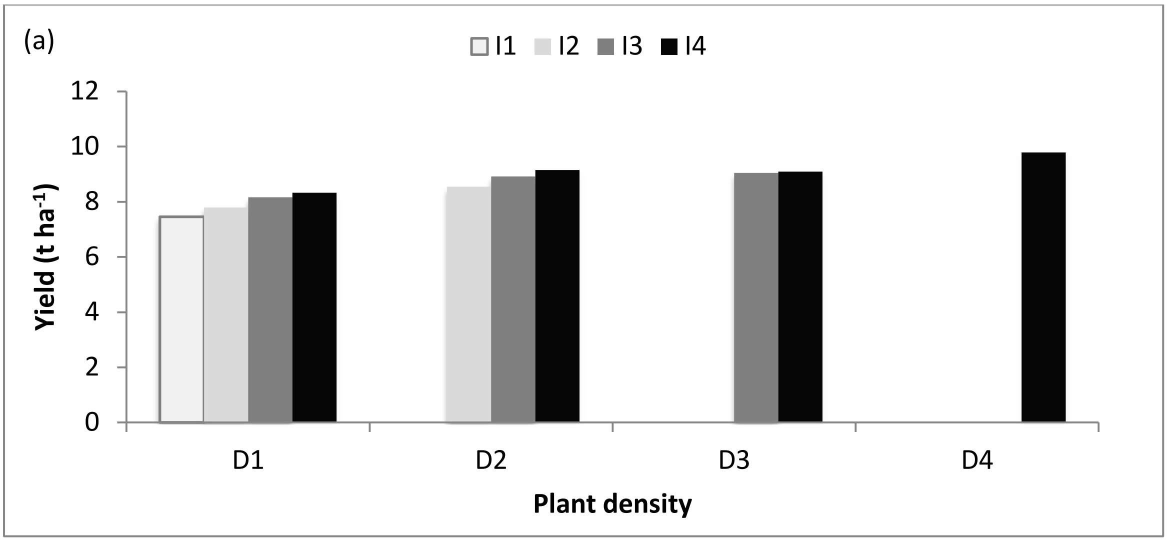

Figure 4.7 Maize yield at different treatments of supplementary irrigation and plant density combination during 2012 experiment in Halaba special Woreda, CRV, Ethiopia.

Maize response to supplemental irrigation

Table 4.5 shows grain and biomass yield for the 4 irrigation treatments (averaged over all combinations with density) and for the 4 plant density treatments (averaged over all combinations with SI). The rainfed grain yield at (SI1) showed significant difference from the grain yield at all other levels of SI. The grain yield from the two highest irrigation levels (SI3) and (SI4) are not significantly different. On the other hand, the total biomass showed significant difference between each of the SI levels.

The percentage yield increase due to irrigation was calculated under each plant density level (Table 4.6). Under D1 plant density, the yield increase from SI1 to SI2 and from SI2 to SI3 are 4.6% and 4.7% respectively, showing almost the same yield increase. The increase of SI from SI3 to SI4 was only 2%. The increase of SI from rainfed (SI1) to non-stressed level (SI4) is 12%. The yield increase observed during the increase of SI from SI2 to SI3 and from SI3 toSI4 under D2 plant density, showed almost the same yield increase shown under D1 plant density (Table 4.6). But, the least yield increase (only 0.6%) observed when SI increased from SI3 to SI4 under D3 plant density.

Maize response to plant density

In 2012 experimental year, the increase in plant density from 30000 plants ha^{-1} to 75000 plants ha^{-1} under the same irrigation level (SI4) increased maize grain yield from 8.32 t ha^{-1} to 9.78 t ha^{-1} (18%), which could be attributed to only plant density increase (Table 4.6). Similarly, during the year 2013, the increase in plant density from 30000 plants ha^{-1} to 75000 plants ha^{-1}increased maize grain yield from 7.81 t ha^{-1} to 9.55 t ha^{-1} (22%) (Figure 4.8).

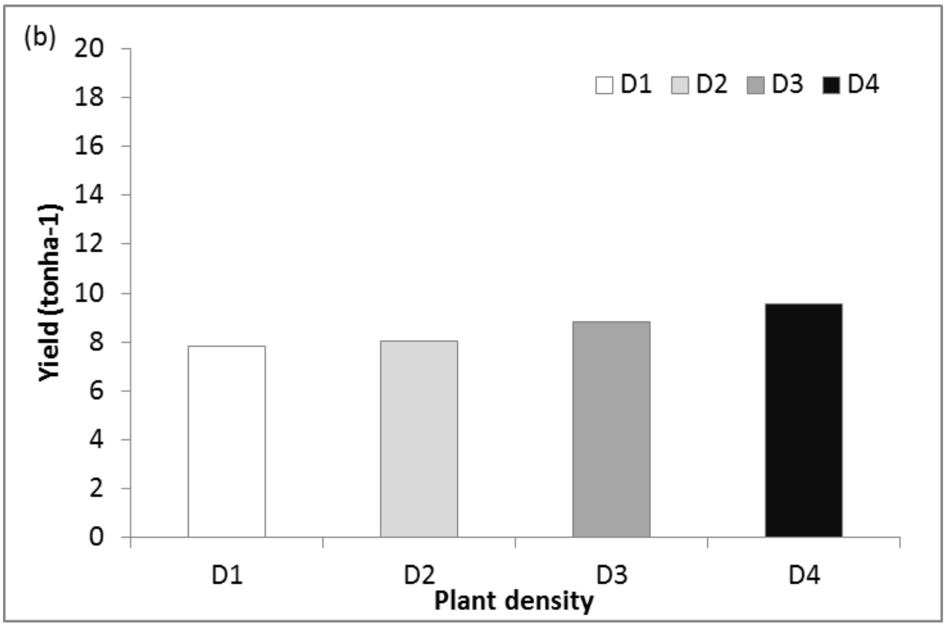

Figure 4.8 Maize yield at only plant density treatment during 2013 experiment year in Halaba special Woreda, CRV, Ethiopia.

The 2012 and 2013 average grain and total biomass yield increased as the plant density increased from D1 to the higher densities (D2, D3 and D4), but statistically significant yield difference was only observed with D4 plant density (Table 4.5).

The percentage yield increase due to plant density was calculated under each of the SI levels (Table 4.6). The maize yield increase when the plant density increases from D1 to D2 is almost the same under SI2 and SI3 irrigation levels which is 9.63% and 9.19% respectively. Almost no maize yield increase when the plant density increases from D2 to D3 under both SI3 and SI4 irrigation levels. The maximum yield increase (≈ 18%) was obtained when the plant density increase from D1 to D4 under SI4 SI level.

Comparison of on-farm experimental maize yield with the yield of neighboring farmers

Table 4.7 shows yield difference between on-farm research result and neighboring farmers. In our on-farm experiment we addressed the effect of SI and optimum planting density under optimum fertilizer application: all treatments were fully fertilized at 150% of the recommended amount.

Farmers own practice use half the amount of the recommended. The grain yield and total biomass difference between farmers own practice and our on-farm research was 101% and 84% respectively during 2012 and 61% for both grain yield and total biomass during the 2013 cropping season. The two years average (2012 & 2013) grain yield and total biomass difference between farmers own practice and our on-farm research was (101%+61%)/2=81% and (84%+61%/2) =72.5% respectively. The main factor for this yield difference between farmers own practice and research yield could be attributed to the amount of fertilizer applied.

Table 4.5 Means of grain yield and total biomass at different levels of supplementary irrigation and plant density

Treatments	Grain yield (t ha^{-1})	Total Biomass (t ha^{-1})
Supplemental irrigation= 2012 experimental year		
SI1 (D1)	7.45^{a}	15.81^{a}
SI2 (D1,D2)	8.17^{b}	16.83^{b}
SI3 (D1,D2,D3)	8.70^{c}	18.78^{c}
SI4 (D1,D2,D3,D4)	9.08^{c}	20.10^{d}
Density= average of 2012 &2013 experimental years		
D1	7.87^{a}	16.17^{a}
D2	8.45^{ab}	17.88^{ab}
D3	8.94^{ab}	19.84^{ab}
D4	9.67^{b}	21.83^{b}

Means sharing similar letter in respective column do not differ significantly at 5% level of probability (Bonferroni test, P<0.05

Table 4.6 Percentage increase between each irrigation and plant density treatments used in 2012 on-farm experiment, Halaba special Woreda, CRV, Ethiopia

	Irrigation	% increase
D1	SI1 to SI2	4.6
	SI2 to SI3	4.7
	SI3 to SI4	2.0
	SI1 to SI4	12.0
D2	SI2 to SI3	4.3
	SI3 to SI4	2.6
	SI2 to SI4	7.0
D3	SI3 to SI4	0.6
	Density	
SI2	D1 to D2	9.6
SI3	D1 to D2	9.2
	D2 to D3	1.5
SI4	D1 to D2	9.9
	D2 to D3	-0.6
	D3 to D4	7.6
	D1 to D4	17.6

Table 4.7 On farm maize grain yield and total biomass in farmers' fields (own practice) and in research-managed farmers' fields with different rate of fertilizer application in Halaba *special Woreda*, CRV, Ethiopia

year	On-farm research		Farmers own practice		The difference between On-farm research and farmers own practice	
	150 kg ha^{-1} fertilizer (Optimal fertilizer)		50 kg ha^{-1} fertilizer (Half the recommended)			
	Yield (t ha^{-1})	Biomass (t ha^{-1})	Yield (t ha^{-1})	Biomass (t ha^{-1})	Yield (%)	Biomass (%)
2012	7.45	15.81	3.70	8.60	101.4	83.8
2013	7.81	15.27	4.85	9.50	61.0	60.7

Water productivity

In 2012 the highest water productivity was obtained at the SI2. For grain yield it is the SI2D2 combination that gave maximum water productivity of 2.0 kg m^{-3} and for (dry matter) it is the SI2D1 combination that gave maximum water productivity of 4.1 kg m^{-3} (Table 4.8). The lowest values were from SI4 (full SI). For grain yield the lowest water productivity value was 1.3 kg m^{-3} obtained from the combination SI4 with D1, D2 and D3 plant densities. For dry matter yield the lowest water productivity value was 2.8 kg m^{-3} obtained from the combination SI4 with D1 plant density. So, the investment of the extra water is not worth the effort. In 2013 (without irrigation) the highest water productivity (both grain and dry matter) was obtained with D4 and the lowest with D1.

4.4 Discussion

We conducted this study to prove that by using SI from water harvesting ponds together with improved soil fertility and optimum plant density, it is possible to reduce maize crop failure from extreme dry spells, thus improve food security. First we identified the risk of long dry spells occurrences in our experimental area using long term rainfall data (1970-2011). Then the potential of SI from water harvesting ponds was assessed. Finally an optimum combination of plant density and irrigation rate for grain yield, total biomass and water productivity was identified. To generate data for our study we used both on-farm experiments and available long term rainfall data. We measured the yield gap between farmers own practice and our on-farm experimental results.

Table 4.8 Crop water productivity at different combinations of supplemental irrigation and plant density during 2012 and 2013 in Halaba special Woreda, CRV, Ethiopia

2012 experiment- With SI*		water use	Y (grain)	Y (dry matter)	WP (grain)	WP (dry matter)
		(mm)	(t ha^{-1})	(t ha^{-1})	(kg m^{-3})	(kg m^{-3})
SI1	D1	438	7.5	15.8	1.7	3.6
SI2	D1	411	7.8	16.8	1.9	4.1
	D2	435	8.5	16.8	2.0	3.9
SI3	D1	477	8.2	17.6	1.7	3.7
	D2	501	8.9	18.9	1.8	3.8
	D3	508	9.0	19.8	1.8	3.9
SI4	D1	653	8.3	17.9	1.3	2.8
	D2	680	9.1	21.4	1.3	3.1
	D3	674	9.1	19.9	1.3	3.0
	D4	679	9.8	21.2	1.4	3.1
2013 experiment- without SI						
	D1	703	7.8	15.3	1.1	2.2
	D2	635	8.0	16.7	1.3	2.6
	D3	642	8.8	19.9	1.4	3.1
	D4	643	9.6	22.5	1.5	3.5

SI*= supplemental irrigation

Dry spells and our experimental years 2012 and 2013

From the 42-year dry spell analysis, the probability of getting >10 consecutive dry days is more than 50% from March until May. Dry spells exceeding 10 days are known to cause potentially yield-limiting water deficit to crops in East Africa (Barron et al., 2003; Segele and Lamb, 2005). Particularly 10-20 consecutive dry days during flowering can severely limit maize productivity (Biazin and Sterk, 2013; Muluneh et al., 2015).

During July and August, the probability of >10 consecutive dry days is almost non-existent. This is consistent with a previous study in the area which reported 3-5 days of dry spells quite commonly occurring in the *Kiremt* season (mainly July and August)(Muluneh et al., 2015). Whereas dry spells greater than 10 days are limited to the lowland areas in western and north-eastern Ethiopia where rainfall variability is high (Segele and Lamb 2005). On the other hand, in September the probability of all dry spell lengths (>5 days, >10 days,> 15 days and >20 days) increased as a result of *Kirem*t season cessation. Therefore, late sowing of late maturing maize cultivar may face long dry spells in September that can negatively affect yield. Thus, for longer/ late maturing maize, delayed planting may not be desirable rather using SI is a better option.

Thus, long cycle maize sown during the *Belg* season and harvested around the end of *Kiremt* (September/October) always faces long dry spell during *Belg* or most often during early *Kiremt*(June). In our 2012 experimental year there was >10 dry days during May and June which is consistent with the long term trend. But, the second year of the experiment (2013) was one of the wettest years in terms of seasonal total rainfall (983 mm**)** and in terms of short dry spell periods (< 10 days of dry spell).

Water supply

The question was: is there sufficient runoff that can be harvested in the farm ponds and used for SI for maize during drought years? In the study area, most farmers allocate about 0.5 ha of land for maize crop (Gebremedhin et al., 2007). As water harvesting catchment, we took the 2.2 ha, which is the size of the catchment area that feeds runoff to our experimental farm ponds. The size of catchments for household RWH systems in Ethiopia in general ranges between 1 and 2 ha (Moges *et al.*, 2011). In Ethiopia average capacity of farm ponds is about 65 m^3 and the catchment area varies from 0.4 to 2.5 ha (Wakeyo and Gardebroek, 2013). In our study area, after we compared, the crop water requirement (calculated with FAO/Allen method) with the potential runoff, we find out that there is sufficient runoff that can be harvested in the farm ponds and used for SI for maize during drought years (Table 4.4). Hartog (2012) similarly reported the possibility of irrigating 0.3-0.8 ha of maize field between May – July using water harvesting ponds with the capacity of 350 m^3 volume of water. Other evidences also indicate that SI ranging from 50-200 mm per season (500-2000 m^3 ha^{-1}) is sufficient to mediate yield reducing dry spells in most years and rainfed systems, and thereby stabilize and optimize yield levels (Wani and Ramakishna, 2005).

An inherent limitation of RWH systems is that they can only provide SI water in or near to the rainy season (Moges *et al.*, 2011) and may not deliver the required quantities at the time it is most critically needed.

Seasonally there is >4 times more runoff water that can be harvested from 2.2 ha catchment area (1670 m^3) than the water required for SI (356 m^3). Most of this surplus runoff is collected during the *Kiremt* (July and August) (Table 4.4).Therefore, runoff water can also be used for domestic uses for farmers since ponds lined with concrete can retain captured water up to three months after the rainy season (Tefsaye, 2007). In this study we did not consider other uses of water from the water harvesting ponds such as SI of high value crops, domestic use etc. that can compete for a significant amount of water. There can also be losses of runoff before it reaches to the ponds like overtopping of the sediment trap (Figure 4.2) and other agricultural practices that decrease run-off (like *shilshalo*) and decrease the efficiency of water harvesting ponds.

The effect of supplemental irrigation

During the 2012 on-farm experiment, there were ten different combinations of SI and plant density. Statistically significant grain and biomass yield was observed between rainfed and all other irrigation levels and between SI2 and SI3 but the grain yield between SI3 to SI4 remained almost level. Grain yield increased 31 % from rainfed and 30000 plants to non-stressed SI and 75000 plants. The maximum yield increase which could be attributed solely to SI was 12%.

The year 2012 was one of the drought years in terms of total seasonal rainfall (March-September) due to the very low *Belg* (March-May) rainfall. However, during the critical growth stages of maize which is flowering and grain filling (July and August) there were no long dry spells. The dry spells that occurred were during May and June which were the vegetative stages of maize. Therefore, the year 2012 was not critical drought year in terms of dry spells rather it was moderate drought year.

Yield increase from SI varies on the growth stage when the crop is exposed to moisture stress. To use SI efficiently, it is essencial to have knowledge of the impact of water shortage during critical crop growing stages (Kahinda et al., 2007).

The effect of increased plant density

Increasing plant density from what farmers currently is using 30000 plants ha^{-1} to 75000 plants ha^{-1} increases grain yield by about 18% (Table 4.6) which is also statistically significant. However, the subsequent increase of plant density from 30000 to 45000 and 60000 plants ha^{-1} didn't bring statistically significant yield increase. Therefore, we would advice farmers to use the highest plant density (75000 plants ha^{-1}). A similar study conducted in Sri Lanka by Malaviarachchi et al. (2007) under SI and fully fertilized maize showed a 33% grain yield increase when the plant density increased from 55000 to 110000 plants ha^{-1}.

Water productivity

The lower values of water productivity (WP) at SI4 indicate that the use of SI4 SI is not as efficient in terms of water use as compared to SI2. This is in line with other studies which show a decrease in WP as the amount of SI increased (Zwart and Bastiaanssen 2004). Overall the grain water productivity in this study is by far greater than the farmers own practice grain water productivity 1.14 kg m^{-3} (Debela et al., 2013). However, it remains within the range of globally measured WP (grain) values 1.1-2.7 kg m^{-3} with average WP (grain) of 1.80 kg m^{-3} which was reported after synthesizing 84 literature sources by Zwart and Bastiaanssen (2004). In our study, the relatively higher WP obtained as compared to farmers practice could be mainly attributed to the use of optimum fertilizer that significantly increased the yield.

Planting time

Planting time is an important water management instrument (Ngigi et al., 2005, Araya et al., 2012). April is the month where the *Belg* season rainfall (March-April) normally reaches peak. That is why the long term average onset of the CRV region is in April (Muluneh et al., 2015). However, though April has relatively high rainfall still there is a high probability of long dry spells (Figure 4.3). Most farmers often sow maize in April, but the subsequent long dry spells during April, May and June leads to risk of low yield or crop failure. The other likely risk of sowing maize in April is that, the moisture sensitive stages of maize could coincide with long dry spell months of May and June. So, later sowing of maize (e.g May) in the CRV could reduce risk of long dry spells. For example, in our 2012 and 2013 experimental years where the sowing of maize was early May and late May respectively, there was no critical moisture stress during critical maize growth stages (during flowering and grain filling). So, we recommend a later onset for maize in the CRV. Similar argument has been given by Biazin and Sterk (2013) who reported a higher simulated yield in response to sowing in May as compared to early sowing in April. The effect is likely attributed to the lower probability of long dry spells between mid-July and mid-August which are the flowering and grain-filling stages of the local maize that is planted in May in the semi-arid part of CRV. Similarly, Bello (2008) suggested late season cropping of maize to be encouraged with rainfed SI to reduce drought in case of rain failure.

The role of soil fertility

The yield gaps between farmers own practice and our on-farm research (Table 4.7) were attributed to the difference in the amount of fertilizer use. Fertilizer use plays a significant and positive effect on maize grain yield. Some indicate that a 1% increase of fertilizer use per hectare on maize, increases yield by 6% (Gebremedhin et al., 2007). A study in Zimbabwe also found that fertilizer use, not irrigation was determining the final yield (Maisiri et al., 2005).

The farmers own practice yield in our study also looks higher than the yield reported by other previous studies in the same region. For example, Kassie et al. (2014) for example reported an average farmers maize yield of 2.0-2.3 t ha^{-1} in the CRV. One of the reasons for such variation of yields could be due to the different rate of fertilizer use by farmers. Farmers normally use different rates of fertilizer in the region like 25 kg ha^{-1}, 50 kg $ha^{-1}$and including farmers that do not use fertilizer at all due to fear of crop failure from drought or because they cannot afford to buy (Hulst 2012).

The yield difference between 2012 and 2013 from farmers own practice could be due to low rainfall and a dry spell during early stage of crop growth during 2012 and high rainfall with less than 5 dry days during 2013,which was one of the wettest years in almost 40 years period.

Thus, applying optimum fertilizer during good rainfall years is a possibility of increasing maize yield by more than half from what they are producing now. Some argue that nutrient supply, rather than water, is the main yield-limiting factor in sub-Saharan Africa (Penning de Vries and Djiteye, 1991; Breman and Debrah, 2003). Even in low and irregular rainfall conditions, the low fertility of the soils is often considered much more a limiting factor than water (Penning de Vries and Djiteye, 1982; Tittonell and Giller, 2013). Similarly, in maize growing areas of Ethiopia soil fertility is considered one of the principal factors that limit maize productivity (Abebayehu et al., 2011; Wondosene and sheleme, 2011). However, for sustainable yield increase an integrated approach is important which includes SI and fertilizer (Awulachew et al., 2005).

Benefits of increased dry matter

For farmers in the CRV, where mixed crop-livestock farming is their means of livelihood, crop improvement to increase grain yields and biomass can help to secure both human food and animal feed. Livestock plays an important role in providing draft power, cash and food. The feed sources commonly used for livestock, depend on natural grazing and crop residues. Due to a shortage of grazing land most farmers depend on plant residues for their animals. Thus, the 84% and 61% increase in total above ground biomass between on-farm research and farm practice provide additional advantage for farmers as a source of animal feed.

Studies have also indicated that in east Africa particularly in the CRV of Ethiopia, crop-livestock mixed farming is considered as a better strategy for coping climate change impact in the future (Thornton, 2009; Birhanu and Sterk, 2013).

Financial feasibility

The financial feasibility of RWH ponds for SI was assessed by Hartog (2012) in the same area. The analysis includes the initial investment for constructing farm ponds, maintenance costs and a drip kit for irrigation. The analysis showed that, for construction of farm ponds and irrigating maize to be financially feasible for farmers the productivity of maize need to be 1.18 t ha^{-1} more than what farmers are currently getting (2.0-2.3 t ha^{-1})(Kassie et al., 2014) (Table 4.3). In our experiment, the maximum yield increase which could be attributed solely to SI during non-critical drought year was 12%. This yield increase from only SI is not financially feasible to use SI from farm ponds, which indicates that investment in SI during non-critical drought years is probably not worth the effort. But, using optimum fertilizer even without SI during non-critical drought year (e.g. 2012) maize grain yield increased by more than half (Table 4.7). Given the variability of the Ethiopian market value of goods/items market value estimations could be significantly variable by time.

4.5 Conclusions

Finally, based on the two years of on-farm field experiment we can conclude the following:

1. Our long term daily rainfall (1970-2011) analysis proves the erratic nature of the rainfall in terms of occurrence of dry spells during the cropping season mainly during the *Belg* months. We recommend early May as the sowing of maize for short and moderate maturing maize cultivar (<120 days of maturity) in the CRV. However, for longer/ late maturing maize delayed planting may not be desirable rather using SI is the best option
2. The fact that the grain yield increase from SI3 to SI4 was insignificant and the water productivity of SI4 is the least of all treatments indicates that the SI4 situation probably is too wet and undesirable. The investment of the extra water is not worth the effort.
3. Despite the use of SI significantly increased yield as compared to rainfed yield in 2012, it is not financially feasible. This indicates that the investment in SI during non-critical drought years (like 2012) is probably not worth the effort.
4. Due to a significant effect of increasing plant density from 30000plants ha^{-1}to 75000 plants ha^{-1} (D1 to D4), we advise farmers to use 75000 plants ha^{-1}plant density.
5. The large increase in grain yield compared to the adjacent farmers is contributed to the higher use of fertilizer (150% recommended) against the current use (50% or less) by adjacent farmers. So, our experiment, once again, suggests that yield lower than attainable is not a matter of water shortage but more superior effect of fertilizer.
6. Our hypothesis was that SI in combination with increased plant density would bridge dry spells, reduce risk of crop failure and increase grain yield. This hypothesis could not be fully proven with our 2 years experiment.
7. With our 2 years experiment we could not prove the response of SI during critical drought years. Therefore, we could further hypothesize that it is possible that SI during a longer dry spell than observed in 2012 and 2013 (from the analysis of long-term data) show more (and dramatic) effect on grain yield. Maybe even survival versus total crop failure. Modeling can be used to look into more critical drought years.
8. When we compare the volume of water required to the volume water that can be harvested for SI, we conclude that irrigating maize area of 0.5 ha with SI is technically feasible for this size and type of catchment.

Chapter 5

Adapting to climate change for food security in the Rift Valley dry lands of Ethiopia: supplemental irrigation, plant density and sowing date

Abstract

Studies on climate impacts and related adaptation strategies are increasingly becoming important to counteract the negative effects of climate change. In Ethiopia, climate change is likely to affect crop yields negatively and therefore food security. However, quantitative evidence is lacking about the ability of farm level adaptation options to offset the negative impacts of climate change and to improve food security. The MarkSimGCM weather generator was used to generate projected daily rainfall and temperature data originally taken from the ECHAM5 general circulation model and ensemble mean of six models under high (A2) and low (B1) emission scenarios. We validated the FAO AquaCrop model and subsequently used it to predict maize yields and explore three adaptation options: supplemental irrigation (SI), increasing plant density and changing sowing date**.** The optimum level of maize yield was obtained when the second level of SI (SI2), which is the application of irrigation water when the soil water depletion reached 75% of the total available water in the root zone, is combined with 30000 plants ha^{-1} plant density. We also found that SI has a marginal effect in good rainfall years but using 94-111 mm of SI can avoid total crop failure in drought years. Hence, SI is a promising option to improve food security in the Rift Valley dry lands of Ethiopia. Because more dry spells are expected during the *Belg* season in the future, with a negative effect on maize production, and because the predicted lower maize production is only partly compensated by the expected increase in CO_2 concentration. Our results also show that shifting the sowing period of maize from the current *Belg* season (mostly April or May) to the first month of *Kiremt* season (June) can offset the predicted yield reduction. In general, the present study showed that climate change will occur and without adaptation have negative effects. Use of SI and shifting sowing date are viable options for adapting to the changes, stabilizing or increasing yield and therefore improving food security for the future.

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Journal of Agricultural Sciences

Adapting to climate change for food security in the Rift Valley dry lands of Ethiopia: supplemental irrigation, plant density and sowing date

5.1 Introduction

Agricultural production still remains the main source of income for most rural communities in Africa. Current agricultural systems are adapted to the current prevailing climate of the region. Changes in the climate can influence the sustainability of these systems and will therefore challenge vulnerable people who depend on these systems. The Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) predicts that climate change is likely to have a significant effect on agricultural production in many African countries (Boko et al. 2007). Droughts and dry spells are predicted to be more frequent, rain more inconsistent (Below et al. 2010). Ethiopia is one of the countries most vulnerable to climate change and with least capacity to respond (Thornton 2006). The nature of Ethiopia's agriculture, primarily rain-fed, means that production is sensitive to fluctuations in rainfall. Therefore, studies on climate impact and related adaptation strategies are increasingly important to help counteract the negative effects of climate change on the livelihoods of the people in developing countries in general and Ethiopia in particular.

Climate change impacts will likely vary substantially within individual regions in Africa (Downing et al. 1997) due to differences in biophysical resources, management, climate change and other factors. Therefore, studies at fine spatial scales are needed to resolve local climate change hot spots within regions (Lobell et al. 2008). Research at the local level forms the basis of a community-led solution that is ideal for smallholder farmers (Ngigi 2009).

Although rainfall within the short-rainy season (March -May) (*Belg*) is often unreliable , farmers in the Ethiopian Rift Valley often plant longer-season maize varieties during the short-rains so they can mature during the long rains (*Kiremt*). However, due to long dry spells in most years, these plantings suffer severe water stress (Funk et al. 2012). In the Central Rift Valley (CRV) of Ethiopia, the maximum number of consecutive dry days during *Belg* has increased for the past 40 years (1970-2009) (Muluneh et al.2014; manuscript accepted for publication). This trend is expected to continue in the future and will affect the yield of maize negatively especially in the semi-arid and dry sub-humid areas (Funk et al. 2012; Muluneh et al., 2015). Therefore, farmers need management alternatives to overcome the dry spell problems particularly those that occur during moisture-sensitive stages of the crop.

Though most studies conducted in Ethiopia indicate that climate change is likely to affect crop yields negatively (e.g., Deressa 2007; Deressa and Hassan 2009; Muluneh et al., 2015), there is little quantitative evidence about effective climate change adaptation options to improve food security (Bryan et al. 2009; Di Falco et al. 2011*;* Conway, D. & Schipper 2011). Quantitative assessment of adaptation strategies to climate change impacts at farm level is important, since "effective adaptation measures are highly dependent on specific, geographical and climate risk factors" (IPCC 2007).

The process of planning adaptive strategies requires an inventory of potential options (Downing et al.1997). Potential adaptation strategies such as use of fertilizers, altering planting dates and supplemental irrigation (SI) have been suggested to offset negative climate change impacts on food security (Travasso et al. 2006; Ngigi 2009; Bryan et al. 2009). Oweis and Hachum, (2003) defined supplemental irrigation as 'the addition of small amounts of water to essentially rainfed crops during times when rainfall fails to provide sufficient moisture for normal plant growth, in order to improve and stabilize yields'. The key challenege, however, continues to be the identification of the most sucessful combination of possible strategies and technologies in a particular context (Burney et al. 2014).

From on-farm field experiments conducted in the CRV of Ethiopia, the use of SI with optimum plant density and optimum fertilizer application proved effective in bridging dry spells and increasing crop yields under current climate conditions (Muluneh et al.2014; manuscript submitted for publication). But how these strategies could work during severe drought years and for projected climate change scenarios has not yet been tested. The present research addresses this issue using the AquaCrop yield simulation model to assess those possible adaptation strategies for their capability to overcome or reduce the adverse effects of climate variability and climate change, and therefore improve food security.

The objectives of this study were: (1) to assess the drought conditions for the baseline and climate change scenarios using dry spells, (2) to assess the change in maize grain yield under reference and projected CO_2 levels, (3) to determine the optimum combination of SI and plant density from the baseline yield simulation (4) to evaluate the response of maize yield to SI, plant density and shifting of the sowing period adaptation options under future climate change scenarios (2020-2049).

5.2 Materials and methods

Site description

The field experiment was located in the Halaba Special Woreda (district) of the CRV of Ethiopia which is geographically located at 7° 17'N and 38° 06'E and situated 315 km south of Addis Ababa. The study area has an altitudinal range of 1554-2149 m.a.s.l., but most of the *woreda* is found at about 1800 m.a.s.l., with the topography ranging from flat (61.3% of the area), to rolling (21.3%) and hilly (17.4%) terrain. The experimental farms are located in the rolling terrain.

The climate of the study area is a dry sub-humid, with an aridity index of 0.56 computed as the ratio of mean annual precipitation to mean annual reference evapo-transpiration (ET_O). The study area is characterized by two rainy seasons: *Belg* and *Kiremt.* The small rainy season (*Belg)* is during March-May and the main rainy season (*Kiremt*) is during June-September. The annual rainfall varies between 675 and 1221 mm with a mean of 922 mm for the past 42 years (1970-2011).

According to the FAO classification system, the most dominant soil of the *woreda* is Andosol (Orthic), followed by Phaeozems (Ortic) and Chromic Luvisols (Orthic). This means that soils contain mostly 'silt' and 'ash' (white, volcanic) characterized by a high water infiltration capacity.

As a result of a long history of agriculture and high population pressure in the area, vegetative cover is very low. This, in combination with the high soil erodibility of the Andosols, means that there is a soil erosion hazard in sloping areas. In addition to sheet erosion, gullies are also common in many parts of the study area.

Field experimental design and data inputs for model validation

A field experiment was conducted during the 2012 and 2013 growing seasons in the study area. A maize cultivar that is widely used in the CRV, BH540 (Bako hybrid-540) with a growing period of 145 days, was used for this experiment. It is highly suitable for areas with altitudes varying from 1200-1800 m.a.s.l., and well suited to a climate zone with rainfall between 980 and 1040 mm and temperature between 17-23 ^{O}C. Soil physical characteristics such as bulk density, field capacity, permanent wilting point and water content at saturation were determined in the laboratory (Table 5.1).

Table 5.1 Soil physical properties (n=9), Halaba special Woreda, CRV, Ethiopia

Soil layer (m)	Soil water content (vol %)			
	Sat	FC	PWP	BD (g cm^{-3})
0.00-0.20	42.79 (1.98)	27.71 (1.07)	10.43 (0.49)	1.02 (0.032)
0.20-0.40	42.56 (1.05)	30.99 (1.40)	11.43 (0.22)	0.94 (0.038)
0.40-0.60	44.30 (2.45)	28.13 (0.77)	12.13 (0.97)	0.94 (0.104)

Sat, water content at saturation; FC, field capacity; PWP, permanent wilting point; BD, bulk density.
Standard error of the mean in parenthesis.

Ten different combinations of SI level and planting density were tested in the field for two consecutive growing seasons (Muluneh et al. 2015; manuscript submitted for publication). One experimental plot of 4 x 5 m was established in three different farmers' fields having similar conditions. Hence, there were 30 plots (10 treatments x 3 replications). The description of the treatments is presented in Table 5.2.

The first treatment, SI1 is with no supplemental irrigation and dependence entirely on natural rainfall. In SI2 we applied supplemental irrigation when the percentage of soil water depletion (SWD) reached 75% of total available water (TAW), i.e. when available water (AW) reached 26 mm, where the TAW in the root zone (60 cm) is about 105 mm. In SI3 we applied supplemental irrigation when the SWD reached 60% of TAW, i.e. when AW reached 42 mm. In SI4 we kept AW as much as possible close to TAW. Since it was practically difficult to keep the moisture content all the time at field capacity, we irrigated when SWD dropped below 20%, i.e. when AW reached 84 mm.

The SI was applied using a low-cost drip irrigation kit. Based on periodical soil moisture measurements, the application date and quantity of SI were scheduled. Soil water content profiles were measured at soil depths of 20, 40 and 60 cm every week with a Time-Domain-Reflectometer (TDR) (Eijkelkamp Equipment, Model 14.62, Giesbeek, Netherlands) by installing access tubes at the center of each experimental plot.

The SI treatments were combined with four different plant densities: D1, D2, D3 and D4, where D1 is a density of 30 000 plants ha^{-1}, D2 is 45 000 plants ha^{-1}, D3 is 60 000 plants ha^{-1} and D4 75 000 plants ha^{-1}. Traditionally, farmers in the CRV use 30 000-40 000 plants ha^{-1} for maize.

Fertilizer was applied at 150% of the recommended amount to keep soil fertility at a non-limiting level. For the CRV, the recommended fertilizer level is 100 kg of urea and 100 kg of DAP (Debelle et al. 2001; Demeke et al. 1997). DAP was applied at planting whereas urea was side dressed at about 4 weeks after planting.

The Canopy Cover (CC) was estimated by the line-transect method (Eck & Brown 2004), using the amount of shadow under the crop. A rope is stretched diagonally across the crop rows. This cord has knots at intervals of 10 cm. The knots that are shaded from sunlight are counted. For every plot, six diagonals are measured. For each transect, the number of shaded knots is divided by the total number of knots on that transect. The resulting average number is an estimate of the percentage of soil that is covered by the crop. For the period of assessment, the CC measurements were taken every 10 days for each plot between 11:20 and 13:30 hour when the sun was overhead.

Total above ground biomass and grain yields were determined at maturity by hand-harvesting the crop from three one square meter areas in each plot. The biomass and grain yield was weighed after oven drying at 70°C for 48 hrs.

Table 5.2 Supplemental irrigation and plant density combination during the field experiment in 2012, Halaba special Woreda, CRV, Ethiopia

Supplemental irrigation	Plant Density	Combination	Description
SI1	D1	SI1D1	Rainfed and 30,000 plants ha^{-1}
SI2	D1	SI2D1	75% TAW depleted and 30 000 plants ha^{-1}
	D2	SI2D2	75% TAW depleted and 45 000 plants ha^{-1}
SI3	D1	SI3D1	60% TAW depleted and 30 000 plants ha^{-1}
	D2	SI3D2	60% TAW depleted and 45 000 plants ha^{-1}
	D3	SI3D3	60% TAW depleted and 60 000 plants ha^{-1}
SI4	D1	SI4D1	No water stress and 30 000 plants ha^{-1}
	D2	SI4D2	No water stress and 45 000 plants ha^{-1}
	D3	SI4D3	No water stress and 60 000 plants ha^{-1}
	D4	SI4D4	No water stress and 75 000 plants ha^{-1}

In SI2 we applied supplemental irrigation when the percentage of soil water depletion (SWD) reached 75% of total available water (TAW)

Baseline climate data and agro-meteorological analyses

We used 30 years (1966-1995) of daily rainfall and temperature data from the National Meteorological Agency of Ethiopia at Halaba station. This station is located closest to our experimental site. Reference evapotranspiration (ET_O) was determined from the daily long term temperature data (1970-2011) using the FAO Penman-Monteith method. The FAO Penman-Monteith equation was calibrated using full climatic data observed during 2012 and 2013 from an automatic weather station (Eijkelkamp Equipment, Model 16:99, Giesbeek, the Netherlands) installed at the study area, and the empirical coefficients (R^2=0.88;N=188) were determined with the following equation (Eq. 5.1).

$$ET_O = 1.10ET_{O_{tmp}} - 0.82 \qquad (Eq.5.1)$$

Where ET_O is the reference evapo-transpiration value based on calibration, and $ET_{O\ tmp}$ is the reference evapotranspiration obtained from only long-term maximum and minimum temperature data by FAO Penman-Monteith.

The observed meteorological variables during the 2012 and 2013 experimental period included rainfall, temperature, wind speed, sunshine hours, relative humidity and incoming radiation. Therefore, reference evapo-transpiration during the two experimental years was determined using the FAO Penman-Monteith equation as described in Allen et al. (1998) and using the ET_O calculator (Raes 2009).

Climate change data

For this study, we used the ECHAM5 Global Climate Model (GCM) (Roeckner et al. 2003) and ensemble mean of six GCMs under A2 (high) and B1 (low) emission scenarios for the future period 2020-2049. The ECHAM5 model is known for its good performance in estimating average annual rainfall (McHugh 2005) and abrupt declines of March-May rainfall due to changes in Sea Surface Temperature (SST) in east Africa (Lyon and DeWitt 2012). Doherty et al. (2010) also reported that the climate simulated by ECHAM5, along with the CCSM3 and HadCM3 models, is in closest agreement with observations for East Africa. Similarly, in their study about assessing the regional variability of GCM simulations, Cai et al. (2009*)* showed that ECHAM5 along with HadCM3 is best for East Africa.

Thornton et al. (2011) indicated that yield changes in East Africa do not show much variability under different climate models and emissions scenarios. However others believe that multi-model ensemble means are more reliable in climate projections (Semenov and Stratonovitch 2010) and reduce the error in both the mean and variability (Pierce et al. 2009). For instance, Giorgi and Coppola (2010) suggest a minimum of four to five models to obtain robust regional precipitation change estimates. In this study, ensemble mean of six GCMs (Average climatology of 6 GCMs embedded in MarkSimGCM module) were used. The GCMs included were: BCCR_BCM2.0 (Bjerknes Centre for Climate Research, University of Bergen, Norway, 1.9° × 1.9°), CNRM-CM3 (Météo-France/Centre National de Recherches Météorologiques, France, 1.9° × 1.9°), CSIRO-Mk3.5 (Commonwealth Scientific and Industrial Research Organization Atmospheric Research, Australia, 1.9° × 1.9°), ECHam5 (Max Planck Institute for Meteorology, Germany, 1.9° × 1.9°), INM-CM3_0 (Institute for Numerical Mathematics, Moscow, Russia, 4.0° × 5.0°) and MIROC3.2 (Center for Climate System Research, National Institute for Environmental Studies, and Frontier Research Center for Global Change, University of Tokyo, Japan, 2.8° × 2.8°).

Climate change impact studies usually require information at finer spatial and temporal scales than the typical GCM grid resolutions. To address this we used the web-based MarkSimGCM module with a user interface in Google Earth (Jones and Thornton, 2013) to generate daily rainfall and temperature data. It is an updated version of the MarkSim model, a detailed description of which can be found in Jones and Thornton (2000). MarkSim, a third-order Markov rainfall generator, is a generalized downscaling and data generation method used as a GCM downscaler which uses both stochastic downscaling and climate typing. It takes the output of the original resolution of each GCM and interpolates it to 0.5 latitude-longitudes. Generally, the model uses a mixture of methods, including simple interpolation, climate typing and weather generation to generate daily weather data that are to some extent characteristic of future climatology. To make a globally valid model that does not need recalibration every time that it is used, the developers of the model calibrated MarkSim using over 10,000 stations worldwide with more than 10 years of continuous data, which were clustered into 702 climate clusters of monthly precipitation and monthly maximum and minimum temperatures. Accordingly, MarkSim has been widely tested and used in East Africa and reportedly provides a realistic simulation of daily precipitation and temperature distributions (Jones and Thornton 1993; Jones and Thornton 1997; Thornton et al. 2009; Lobell and Burke 2010; Thornton et al. 2011; Jones and Thornton 2013). Dixit et al. (2011) and Farrow et al. (2011) have demonstrated that MarkSim can generate synthetic time series that show patterns of rainfall variability over East Africa with acceptable accuracy (without statistically significant difference between observed and MarkSim generated data) for applications in agriculture. Muluneh et al. (2015) have also tested MarkSimGCM generated data in the CRV Ethiopia and found simulated rainfall values close to the historical values.

AquaCrop model description, and data inputs

To assess crop response and yield we employed the FAO's AquaCrop model. AquaCrop is a dynamic crop-growth model developed to simulate attainable crop yield in response to water, and is particularly suited to address conditions where water is a key limiting factor in crop production (Hsiao et al. 2009; Raes et al. 2009; Steduto et al. 2009). Hsiao et al. (2009) showed that AquaCrop was able to simulate the canopy cover, biomass development and grain yield of maize cultivars over six different cropping seasons that differed in plant density, planting date and evaporative demands. Thus it was well suited to our research.

The input parameters of the AquaCrop model encompass (i) the climate, with its thermal regime, rainfall, evaporative demand, and carbon dioxide concentration; (ii) the crop, with its growth, development and yield processes; (iii) the soil, with its water balance; and (iv) the management, which includes major agronomic practices such as planting dates, fertilizer application and irrigation (Raes et al. 2009; Steduto et al. 2009). Accordingly, there are five input files for the model simulations: climate, crop, soil, management and initial soil water content.

The climate file includes user-specific daily values of (i) minimum and maximum air temperature, (ii) reference evapotranspiration ET_O and (iii) rainfall. The mean annual CO_2 input for AquaCrop during the baseline climate (1966-1995) came from the Mauna Loa Observatory records in Hawaii (Steduto et al. 2009) while the future period came from SRES emission scenarios projection (Houghton et al. 2001). We used series of daily precipitation, minimum temperature and maximum temperature values for cropping seasons from the Ethiopian National Meteorological Agency, Halaba station for the baseline climate, and MarkSimGCM generated data for the future period. No data was available on relative humidity, solar radiation and wind speed. Hence, ET_O estimated from daily maximum and minimum temperature data using FAO Penman-Monteith method was calibrated from observed data in Eq. 5.1 and used for the AquaCrop simulation model. Based on his analysis of evapo-transpiration in Ethiopia using data over the last half century, Tilahun (2006) reported that the FAO Penman-Monteith method is a better estimator of ET_O than more simplified methods such as Hargreaves, even when there is only limited data.

Crop input parameters used in the AquaCrop model are known as conservative (i.e., constant) and user specific. Conservative crop input parameters do not change with geographic location, management practices and time and, while determined with data from favorable and non-limiting conditions, they remain applicable for stress conditions via their modulation by stress response functions (Steduto et al. 2009; Raes et al. 2009). The other parameters are user specific and affected by environmental conditions. Therefore, they need to be adjusted for local conditions, cultivars and management practices. AquaCrop has been parameterized and tested for several crops (e.g. for maize, Heng et al. 2009; Hsiao et al. 2009; Zinyengere et al. 2011) and was able to properly simulate canopy cover, biomass development, and grain yield. In this study, the conservative crop input parameters derived from Hsiao et al. (2009) were used (Table 5.3a), except for water productivity. We adjusted water productivity from 33.7 g m^{-2} to 30.7 g m^{-2} following the work of Biazin and Stroosnijder (2012) in the CRV. The user specific crop input parameters for BH540 local maize variety were adjusted from the field experiment conducted during 2012 and 2013 cropping season in the study area (Table 5.3b).

Table 5.3a Conservative crop input parameters of AquaCrop for maize

Description	Value	Unit/meaning
Base temperature	8	oC
Cut-off temperature	30	oC
Canopy cover (CC) per seedling at 90% emergence	6.5	cm^2
Canopy growth coefficient (CGC)	0.013	Increase in CC relative to CC per GDD*
Crop coefficient for transpiration at CC=100%	1.03	Full canopy transpiration relative to ET_O
Crop coefficient decline after reaching CCx**	0.003	Decline per day due to leaf aging
Canopy decline coefficient (CDC) at senescence	0.0106	Decrease in CC relative to CC_x per GDD
Leaf growth threshold p- upper	0.14	Fraction of TAW, above this leaf growth inhibited
Leaf growth threshold p- lower	0.72	Leaf growth stops completely at this point
Leaf growth stress coefficient curve shape	2.9	Moderately convex curve
Stomatal conductance threshold p- upper	0.69	Above this stomata begin to close
Stomatal stress coefficient curve shape	6	Highly convex curve
Senescence stress coefficient p- upper	0.69	Above this stomata begins to close
Senescence stress coefficient curve shape	2.7	Moderately convex curve
Reference harvest index (HI_0)	0.48	Harvest index (HI)
Volume % below saturation	6	%, Moderately tolerant to water logging
Coefficient, inhibition of leaf growth on HI	7	HI increased by leaf growth inhibition at anthesis
Coefficient, inhibition of stomata on HI	3	HI reduced by stomata inhibition at anthesis
Water productivity, normalized to year 2000	30.7	g m^{-2} (biomass/m^{-2}) function of atmospheric CO_2

GDD*=growing degree-days

CCx**= Maximum canopy cover

Table 5.3b User-specific crop input parameters from Phenological observations of local maize (BH540) cultivar

Description	Value	Unit/meaning
Time from sowing to emergence	7	Calendar days
Time from sowing to maximum canopy cover	70	Calendar days
Time from sowing to flowering	65	Calendar days
Duration of flowering	15	Calendar days
Time from sowing to start of senescence	120	Calendar days
Time from sowing to harvest	145	Calendar days
Maximum rooting depth	0.6	Meter
Plant density	30 000-75 000	Plants ha^{-1}
Maximum canopy cover (CC_x)	70-95	%, Plant density function

The soil input parameters described in Table 5.1 were used for all simulations and consisted of volumetric soil water content (SWC) at permanent wilting point, field capacity and saturation, and saturated hydraulic conductivity at saturation (Ksat). Non-limiting soil fertility levels were used. Based on historical simulations in the CRV of Ethiopia, the initial soil water content was fixed at 75% of the field capacity (Biazin and Stroosnijder 2012).

The management component of the model comprises irrigation and field management options. In this experiment four different levels of SI and four planting densities were evaluated (Table 5.2). The field management also includes surface characteristics such as runoff. However, since the plots were very flat, runoff was insignificant and therefore not a factor.

Model calibration and validation

AquaCrop has been parameterized and tested under a wide range of environmental conditions for different crops in Ethiopia (Araya et al. 2010, Erkossa et al. 2011; Biazin and Stroosnijder 2012; Abrha et al. 2012; Muluneh et al., 2015) and elsewhere (Heng et al. 2009; Hsiao et al. 2009; Andarzian et al. 2011; Salemi et al. 2011; Mhizha et al., in press). It was designed to be widely applicable under different climate and soil conditions, without the need for local calibration after it has been properly parameterized for a particular crop species (Hsiao et al. 2012). Thus, in this study we used the conservative parameters established by Hsiao et al. (2009) and validated the model under local conditions.

To evaluate the performance of the model for maize, validation was done based on the data obtained during the 2012 field experiment. The model performance was evaluated using absolute (RMSE) and normalized Root Mean Square Error (NRMSE) statistical indices as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(M_i - S_i)^2} \qquad (Eq. 5.2)$$

$$NRMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(M_i - S_i)^2} * \frac{100}{M} \qquad (Eq. 5.3)$$

Where n is the number of measurements, M*i* and *Si* are observed and simulated values respectively, and M is the mean of observed values. The unit for absolute RMSE is the same as that for M*i* and Si. The closer the value is to zero, the better the model simulation performance. NRMSE gives a measure (%) of the relative difference of simulated versus observed data. The simulation is considered excellent if the NRMSE is less than 10%, good if it is between 10% and 20%, fair if NRMSE is greater than 20 but less than 30% and poor if it is greater than 30% (Jamieson et al. 1991). Additional model performance evaluations were conducted using the percentage deviations between measured and simulated biomass and grain yield. Deviation (%) = (Simulated-Measured) x100/measured.

The optimum level of SI and plant density

Using the baseline climate, 30 years of maize grain yield, total biomass and water productivity were simulated. The results were compared in three different ways: (i) comparison amongst the four SI levels for determining optimum SI, (ii) comparison amongst the four density levels to determine optimum plant density, and (iii) comparison amongst the 10 different combinations of SI and plant density for determining the combination that gives optimum yield. The Bonferroni statistical method for multiple mean comparisons was used **(**Bland and Altman 1995). This method is a type of multiple comparison test used in statistical analysis and is robust enough to work with unbalanced designs where there are different numbers of observations in each subgroup (Lomax, 1992; Rafter et al. 2003). The Bonferroni method is a relatively simple way to reveal any results that may be significant in essentially any multiple test situations (Bender and Lange 2001) where a large number of tests are carried out without pre-planned hypotheses (Armstrong 2014). The Bonferroni method is straightforward to use, requiring no distributional assumption and enabling individual alternative hypotheses to be identified (Simes 1986).

Dry spells and onset definition

The analysis of dry spells for each month during the potential maize growing period was carried out using the statistical package Instat+3.37 (Stern et al. 2006). A dry spell is defined as a continuous period of "no rainfall" (< 0.85 mm day^{-1}). Defining onset for yield simulation is important. Based on the assumed starting dates of the *Belg* season in the CRV, the starting date of onset for maize crop is the 1 March. For yield simulation, the onset date was defined as the date when accumulated precipitation over 3 days was at least 20 mm and no dry spell of greater than 10 days appeared within the subsequent 30 days. This definition works for the onset window period of maize from 1 March to 30 June and was based on the work of Segele and Lamb (2005) who recommended it for relatively wetter regions in Ethiopia. Sivakumar (1988) used a similar definition of onset elsewhere in Africa.

Climate change impact on maize yield and yield response to elevated CO_2

Assessment of climate change impact on maize grain yield due to projected climate variables (rainfall and maximum & minimum temperature) were determined by subtracting baseline climate simulation from projected climate simulation both using reference CO_2 level (369.14 ppm). For assessing the response of maize grain yield due to elevated CO_2 alone, we first simulated grain yield using projected climate variables with reference CO_2 level (369.14 ppm) and then we simulated grain yield using projected climate variables with elevated CO_2 level. The grain yield difference between the two simulations was the response of yield to elevated CO_2 alone.

Effect of SI on maize yield

Once we determined the optimum combination of SI and plant density on maize grain yield under the 30 years baseline climate data as mentioned in section 2.7. We compared the simulated grain yield under rainfed condition (SI1D1) and the selected supplemental irrigation and plant density combination (in this case SI2D1) during baseline and projected climate scenarios with reference CO_2 level. The difference between the two simulations (simulation under rainfed conditions (SI1D1) and under supplementary irrigation (SI2D1) was considered to be the effect of SI on maize yield under baseline and projected climate scenarios**.**

Effect of shifting the sowing date on maize yield

The response of yield to a different sowing period was determined by simulating yield under 5 different sowing dates in a month (the 1st, 8th, 15th, 22nd, and 29th of a month). The comparison of yields for the baseline climate and the climate change scenarios were determined as follows: first, we simulated yield for baseline climate conditions by running the AquaCrop model using the five onset dates for the month of April, we then simulated yield for the climate change scenarios using the five onset dates for the months of April, May and June, after which we compared the results. We used the month of April for the baseline climate simulation because it is the average onset month for the current climate.

5.3 Results

Validation of AquaCrop

Figure 5.1 and Figure 5.2 show the observed soil water content and canopy cover plotted against the results simulated by the AquaCrop model under (a) only rainfed (SI1), (b) SI2 (75% TAW depleted), (c) SI3 (60% TAW depleted) and (d) SI4 (20% TAW depleted). The scatter plots show that the AquaCrop model did a good job of simulating the soil moisture under both rainfed and SI conditions.

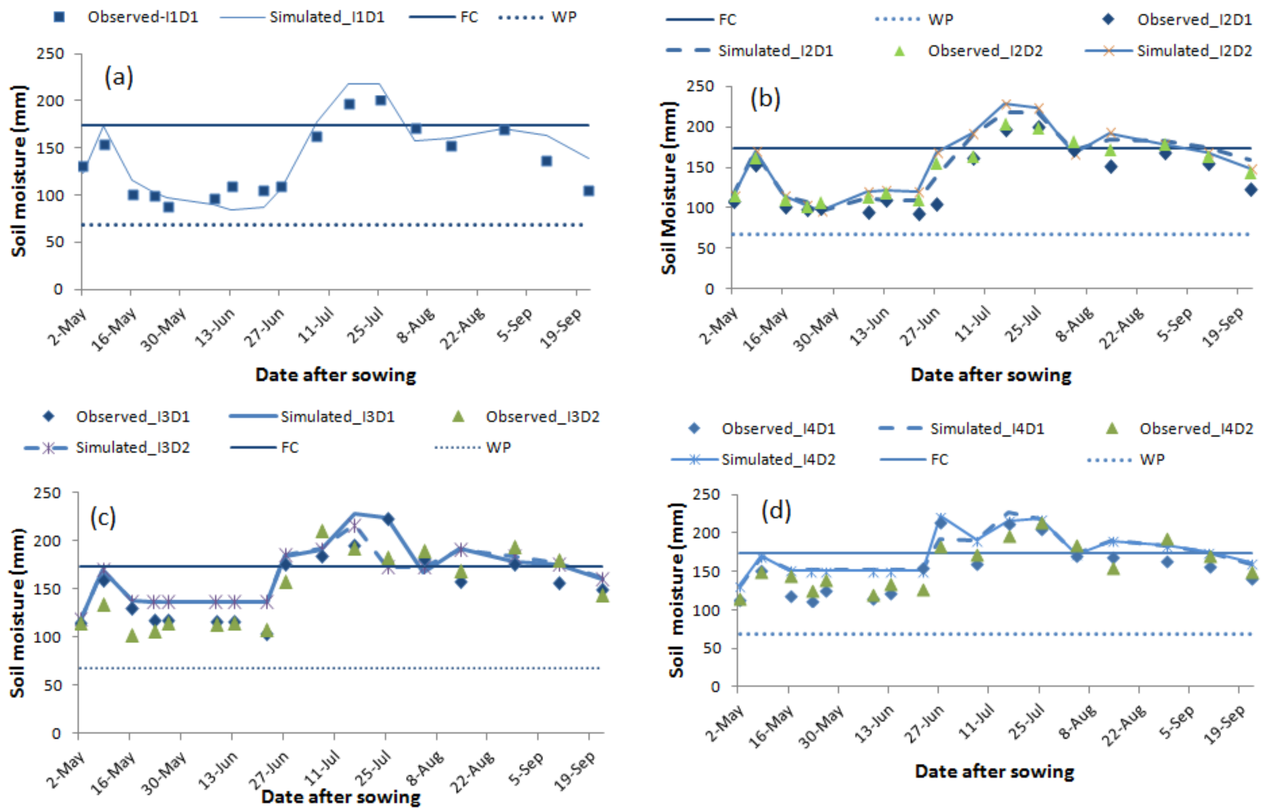

Figure 5.1 Observed and simulated soil moisture in the top 0.6 m under various conditions: (a) only rainfed without irrigation (b) I2 supplemental irrigation (c) I3 supplemental irrigation and (d) I4 supplemental irrigation

Similarly, the simulated canopy cover correlated well with the observed data. There was not much difference between the simulated and observed canopy cover (Figure 5.2). All statistical parameters (RMSE, NRMSE and % deviation) showed acceptable results for simulation of soil moisture and canopy cover (data not shown).

The simulated grain yields and total biomass of maize agreed well with that of the observed values under all treatments (Table 5.4). The NRMSE was between 2% and 7% for grain yield and between 1% and 3% for total above ground biomass both of which indicate excellent performance of the model. Similarly, the percent deviation of the simulated values from the observed values also indicated good agreement.

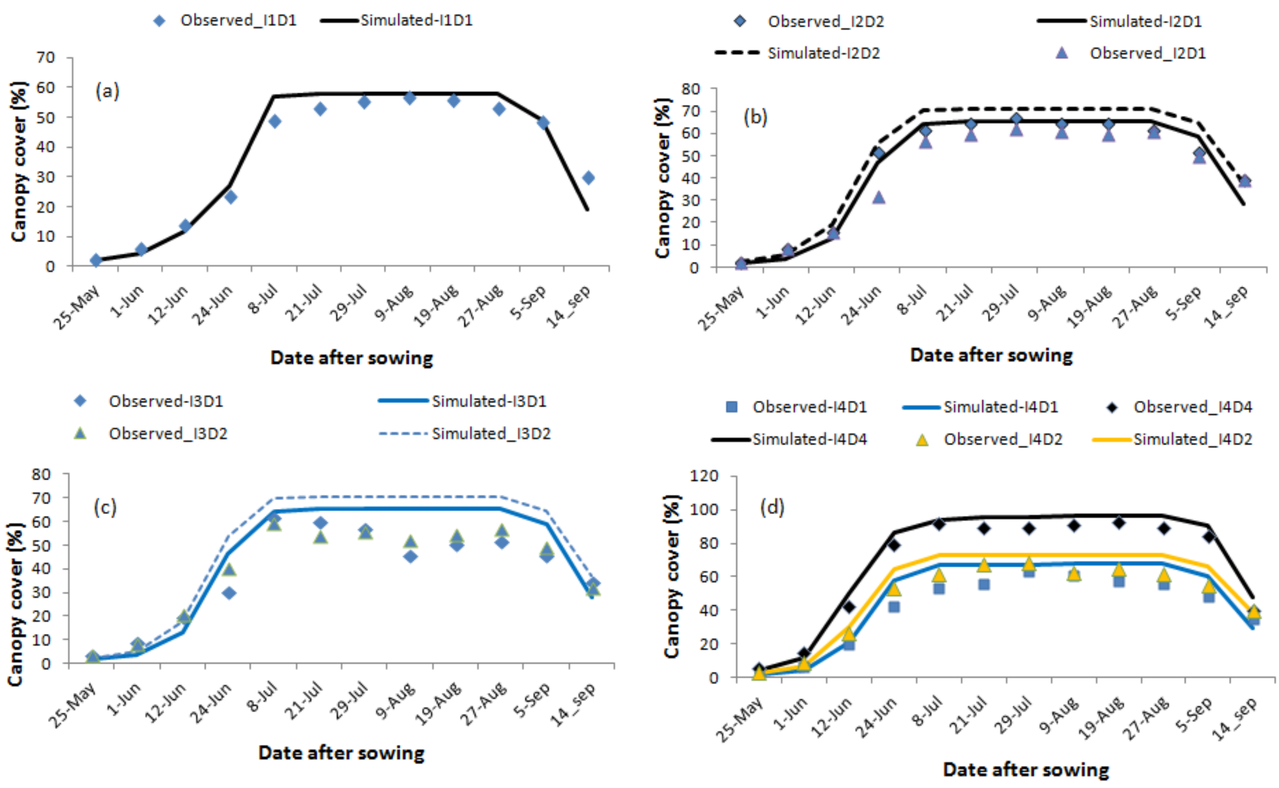

Figure 5.2 Observed and simulated canopy cover under various conditions: (a) only rainfed without irrigation (b) I2 supplemental irrigation (c) I3 supplemental irrigation and (d) I4 supplemental irrigation.

Table 5.4 Mean observed and simulated maize grain yield and total biomass with the root mean square error (RMSE), normalized root mean square error (NRMSE) and percentage deviation (Dev.)

	Grain yield					Total Biomass				
	Observ.	Simul.	RMSE	NRMSE	Dev.	Observ.	Simul.	RMSE	NRMSE	Dev.
Treatment	t ha^{-1}	t ha^{-1}	t ha^{-1}	(%)	(%)	t ha^{-1}	t ha^{-1}	t ha^{-1}	(%)	(%)
SI1D1	7.45	7.83	0.4	5.41	4.99	15.81	16.31	0.52	3.28	3.14
SI2D1	7.79	8.20	0.52	6.63	5.31	16.83	17.09	0.29	1.75	1.56
SI2D2	8.54	8.72	0.34	3.97	2.11	18.1	18.18	0.26	1.44	0.46
SI3D1	8.16	8.46	0.3	3.70	3.63	17.63	17.62	0.27	1.52	-0.1
SI3D2	8.91	8.89	0.14	1.61	-0.22	21.35	18.53	0.18	0.96	0.4
SI3D3	9.04	9.18	0.36	4.00	1.55	19.85	19.53	0.34	1.73	-1.61
SI4D1	8.32	8.79	0.47	5.69	5.59	17.97	18.31	0.39	2.15	1.89
SI4D2	9.14	9.17	0.19	2.08	0.27	18.87	19.12	0.43	2.25	1.31
SI4D3	9.09	9.47	0.39	4.32	4.22	19.94	20.16	0.23	1.15	1.10
SI4D4	9.78	9.55	0.27	2.74	-2.33	21.16	21.22	0.15	0.69	0.3

The optimum level of SI and plant density

Based on the 30-year simulation, the irrigation level SI2 (75% TAW depleted) is a better option in terms of optimizing grain and total biomass yield and water productivity (Table 5.5); SI2 was considered a better option because (i) there is significant difference in yield and water productivity between rainfed (SI1) and the second irrigation level (SI2), (ii) there were no significant further increases in yield and water productivity with higher irrigation levels (SI3 and SI4), (iii) SI2 was enough to save the crop in drought years (when there would have been a total rainfed crop failure) , and (iv) SI2 requires less irrigation water as compared to the higher levels of supplemental irrigation (SI3 and SI4).

Regarding the optimum level of plant density, yield and water productivity results from the lowest density level (D1) were significantly different from those achieved with D3 and D4 but not significantly different from the second level plant density (D2) (Table 5.5). The density levels D2, D3 and D4 also did not show significant difference. Therefore, D1 the density level which is currently used by farmers was selected to be used in our further analysis.

The combined effect of SI and plant density on maize yield shown in Table 5.6 indicates that yield was not significantly different when the irrigation level was increased beyond SI2. Therefore, the combination of SI2 with plant density D1 (SI2D1), which is significantly different from the rainfed grain and total biomass yield (SI1D1), was used for the subsequent baseline and future yield simulations. Since the density level under rainfed (SI1D1) and supplemental irrigation (SI2D1) are the same, the yield difference could arise from the supplemental irrigation. Thus, SI2D1 combination hereafter is simply called supplemental irrigation and abbreviated as SI.

Table 5.5 Means of grain yield, total biomass and grain water productivity at different levels of supplemental irrigation and plant density

Irrigation	Grain yield (t ha^{-1})	Total Biomass (t ha^{-1})	Grain Water productivity (kg m^{-3})
SI1 (D1)	6.04^{a}	12.72^{a}	1.55^{a}
SI2 (D1,D2)	7.40^{b}	15.40^{b}	1.80^{b}
SI3 (D1,D2,D3)	7.51^{b}	15.76^{b}	1.83^{b}
SI4 (D1,D2,D3,D4)	7.58^{b}	16.13^{b}	1.75^{ab}
Density			
D1 (SI1,SI2,SI3,SI4)	6.95^{a}	14.59^{a}	1.65^{a}
D2 (SI2,SI3,SI4)	7.50^{ab}	15.73^{ab}	1.79^{ab}
D3 (SI3,SI4)	7.69^{b}	16.37^{b}	1.86^{b}
D4 (SI4)	7.99^{b}	17.00^{b}	1.97^{b}

Means sharing similar letter in respective columns do not differ significantly at 5% level of probability (Bonferroni test, $P<0.05$)

Table 5.6 Means of grain yield and total biomass at different combinations of irrigation and plant density under baseline climate

Treatments	Grain yield (t ha^{-1})	Total Biomass (t ha^{-1})
SI1D1	6.04^{a}	12.72^{a}
SI2D1	7.26^{b}	15.10^{be}
SI2D2	7.54^{b}	15.7^{bg}
SI3D1	7.31^{b}	15.21^{bc}
SI3D2	7.55^{b}	15.73^{bg}
SI3D3	7.66^{b}	16.33^{bg}
SI4D1	7.20^{b}	15.33^{bg}
SI4D2	7.41^{b}	15.78^{bg}
SI4D3	7.71^{b}	16.40^{bg}
SI4D4	7.99^{b}	17.00^{dfg}

Means sharing similar letter in respective columns do not differ significantly at 5% level of probability (Bonferroni test, $P<0.05$)

Effect of SI in drought years

Under the baseline climate, SI increased maize grain yield by 20% (6.03 to 7.26 t ha^{-1}) (Figure 5.4). This increase in grain yield is the 30 year average which does not clearly show the effect of SI specifically in drought years. Thus, the response to SI in drought years during the baseline climate was assessed separately as shown in Table 5.7. From 30 years of baseline climate simulations under rainfed conditions, the years 1967 and 1972 resulted in total crop failure due to the severe drought related to long dry spells during the critical growth stages. The 1967 crop failure was due to a dry spell of > 30 days in the period of 60-90 DAS, while in 1972 it was due to a dry spell of >20 days that occurred in the 30-60 and 60-90 DAS periods. The crop water requirement for those years was higher than the amount of rainfall, leading to the total crop failure. For instance, in 1967, during the first 90 DAS, the crop water requirement (424 mm) was more than twice the available rainfall (188 mm) (Table 5.7). Simulation results using SI, during those severe drought years, increased the maize grain yield from total crop failure to 6.8 t ha^{-1}.

The amount of SI-water used to save the crop from total failure ranges between 94-111 mm. On the other hand, the year 1973, with the maximum grain yield (8.57 t ha^{-1}) showed a dry spell of only < 5 days during the critical growth stage (60-90 DAS) and also has larger amount of rainfall as compared to crop water requirement during the first 90 DAS. The yield increase due to SI in a year with already high rainfed grain yield (1973) was marginal (2.5%) with the amount of SI water used also very minimal (1.7 mm).

The years 1971 and 1981 despite having limited dry spells (≤ 10 days) during the first 90 DAS, they still showed very low grain yield as compared to the grain yield in 1973. The very low maize grain yield during these years was due to low rainfall amount during the first 90 days after sowing as indicated by very high crop water requirement and low rainfall amount during the first 90 DAS (Table 5.8). During 1981, a dry spell of 39 days on 90-120 DAS contributed to the low grain yield but did not affect the grain yield to the extent of total crop failure. The use of SI increased grain yields between 59-62% for those years with very low rainfed grain yield (1971 and 1981).

The sowing date/onset for the years simulated with crop failure (1967and 1972) and very low grain yield (1971 and 1981) were during the month of March or early April, whereas the sowing date/onset for the year with maximum yield (1973) was on the month of May.

Effect of climate change on dry spells

The projected percent change in the longest dry spell in each month of the *Belg* and *Kiremt* seasons for the future climate (2020-2049) compared to the baseline climate (1966-1995) is shown in Table 5.8. Under the baseline climate, all months of the *Belg* season showed the longest dry spell as being >10 days. During the *Kiremt* season particularly in July, August and September the longest dry spells were <10 days. And October, which is usually considered to be out of the *Kiremt* season, had a longest dry spell of >20 days. We included October because in some years, when the sowing of maize goes as late as the first week of July, a 120-150 DAS growing period can extend into October. Thus rainfall conditions during October month can sometimes affect yield.

Table 5.7 Total crop failure and very low maize grain yield during drought years and maximum achievable yield during wet year under rainfed conditions and the effect of SI on yield and water use.

Year	I-30 DAS	30-60 DAS	60-90 DAS	90-120 DAS	120-150 DAS	Sowing/onset	Rainfed Yield	SI Yield	Yield change	Rainfall 1- 90 DAS	Crop water required 1-90 DAS	SI water used
	Dry spell (days)					Date	(t ha^{-1})	(t ha^{-1})	%	(mm)	(mm)	(mm)
1967	9	11	35	6	3	28-Mar	0.00	6.8	-	188	424	94
1971	7	4	10	11	3	29-Mar	4.60	7.44	62	228	387	69
1972	8	21	27	8	4	3-Apr	0.00	6.85	-	245	420	111
1973*	10	13	4	2	13	15-May	8.57	8.78	2.5	456	308	1.70
1981	5	8	5	39	9	5-Mar	4.63	7.34	59	287	403	119

*A year with the maximum yield simulated under rainfed conditions

Under the ECHAM5 model, the projected dry spell length for March and April increased by 20-25% and 4-5% under A2 (high) and B1 (low) emission scenarios, respectively. By contrast, the projected longest dry spell between June and October decreased by 7-42% and 6-55% under A2 and B1 scenarios respectively, except in August where there was almost no change under the B1 scenario. The projected longest dry spells under the A2 scenario is always higher than under B1 scenario.

Under ensemble mean of models, the projected longest dry spell decreased for almost all months except March and May where there was a modest increase under both scenarios. With both models and scenarios, the decrease in projected longest dry spell was greatest for October.

Table 5.8 Percent change (%) in the longest dry spell for March-October for future climate under ECHAM5 and ensemble mean of models on A2 and B1 SRES scenarios against the baseline longest dry spell (days)

Months*	Baseline (days)	ECHAM5		Ensemble mean	
		A2 scenario	B1 scenario	A2 scenario	B1 scenario
March	15	20	4	11	9
April	12	25	5	7	16
May	12	8	-7	-20	-16
June	11	-9	-31	-19	-25
July	5	-7	-6	0	-11
August	5	-12	1	-10	-14
September	8	-17	-26	-12	-8
October	22	-42	-55	-49	-56

*The first three months (March-May) are the *Belg* (short rainy season) while the five months (June-October) are the *Kiremt* (main rainy season). The *Kiremt* season is usually considered to be June-September but sometimes it can be extended to include October.

Effect of CO_2 level on maize yield

With the ECHAM5 model, the simulated maize grain yield under projected climate change scenarios using the reference CO_2 level (369.14 ppm) showed a decrease of 22% and 9% under A2 and B1 scenarios respectively compared with the baseline climate simulation (Figure 5.3).

Using the ensemble mean of models, the simulated maize grain yield under the same conditions decreased slightly (6%) under the A2 scenarios, whereas it stayed nearly level for the B1 scenario compared with the baseline climate simulation (Figure 5.3).

With elevated CO_2 concentrations, under projected climate variables, grain yield increased compared to the simulations using reference CO_2 with both GCM models. Under ECHAM5, the simulated grain yield increased by 7.5% when CO_2 concentration level increased from the reference 369.41 ppm to 518.88 ppm under the A2 scenario, and by 6.2% when CO_2 concentration level increased from the reference 369.41 ppm to 467.57 ppm under the B1 scenario. Under similar CO_2 increases, for the ensemble mean of models, the yield increased by 7.4% and 6.4% under A2 and B1 scenarios, respectively (Figure 5.3).

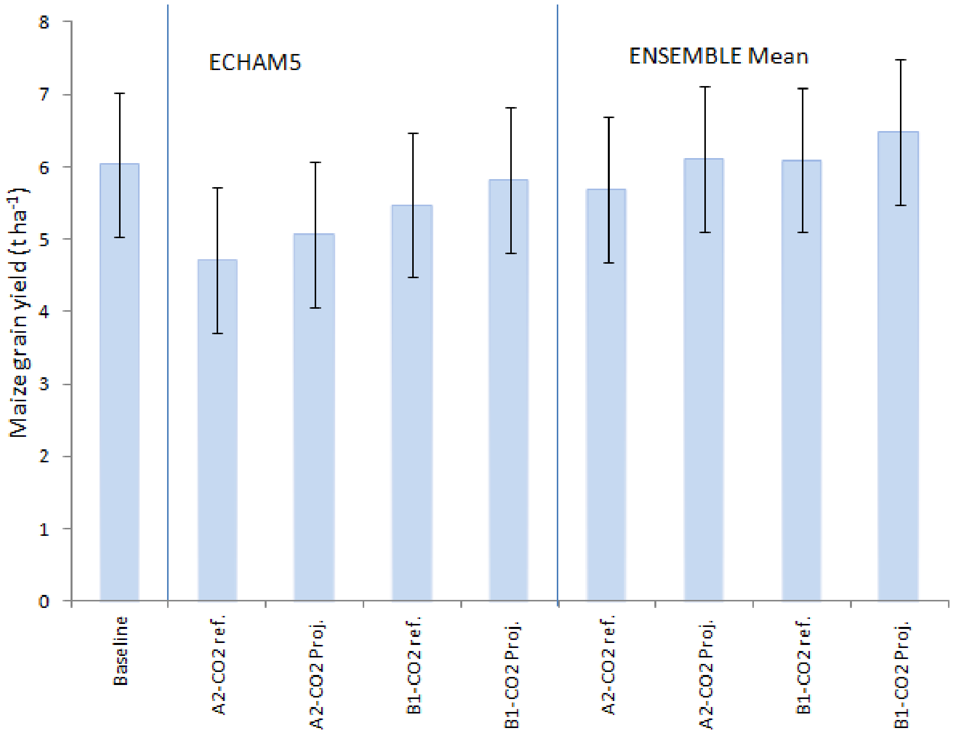

Figure 5.3 Baseline and Projected maize grain yield under reference CO_2 (369.14 ppm) and projected CO_2 level under ECHAM5 and ensemble mean model in Halaba special Woreda, CRV, Ethiopia. Error bars indicate the 95% confidence interval of the mean

Effect of SI on maize yield

Figure 5.4 presents maize grain yield under rainfed and SI conditions for different climate change scenarios. The ECHAM5 model, with the A2 scenario and SI, showed an increase in grain yield of 8% against the baseline yield, and of 38% against the projected rainfed grain yield. Similarly, with the B1 scenario, SI increased the grain yield by 8% against baseline yield and by 19% against the projected rainfed grain yield.

Under the ensemble mean of models with the A2 scenario, SI increased the grain yield by 15% against the baseline yield and by 13% against the projected rainfed grain yield. The ensemble mean of models with the B1 scenario and SI showed an increase in grain yield of 19% against baseline yield and of 11% against projected rainfed grain yield. On both ECHAM5 and ensemble mean of models, when we compared the projected grain yield between rainfed and SI conditions, the effect of SI for the A2 scenario was higher than for the B1 scenario.

Effect on maize yield of shifting the sowing date

Table 5.9 presents the percentage change in grain yield when the sowing dates are in April, May and June compared to the baseline sowing date of April. Using the ECHAM5 model with the A2 scenario, the simulated grain yield decreased by 61% and 2% when sowing date was in April and May respectively, but an increase of 96% when sowing date was delayed until June. The ECHAM5 model with the B1 scenario simulated a grain yield decrease of 37% when sowing of maize was in April but an increase of 35% when sowing was in May. When the sowing of maize was further extended to June, the grain yield increased by 140% under the B1 scenario.

Under the ensemble mean of models, sowing of maize in any of the months will increase yield under both A2 and B1 scenarios except in April where maize grain yield slightly decreased under the B1 scenario. Overall, maximum yield was obtained when the sowing of maize was extended to June under both models and scenarios.

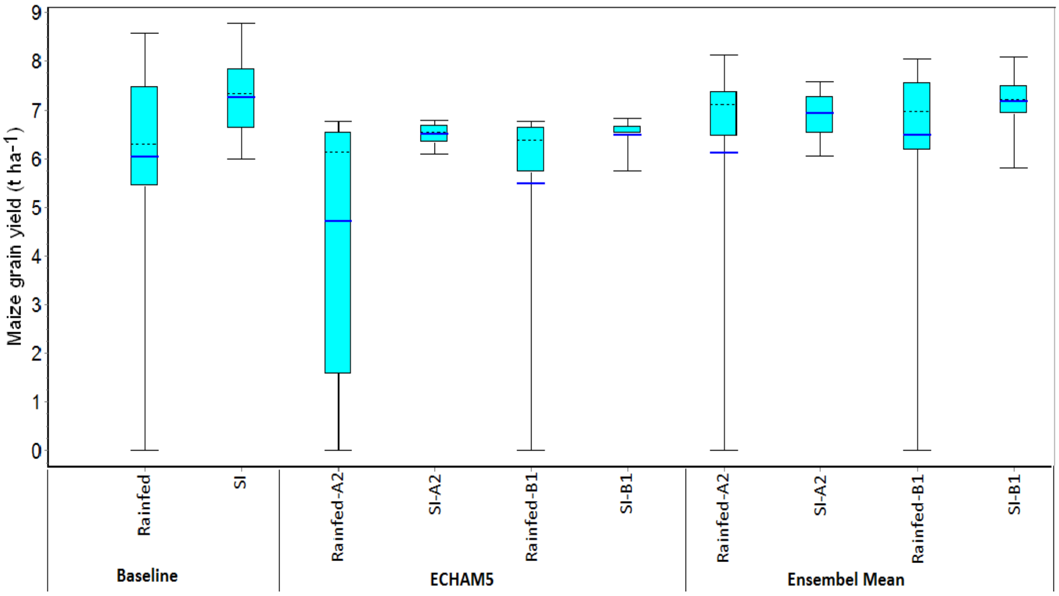

Figure 5.4 Maize *grain yield* (t ha^{-1}) under rainfed and supplemental irrigation for baseline and future climate conditions

Table 5.9 Percent (%) change in projected maize grain yield in different sowing months respective to baseline yield under ECHAM5 and ensemble mean models with A2 and B1 SRES scenarios

Months	ECHAM5		Ensemble mean	
	A2 scenario	B1 scenario	A2 scenario	B1 scenario
April	-61	-37	14	-6
May	-2	35	112	102
June	96	140	150	156

5.4 Discussion

The aim of this study was (i) to determine the optimum combination of supplemental irrigation (SI) and plant density using 30-years of baseline climate, to be used in future climate scenarios, (ii) to assess drought for the baseline and future climate using dry spell analysis and (iii) to evaluate the adaptation options of supplemental irrigation and shifting of the planting date for improving maize grain yield and improved food security.

AquaCrop validation

A key part of achieving the aims of the study was validation of the AquaCrop model. AquaCrop has proven to show good performance in simulating soil moisture, canopy cover, grain yield and total biomass under different levels of irrigation treatments elsewhere (For example, Abedinpour et al. 2012 and 2014). Similarly, AquaCrop has also been validated for maize elsewhere in Ethiopia and reported that it can well simulate grain yield and total biomass (Erkossa et al. 2011; Biazin and Stroosnijder 2012). Therefore, due to its simplicity, accuracy, and robustness, AquaCrop is becoming a widely used crop model for estimating crop yield for climate change scenarios and to test different adaptation options (Mainuddin et al. 2011; Mainuddin et al. 2013; Soddu et al. 2013; Abedinpour et al. 2014; Muluneh et al., 2015; Deb et al. 2014; Shrestha et al. 2014a.; Shrestha et al. 2014b; Vanuytrecht et al. 2014b). We also found the AquaCrop model able to simulate the soil water, canopy cover and crop yields well for the BH540 maize cultivar under both rainfed conditions and different levels of SI with conservative and user specific crop parameters. The values of RMSE, NRMSE and percent deviation for the model validation were all in acceptable ranges.

The optimum level of SI and plant density

After simulating yield with 10 different combinations of SI and plant density for each year of the 30 baseline years, we compared the means of simulated yield to determine the best combination of SI and plant density. The optimum level of SI and plant density in terms of grain yield and total biomass was SI2D1, which means application of SI when the SWD of the TAW reached 75% using 30 000 plants ha^{-1}. The 30 000 plants ha^{-1} is the common maize crop density level where most farmers use in the CRV. However, despite a continuous grain yield increase from a lower SI-plant density combination to higher combinations, the difference was not statistically significant. Therefore the lowest combination was chosen (SI2D1). From a field experimental study conducted in the CRV similar conclusions were drawn (Muluneh et al. 2015). Thus, identifying the best SI level was the more important factor for maximizing yield and saving maize crop from drought.

Effect of SI in drought years

The 30 year mean yield increase from SI was modest (Figure 5.4). However, this long term mean yield cannot show how the crop responds to SI in a particular drought year when there would be total crop failure under rainfed conditions. Therefore, we analyzed the effect of SI on crop yield under conditions where there would be total rainfed crop failure or very low crop yield. Total crop failure during drought years was due to a dry spell of > 30 days during the 60-90 DAS period (1967) and dry spells of >20 days in both the 30-60 and 60-90 DAS periods (1972). Another study in the semi-arid part of the CRV by Biazin and Sterk (2013) found that dry spells longer than 30 days occurring in the first 60 days after onset, or longer than 20 days in the 60-90 DAS period were critical and caused total crop failure for maize crops. This confirms that the most damaging effect of dry spells is manifested during sensitive stages of crops such as flowering and grain filling, which has also been documented by Stern and Coe (1984).

Our analysis showed that using 94-111 mm of SI during sensitive stages of maize crop, it is possible to avoid total crop failure. Similarly, Magombeyi et al. (2009) in South Africa found that using 110 mm of SI in the driest year of their research resulted in the highest yield responses. Since availability of water for SI is also an important factor for evaluating and determining effective SI strategies, we looked at this in an earlier study (Muluneh et al. 2015; manuscript submitted for publication). The results of that research showed that sufficient amounts of water for SI would be available from existing farm ponds, even in drought years.

Effect of climate change on dry spells

With respect to predicting the length of dry spells, the two climate models used did show almost consistent results. Both models do indicate increasing tendency of dry spells during *Belg* (March and April) and a decreasing tendency during *Kiremt* (June-October). However, during *Belg* the ECHAM5 model showed more dryness than the ensemble mean of models. Most other studies also indicate the drying tendency of the *Belg* season mostly in the Ethiopian highlands. For example, recently, Cook and Vizy (2012) using 10 GCM ensembles mean models found that the number of dry days in the Ethiopian Highlands increases by 5-20 days, a 2 – 10% increase during 2041-2060 compared to 1981-2000. This future increase in dryness was associated with a weakening of the *Belg* (March-May) rainfall.

The drying of *Belg* is consistent with the declining March to June rainfall that occurred during the second half of the 20th century, and which is also projected to continue into the future in the East African region, particularly Ethiopia (Funk et al. 2008; Williams and Funk 2011; Lyon and DeWitt 2012; Muluneh et al., 2015). Agricultural production in the Ethiopian CRV takes place in two cropping seasons per year, the *Kiremt* and *Belg* seasons. *Belg* rains are critical for long-cycle crops (such as maize and sorghum) which are harvested at the end of the *Kiremt* season. *Belg*-dependent growing areas are typically the most food insecure cropping areas (WFP 2014). Therefore, the predicted effects of *Belg* season drought could exacerbate future livelihood degradation and food insecurity in the CRV of Ethiopia.

Furthermore the two climate models that we used is consistent in showing the cessation of rainfall in the future likely to be extended compared to the current climate. This may extend the growing season into October which could allow a later sowing date. This could compensate, at least in part, for the predicted increase in dry spells during *Belg* drought.

Effect of CO_2 level on maize yield

With both ECHAM5 and the ensemble mean of models the projected maize grain yield showed a declining tendency in the dry sub-humid area of the CRV. On the other hand, when both GCM models run with elevated CO_2 concentrations they showed grain yield increase. In a previous study, we also reported maize grain yield increase from elevated CO_2 in the CRV (Muluneh et al., in press). Generally, there is a consensus that elevated CO_2 tends to increase growth and yield of most agricultural plants as a result of higher rates of photosynthesis and low rates of water loss that improve water-use efficiency (Allen and Amthor 1995; Parry et al. 2004; Vanuytrecht et al. 2011). However, the question is can the yield increase from elevated CO_2 fully compensate the yield decline caused by climate change? In this study, the ensemble mean of models yield projection elevated CO_2

level was able to offset the negative impact of climate change, because there was no too much difference between the projected simulated yield and the baseline simulated yield (Figure 5.3). However, under the ECHAM5 model projection, despite the 7.5% yield increase from elevated CO_2 level, still shows grain yield to be less than the baseline climate simulation, because the projected simulated yield was much lower than the baseline simulated yield (Figure 5.3). Thus, despite the positive effect of elevated CO_2 to crops, the predicted lower maize production due to the changing rainfall is only partly compensated by the expected increase in CO_2 concentration

Effect of SI on maize yield

Our simulation of yield using SI for future climate scenarios proved that SI can offset the predicted yield reduction due to climate change. With SI, the 22% simulated yield reduction from the ECHAM5 model for the A2 scenario and rainfed climate becomes an 8% increase (Figure 5.4). The ensemble mean of models projected a similar increase in simulated yield under SI. Thus, SI is a promising adaptation option for farmers in the CRV. Although, due to the expected increase in dry spells, sowing of maize under rainfed condition during *Belg* is becoming more risky, SI is a strategy to enable growing of long maturing maize varieties that can still be sown during the *Belg* season.

Effect of shifting the sowing date

The average sowing date for the baseline climate is in April. If the baseline sowing date is used for future climate scenarios, the yield is affected negatively unless additional measures are taken. However, from the results of both ECHAM5 and ensemble mean of models, shifting of the maize sowing from April to June (from mid-*Belg* to the start of *Kiremt*) for future climate conditions increases the maize grain yield (Table 5.9). These results are consistent with research findings elsewhere in Africa. In Ghana, Tachie-Obeng et al. (2013) reported that delaying sowing dates by 6 weeks, from the baseline date of 1st May to 15th June, increased maize yields by up to 12%. For projected future climate conditions, the sowing of maize in June will decrease the risk of crop failure since dry spells continuously decrease from June to October (Table 5.5).

Furthermore, the projected decrease in the longest dry spell as we move further into the *Kiremt* months (June-October) indicates the extending of the cessation of *Kiremt* rainfall, thus increasing the length of the crop growing period. This is consistent with a previous study which reported the lengthening of the growing season in the CRV of Ethiopia due to the extended cessation during *Kiremt* (Muluneh et al., in press). Other studies also indicated that the simulated annual cycle for Ethiopia shows a shift in both the rainfall onset and cessation dates by about a month (Shongwe et al. 2008). This result implies a shift in the whole rainy season with October receiving more rainfall than in the present climate.

Generally, in the Ethiopian highlands, climate change may extend the agricultural growing seasons as a result of increased temperatures and rainfall changes (Thornton et al. 2006; Boko et al. 2007). According to Tessema & Lamb (2003), warm SSTs in the Indian Ocean and Arabian Sea are likely to be associated with delayed *Kiremt* cessation and hence prolonged rain. Therefore, shifting the sowing period of maize from the baseline *Belg* season (mostly April or May) to the first month of *Kiremt* season (June) seems to be a promising adaptation to increase food security in the face of expected climate change.

5.5 Conclusions

A change in climate in the CRV of Ethiopia is inevitable and maize yield will decline if no changes in cropping practices are made to adapt to the future climatic conditions (2020-2049). In this paper, we assessed the projected changes in dry spells, rainfall, CO2 levels, and their effect of maize grain yield in dry sub-humid and semi-arid parts of the Ethiopian CRV. We then used a validated crop simulation model to explore three adaptation options: plant density, SI, and shifting of the sowing date. From the results of our assessments and analysis reported above the following conclusions have been drawn regarding the adaptation options:

1 Increasing plant density from 30000 to 75000 plants ha^{-1} showed statistically significant yield increase, so higher plant density is recommended.

2 Supplemental irrigation (SI) is a promising option for improving crop survival and yield and therefore food security. Although SI has a marginal effect in good rainfall years, using 94-111 mm of SI during sensitive growth stages can avoid total crop failure in drought years. In an earlier study (Muluneh et al. 2014; manuscript submitted for publication) we proved that this amount of SI can be available using farm ponds catching runoff, even in drought years.

3 Shifting the sowing period of maize from the current *Belg* season (mostly April or May) to the first month of *Kiremt* season (June) is another promising adaptation for increasing food security in the face of expected climate change. The climate models we used predict a temporal shift in rainfall, meaning even less in *Belg* and more in *Kiremt*, thus extending the growing season. Shifting the sowing period can reduce the risk of crop failure and offset the predicted yield reduction caused by climate change.

Chapter 6

Effect of long term deforestation and remnant forests on rainfall and temperature in the Central Rift Valley of Ethiopia

Abstract

Some evidence suggests that forests attract rain and that deforestation contributes to changes in rainfall and temperature. The evidence, however, is scant, particularly on smaller spatial scales. We investigated the forest-rainfall relationships in the Central Rift Valley (CRV) of Ethiopia, an environmental hotspot. Specifically, we evaluated the long-term trends in rainfall (1970-2009) and temperature (1981-2009) and their relationships with long-term deforestation and the relationship between remnant forests and topographical variables with spatial rainfall distribution. The study used 16 long-term (40 years) and 15 short-term (two years) rainfall data sets. Annual rainfall on the valley floor increased by 37.9 mm/decade despite a continuous decline in forest and woodland cover over the past 40 years (1970-2009). Annual rainfall on the escarpments/highlands, however, decreased by 29.8 mm/decade. The floor of the rift valley also warmed significantly due to long-term deforestation in the CRV. The remnant forests had a significant effect ($R^2 = 0.4$) on the spatial variability of the number of rainy days, indicated by the rainfall systematically observed over two years (2012-2013), but had little effect on the variability of both long- and short-term rainfall distribution.

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Effect of long term deforestation and remnant forests on rainfall and temperature in the Central Rift Valley of Ethiopia

6.1 Introduction

The loss of vegetation in humid and dry tropical regions is believed to increase the incidence of droughts and floods (Charney et al., 1975; Tangkitjavisuth, 1979; Nicholson et al., 1998) and to also contribute to climate change (e.g. de Sherbinin, 2002). The impacts of changes in land use may contribute more than the greenhouse effect to climate change, occurrence of droughts, and desertification (Savenije, 1996). Charney (1975) showed that the radiative heat loss caused by the high albedo of a desert contributes significantly to the sinking and drying of high air and therefore to a reduction in precipitation.

Forest protection and re-vegetation can also mitigate drought and flood risks. For example, the protection of tropical forests in Madagascar and Indonesia has benefited drought and flood mitigation (Kramer et al., 1997; Pattanayak and Kramer, 2000). Replacing bare soils with vegetation is assumed to increase rainfall but can also decrease aridity (Anthes, 1984). Makarieva et al. (2009) recently suggested the potential for forest-mediated solutions to the problems of global desertification and water security.

The need for improving our understanding of the role of vegetative cover in climate is thus becoming more urgent due to the increasing magnitude of change that humans are imposing on vegetation (Sanderson et al., 2012). Climate change caused by changes in vegetation is receiving considerable attention (Dirmeyer and Shukla, 1994). Trends in precipitation and in maximum and minimum temperatures are useful indicators of climatic variability and change (Braganza et al., 2004).

Most empirical and modelling studies, however, have been on global/continental scales (e.g. the Amazon and Congo basins). For example, the recycling of moisture by natural vegetation in large watersheds such as the Amazon basin (with an area of approximately 8×10^6 km^2) (Anthes, 1984), where over half of all precipitation originates from local evapotranspiration (Laurence, 1998), can play an important role in weather generation. A global transect study by Makarieva et al. (2009) similarly found that precipitation declined exponentially with distance from the ocean in non-forested regions, whereas precipitation increased inland for several thousand kilometres in forested regions such as the Amazon and Congo River basins. Such studies on global/continental scales do not clearly show how forests affect rainfall on smaller scales, from a few to about one hundred kilometres in diameter.

Furthermore, some meso- and local-scale observational studies have produced conflicting results. For example, Anthes, (1984) argued that mesoscale isolated forests 50-100 km wide in semiarid regions could increase convective precipitation due to increased surface roughness (compared to bare soil) and initiate small-scale convection and consequently rain over vegetated areas. Bonan (2008) similarly stated that fragmented forest cover can increase localised rainfall as a result of increased atmospheric turbulence due to canopy roughness. Deforestation, though, has been implicated as a contributing factor of declining rainfall in various regions (e.g. Chan, 1986; Zhang, 1986). Deforestation in tropical regions has particularly led to decreases in rainfall of 1-20% (Meher-Homji, 1991; Pielke, 2001; Duriex et al., 2003; Ray et al., 2006). Soman et al (1988) reported a decrease in rainfall over the highlands of Kerala, India, following deforestation in recent decades. Shukla et al. (1990) similarly indicated that replacing forests with degraded pasture reduced annual precipitation by 642 mm and increased temperature by 1.3 °C.

The consequences of deforestation are expressed through the changes in surface albedo, surface roughness, and evaporation (Hasler et al., 2007; Oglesby et al., 2010) by modifying the surface energy and moisture budgets. The role of deforestation in temperature change also has two competing effects: warming due to the reduction in evapotranspiration and cooling due to the increase in surface albedo. The magnitude of warming in most regions is much higher than that of cooling, resulting in warmer and drier conditions (Zhang et. al., 1996; Oglesby et al., 2010).

Other reports place less emphasis on the effect of deforestation on rainfall. For example, Wilk et al. (2001) did not detect significant changes in rainfall totals or patterns in the 12 100 km^2 Nam Pong basin in northeastern Thailand, despite a reduction in forest area from 80 to 27% between 1957 and 1995. Costa et al. (2003) also found no change in rainfall total or distribution following the conversion of shrubs and scattered trees to pasture in >19% of the Tocantins River basin (ca. 33 000 km^2) in east-central Brazil. Dirmeyer and Shukla (1994) also argued that precipitation over deforested areas does not necessarily decline. The impacts of forests and changes in forest cover on rainfall thus remain poorly known and understood.

Small-scale spatial variability of rainfall could also be caused by various topographical parameters such as elevation, slope, and slope aspect (Agnew et al., 2000; Marquínez et al., 2003). Several major zones of air-mass convergence in eastern Africa are superimposed on regional factors associated with influences of lakes and topography, producing markedly complex climatic patterns that change rapidly over short distances (Nicholson, 1996). A chain of lakes and a complex topography in the Ethiopian Rift Valley also abruptly affects rainfall over short distances. Rainfall often increases with elevation due to the orographic effect. Slope and slope aspect influence near-surface temperatures and water availability due to varying exposure to solar radiation and wind (Barry, 1992; Bolstad et al., 1998). Steeper slopes provide stronger orographic lifting, so steeper slopes are expected to be associated with higher rainfall (Buytaert *et al*., 2006).

Water bodies also commonly affect rainfall distribution by influencing local meteorological conditions (e.g. Ba and Nicholson, 1998). Mesoscale (1-30 km radius) and local scale (300 m to 2 km radius) weather is influenced by proximity and size of water surfaces, urbanised areas, and mountain ranges (Aguilar et al., 2003).

Local people in eastern Africa, including the Central Rift Valley (CRV) of Ethiopia, believe that isolated forests can attract rain (Gooch, 2007; Stroosnijder, 2012; Godfrey, et al., 2012). Strong scientific evidence for this phenomenon, however, is still lacking (Sheil and Murdiyarso, 2009). The studies reviewed here at best indicate that the role of vegetation in the amount and spatiotemporal distribution of rain at meso- and local scales remains controversial, indicating the need for region-specific empirical data and research.

Decades of continuous deforestation in Ethiopia make such a study crucial. Forests covered 40-65% of Ethiopia a hundred years ago, but the area of forests had been reduced to near 2.2% by the 1990s (Berry, 2003; EFAP, 1994; Hawando, 1997). The destruction of natural forests has continued despite ongoing reforestation and conservation efforts, and only patches of forests remain, mainly in the western and southwestern parts of the country.

The CRV is, among other Ethiopian areas, threatened by serious environmental degradation, increased soil erosion, decreased water quality, and loss of biological diversity on land and in the lakes (Sissay, 2003). For example, the areas of natural forests and woodlands in the Munessa-Shashemene forest in the southeastern escarpment of the CRV are declining at estimated rates of 1.7 and 2.6% per annum, respectively, while cropland is increasing at the rate of 2.8% per annum (Seifu, 1998). Determining the effects of such a reduction in forest area on regional and local climates is thus important.

The inter-annual variability of rainfall and the prevailing large-scale circulation influencing its distribution have been studied in Ethiopia (e.g. Bewket and Conway, 2007), but the effects of local factors such as isolated forests, terrain, and water bodies on the variability of rainfall is still unclear. Studies at meso- and local scales, to the best of our knowledge, are lacking.

This study explored the relationships among forest cover, rainfall, and the number of rainy days and the relationships between rainfall and local topography in the CRV of Ethiopia. The specific objectives of the study were: (i) to evaluate long-term (1970-2000s) trends in rainfall and temperature and their relationships with change in forest cover, and (ii) to assess the influence of forests and topographical factors on the spatial variability of annual rainfall.

6.2 Materials and methods

The Central Rift Valley of Ethiopia

The CRV covers an area of about 13 000 km^2 at approximately 38°00′-39°30′E, 7°00′-8°30′N (Figure 6.1). It is a sub-basin of the Rift Valley Lakes Basin and encompasses the four major lakes Ziway, Abiyata, Langano, and Shala with areas of 440, 180, 230, and 370 km^2, respectively (Ayenew, 2003), i.e. the lakes together occupy an area of about 1220 km^2 on the floor of the valley (Figure 6.1). The CRV is part of the Great East African Rift Valley, covers the major dryland portion of the country, and has three landscape units (physiographic regions): the valley floor, escarpments, and highlands. The altitude is 1600 m a.s.l. around the rift lakes and ranges from about 2000 m to 3200 m a.s.l. in the eastern and western highlands.

The climate of the CRV is classified as semi-arid, dry sub-humid, and humid in different regions. Annual rainfall and mean annual temperature range from 685 to 1118 mm and from 15 to 20 °C, respectively. The region has three main seasons. A long rainy season (*Kiremt*) extends between June and September and represents 50-70% of the total annual rainfall. *Kiremt* rainfall is mostly controlled by the seasonal migration of the inter-tropical convergence zone (ITCZ). A dry period (*Bega*) extends between October and February, with occasional rains that account for about 10-20% of the total annual rainfall. The dry period occurs when the ITCZ lies south of Ethiopia, during which time the northeasterly trade winds traversing Arabia dominate the region (Muchane, 1996). A short rainy season occurs during March to May, with 20-30% of the total annual rainfall, which coincides with a decrease in the Arabian high as it moves towards the Indian Ocean, causing warm, moist air with a southerly component to flow over most of the country (Griffiths, 1972). The intense heating of the high plateau causes the convergence of the wet monsoonal currents from the southern Indian and Atlantic Oceans, bringing rain to the region (Griffiths, 1972). The pattern of rainfall on the valley floor is mostly from relatively intense (up to 100 mm/h) storms compared to the highlands with highest intensities only up to 70 mm/h (Makin et al., 1975).

The soils of the CRV are mainly derived from young volcanic rocks, with textures ranging from sandy loam to clayey loam with varying levels of fertility and degradation.

The distribution of plants in the study area is highly influenced by elevation, which also dictates the rainfall pattern (Musein, 2006). The floor of the valley is largely dominated by deciduous acacia woodland and wooded grassland that are increasingly becoming more open (Feoli and Zerihun, 2000), whereas deciduous woodlands (*Olea europaea*, *Celtis*, *Dodonaea viscosa*, and *Euclea*) occupy the escarpments (Mohammed and Bonnefille, 1991). Montane forests dominated by *Podocarpus gracilior* grow between 2000 and 3000 m on the eastern plateaus bordering the rift (Friis, 1986).

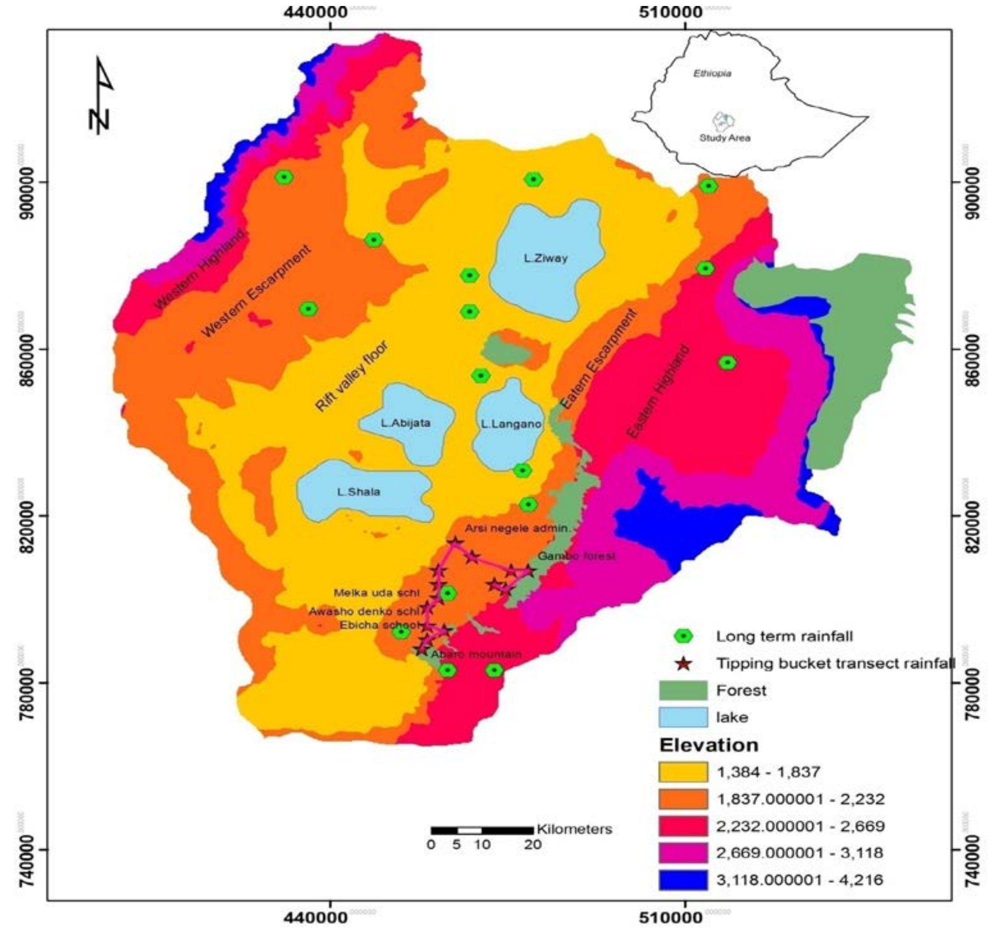


Figure 6.1 Location of meteorological stations, lakes and existing isolated forests in the Central Rift Valley of Ethiopia.

Land cover change in the CRV, Ethiopia

Land-cover change in the CRV commenced before the 1970s (Makin et al., 1975), but the country lost a significant amount of forest cover between the 1970s and the early 1990s due to increasing pressure from the growing population and an unstable political system (Seifu, 1998; Bekele,2003). Increasing and progressive settlement since the 1970s has replaced rangelands around the lakes and the montane forests on the escarpments and plateaus with small- to medium-scale farms, some of which are mechanised (Makin *et al*., 1976; Woldu and Tadesse, 1990).

The Munessa-Shashemene forest on the southeastern escarpment of the CRV (Figure 6.1) is comprised of natural woody vegetation such as podocarps, junipers, and forest plantations dominated by a few exotic species such as eucalyptus, cypresses, and pines. The forest comprises approximately 25000 ha of disturbed natural forest and 6791 ha of plantation forests (Teshome and Petty, 2000). The vegetation of the Munessa-Shashemene forest is a conspicuous remnant of the once dense dry tropical Afromontane vegetation. The forest is now designated as a High Priority Forest Area protected by the government. The Munessa-Shashemene forest has been increasingly deforested for a long time, a process that is still ongoing mainly due to commercial logging and agricultural expansion (Tolera, 1996; Seifu, 1998). Only 650.6 ha (5.4%) of 11832.4 ha of woodlands in 1973 remained unchanged in 2012 (Kindu et al., 2013). The same study reported that the natural forest cover declined from 21 723.3 ha in 1973 to 9588 ha in 2012, a loss of nearly 56% in four decades.

The areas of water bodies, forests, and woodlands in the CRV decreased by 15.3, 66.3, and 69.2%, respectively, between 1973 and 2006and by 8.6, 62.7, and 55.6% between 1985 and 2006 (Figure 6.2) (Meshesha et al., 2010). Woodlands and forested areas declined by 30.7 and 9.5%, respectively, in 1973-1985, mainly due to their conversion to agricultural land. Forests decreased from 2512.15 km^2 in 1973 to 848.72 km^2 in 2006, and woodlands decreased from 4681.01 km^2 in 1973 to 1442.59 km^2 in 2006 (Meshesha et al., 2012). Woodlands and forests were mainly converted to agricultural land, and the intensively cultivated agricultural land was highly degraded over time (Figure 6.2).

Rainfall and temperature data

We used two sets of rainfall data. (i) Long-term (1970-2009) daily rainfall data were collected at 16 meteorological stations (five on the valley floor and 11 in the escarpments/highlands) by the National Meteorological Agency of Ethiopia (NMA) (Table 6.1). (ii) Short-term (2012-2013) rainfall data were directly collected from a network of 15 Watchdog Tipping Bucket rain gauges systematically installed along transects of approximately 60 km traversing both forested and open areas (Figure 6.1). The distance between neighbouring rain gauges was <5 km, as suggested by Hubbard (1994) for explaining at least 90% of the variation between sites. Increasing the density of the monitoring network can also improve the quality of spatial rainfall estimation. Rainfall and the number of rainy days were the two important variables used for the subsequent analysis.

We analysed the temperature trend in the region using data for the maximum and minimum temperatures from the six meteorological stations from which we were able to obtain quality temperature data for 1981-2009, all 16 meteorological stations collected data for 1970-2009.

Forest data

Two types of forest data were used. (i) The long-term changes in forest cover were required to assess the effect of deforestation on rainfall patterns. A continuous decline in forest and woodland cover, described as the annual percentage of remaining forest and woodland area for 40 years (1970-2009), was determined using exponential interpolation based on measurements of existing forest and woodland cover from an analysis of remotely sensed data for 1973, 1986, and 2006 (Figure 6.2) (Meshesha et al. 2012). This type of interpolation has been used previously by Gebrehiwot et al (2010). (ii) The distances between the remnant forests and each of the rainfall stations were used as independent variables to assess the influence of the remnant forests on rainfall distribution. Euclidean distances were computed to determine the distance of each rain gauge from the forest.

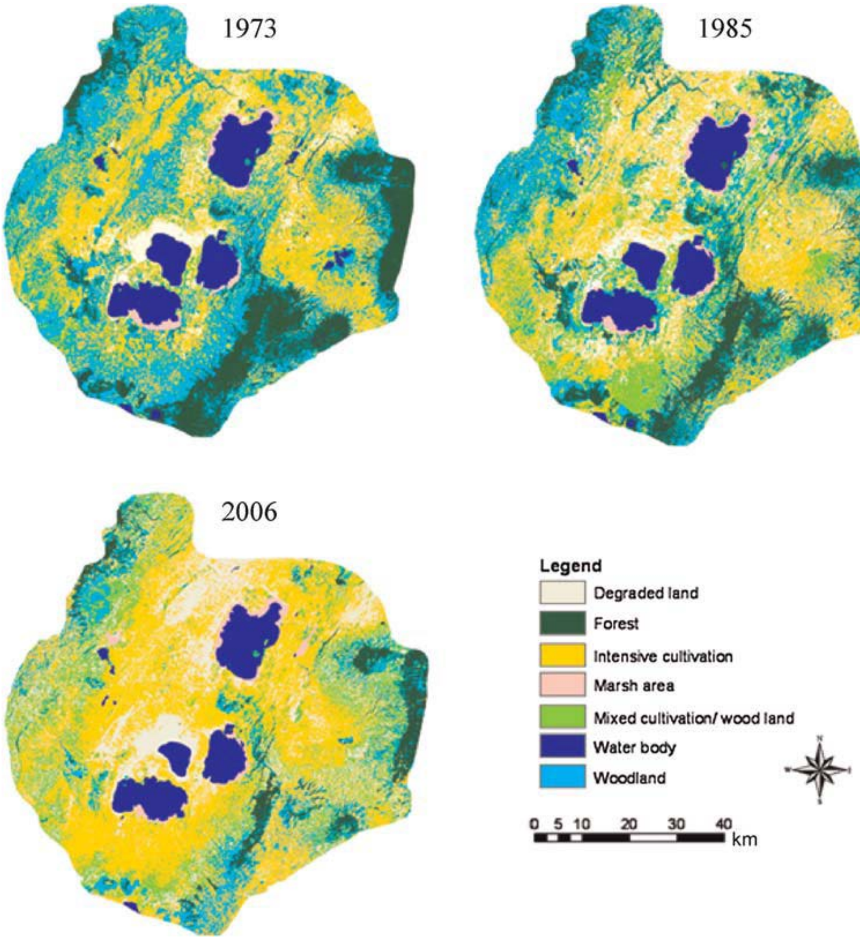


Figure 6.2 Change in land use and cover maps of the Central Rift Valley, 1973–2006 (Adapted from Meshesha et al., 2012)

Topographical variables (elevation, slope and slope aspect)

Data for elevation, slope, and slope aspect were collected at each of the meteorological stations using a digital elevation model (DEM) with a pixel size of 30 m. These data were the explanatory variables in our analysis. The mean values of the topographical variables within a radius of 2 km were used rather than only the value at the station to normalise local effects (Daly et al., 1994; Wotling et al., 2000). Large-scale topographical features at a resolution of 2-15 km yield a high correlation with precipitation (Daly *et al*., 1994). Aspect is a circular variable, so the vector was decomposed into two orthogonal components: sin (aspect) and cos (aspect). Sin (aspect) yields a measure of east/west exposure (+1 represents due east, −1 represents due west), and cos (aspect) yields a north/south exposure (+1 represents due north, −1 represents due south) (Hession and Moore, 2011).

Long term rainfall and temperature trend

A long-term rainfall data set was used (i) to assess the long-term rainfall pattern in the CRV by analysing the long-term trend of rainfall and comparing this decline to the rate of deforestation. The long-term rainfall data were also used as dependent variables for analysing the effect of forest cover and topographical variables on the local rainfall distribution.

We assessed the effect of deforestation on rainfall distribution by the following two approaches (Gadgil, 1978; Meher-Homji, 1980). (i) We analysed the rainfall pattern at the same station over a long period during which deforestation occurred. (ii) We compared rainfalls between areas within the same climatic type, one area forested and the other without natural vegetation. The annual rainfall trends were spatially distinct between the valley floor and the adjoining highlands (Muluneh et al.2015) so we determined the relationship between forest depletion and rainfall pattern separately for the valley floor and the escarpments/highlands (Figure 6.3).

We analysed the long-term temperature trend by categorising the meteorological stations with temperature data in their respective landscape units: valley floor and escarpments/highlands. Based on this categorisation, each landscape unit had three meteorological stations with temperature data for the trend analysis.

We investigated the trends of rainfall and temperature at station and regional levels using Mann-Kendall (MK) and Regional Kendall (RK) tests, respectively (Helsel and Frans, 2006). MK tests have been used with Sen's Slope Estimator for the determination of trend magnitude. The MK test is especially suitable for non-normally distributed data, data containing outliers, and non-linear trends (Helsel and Hirsch, 2002). The RK test is applicable to data from numerous locations, and one overall test can determine whether the same trend is evident across those locations (Helsel and Frans, 2006). We did not analyse the station-level trend for rainfall because this analysis for most of the stations in this study has been published (Muluneh et al. 2015).

Effect of deforestation on rainfall and temperature

A simple linear regression was used to determine the relationships between deforestation (described as percentage of remaining forest cover each year) and annual rainfall and number of rainy days. The effect of deforestation on temperature, however, was not determined using linear regression, because the period of available temperature data (1981-2009) did not coincide with the period of deforestation (1970-2009). We therefore made simple parallel qualitative comparisons between long-term temperature trends and long-term deforestation.

Influence of forests and topographic variables on spatial variability of rainfall

Stepwise multiple regression was used for selecting significant predictive variables. We used annual rainfall and number of rainy days as dependent variables and used distances from forests, elevation, slope, and slope aspect as explanatory variables. Distance to lakes was another predictor, but we did not include it in the analysis because the stations on the valley floor were in similar proximities to the lakes, but the stations in the escarpments/highlands were in different climatic zones, and most stations in the highlands were far from the range of lake penetration distances of 15-45 km (e.g. Moroz, 1967; Lyons 1972; Estoque et al., 1976; Ryznar and Touma, 1981; Gálvez et al., 2006).

Multiple regression models are statistical techniques that can analyse the relationship between a single dependent (criterion) variable and several independent (predictor) variables with the form:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p \qquad (Eq. 6.1)$$

where Y (the dependent variable) is the annual rainfall and X is the number of rainy days in a selected subset of p explanatory variables, β is the slope of each explanatory variable, and α is the intercept.

We used a stepwise multiple regression analysis to identify the set of explanatory variables that best explained the variance in annual rainfall and number of rainy days. Many studies have used stepwise regression to examine the relationship between rainfall and topographical variables (Agnew et al., 2000; Marquínez et al., 2003; Oettli et al., 2005). The method applied here began by identifying the 'best' explanatory variable and incorporating it into the model and then iteratively identifying the next 'best' predictor until the model could no longer be improved. Two criteria were used to select the 'best' explanatory variables: statistical significance (at $P < 0.05$) and the tolerance criterion for evaluating the underlying assumption of independence between explanatory variables. If two variables were significantly alike, their contribution to the variance in the dependent variable becomes impossible to determine. The problem primarily occurs when predictor variables are more strongly correlated with each other than with the response variable.

The tolerance of a variable X_j, Tol_j, with the other variables is defined as:

$$Tol_j = 1 - R_j^2 \qquad (Eq. 6.2)$$

where R_j is the multiple correlation coefficient between variables X_j and X_1, X_{j-1}, X_{j+1}…, X_n. If the tolerance is close to 0, the variable X_j is a linear combination of the others and is removed from the equation, and tolerances close to 1 indicate independence. Tolerances and P-values were calculated for each independent variable at each step in the process. Independent variables with associated tolerances ≥0.1 and P-values ≤0.05 were entered stepwise into the model.

6.3 Results and discussion

Rainfall trends

The Regional Kendall test indicated that the general trend of annual rainfall and number of rainy days tended to increase significantly on the valley floor and to decrease significantly in the escarpments/highlands (Table 6.2). The decadal increase in rainfall on the valley floor was approximately 38 mm, and the decrease in the escarpments/highlands was 29 mm. Annual rainfall for the entire region decreased significantly, and the number of rainy days tended to decrease, although not significantly (Table 6.2). The previous analysis of the station-level rainfall trend (Muluneh et al.2015, accepted manuscript) was consistent with our analysis of the regional trend where stations on the valley floor showed an increasing trend and stations in the escarpments/highlands showed a decreasing trend.

Table 6.1 Characteristics of the meteorological stations used in the study, CRV, Ethiopia

40 years rainfall data (1970-2009)									
Landscape unit	Station	Northing (m)	Easting (m)	Elevation (m)	Slope (degree)	Sin (aspect)	Cos (aspect)	Distance to forest (km)	Period
Rift valley floor	Langano	477935	830871	1600	3.3	0.17	0.98	2	1981-2009
	Bulbula	469732	853566	1610	1.03	-0.70	-0.70	23	1970-2009
	Adami Tulu	467545	868876	1636	1.6	0.70	-0.70	27	1970-2009
	Ziway	467545	877624	1640	2.0	1	0	31	1981-2009
	Meki	480121	900589	1664	1.03	0	-1	44	1970-2009
Escarpment/highland	Wondo Genet	463190	782974	1880	6.25	-0.92	-0.39	6	1970-2009
	Koshe	448575	886170	1910	1.7	0.17	0.98	31	1970-2009
	Kuyera	806928	461367	1932	1.72	-1	0	13.5	2012-2013
	Shashemene	453994	792195	1933	1.03	-0.64	0.76	19	1970-2009
	Tora	435696	869603	1998	1.0	-1	0	35	1970-2009
	Butajira	430910	901136	2000	2.5	0.37	-0.92	55	1970-2009
	Degaga	479097	822688	2076	3.3	-0.64	0.76	4	1970-2009
	Kulumsa	514688	899040	2202	4.5	-0.70	-0.70	18	1970-2009
	Assela	514021	879265	2390	4.7	-1	0	6	1970-2009
	Sagure	518378	856664	2480	2.0	-0.70	-0.70	18	1970-2009
	Kofele	472392	782968	2620	1.7	-1	0	8	1970-2009
	2 years rainfall data (2012-2013)								
Escarpment/highland	Abaro mount	788137	458040	2325	8.5	-0.93	0.38	0.01	2012-2013
	Gambo forest	806917	479028	2187	5.0	-0.93	0.38	0.3	2012-2013
	Reji schl	802498	474611	2176	4.5	-0.93	0.38	0.4	2012-2013
	Sole forest	792556	462460	2153	2.5	-0.93	0.38	0.1	2012-2013
	Asheka leps	806919	475717	2145	1.7	-0.93	0.38	2.5	2012-2013
	Kalo	803604	472403	2138	1.7	-0.93	0.38	2.8	2012-2013
	Ebicha	790347	459146	2127	2.5	-1	0	1	2012-2013
	Awasho	793664	459149	2035	2.5	0.17	0.98	2	2012-2013
	Seyo meja	810240	467992	2035	1.7	0.7	0.7	11	2012-2013
	Melka uda	798086	459152	1977	0.86	-0.93	0.38	7.5	2012-2013
	Kerara fana	800295	461362	1973	1.7	-0.93	0.38	6.5	2012-2013
	Augeta ilala	803612	461365	1972	0.86	-1	0	13.5	2012-2013
	Arsi Negele	813559	464683	1941	2.5	-0.93	0.38	15	2012-2013
	Shashemene	453994	792195	1933	1.03	-1	0	4	2012-2013
	Kuyera	806928	461367	1932	1.72	-0.64	0.76	14.5	2012-2013

Table 6.2 Trends in annual rainfall amount and rainy days based on Sen's method with p-values using Regional Mann-Kendall test for the rift valley floor and escarpments/ highland of the CRV. (* significant at p < 5%)

Stations	*Annual rainfall (mm/decade)*	*P-value*	*No of rainy days (days/decade)*	*P-value*
Rift valley floor (5 stations)	*37.9*	*0.0014**	*4.1*	*0.0029**
Escarpment/highland (11 stations)	*-29.8*	*0.000**	*-1.6*	*0.031**
Regional (valley floor +escarpment/highland) (16 stations)	*-12.5*	*0.035**	*-0.19*	*0.72*

Temperature trends

Table 6.3 presents the trends of mean annual maximum and minimum temperatures for 1981-2009. The mean maximum temperature increased significantly at all three stations on the valley floor that recorded temperatures (Ziway, Langano, and Adami Tulu). All three stations recorded an increasing tendency in mean minimum temperature, but the increase was statistically significant at only one station. A significant increase in maximum temperature was recorded in the escarpments/highlands only at the Butajira station. The mean minimum temperature decreased significantly at two of the three highland stations (Kulumsa and Butajira). The maximum temperature increased significantly both on the valley floor and in the escarpments/highlands. The minimum temperature increased significantly on the valley floor but not significantly in the escarpments/highlands. We can thus infer that the rate of warming was generally higher on the valley floor than in the highland areas.

The mean maximum temperature in the CRV increased by 0.4°C/decade during 1981-2009, but the mean minimum temperature remained relatively stable. The results of this study are consistent with those by Kassie et al. (2013) who reported a warming trend in the CRV, with the exception of Butajira and Kulumsa where the annual minimum temperature tended to decrease. Other studies have also reported warming trends in Ethiopia over the past few decades for both maximum and minimum temperatures (NMA, 2007; McSweeney *et al.*, 2008; ACCRA, 2012; Jury and Funk, 2012; Taye and Zewdu, 2012; Tesso *et al.*, 2012).

Forest and woodland decline

The forest and woodland cover continuously declined in the CRV over the 40 years of the study period (1970-2009) (Figure 6.4). The forest and woodland cover steadily decreased from 52% in 1970 to 13% in 2009. Most of the degraded areas were on gentle to moderate slopes on the valley floor (Figure 6.1).

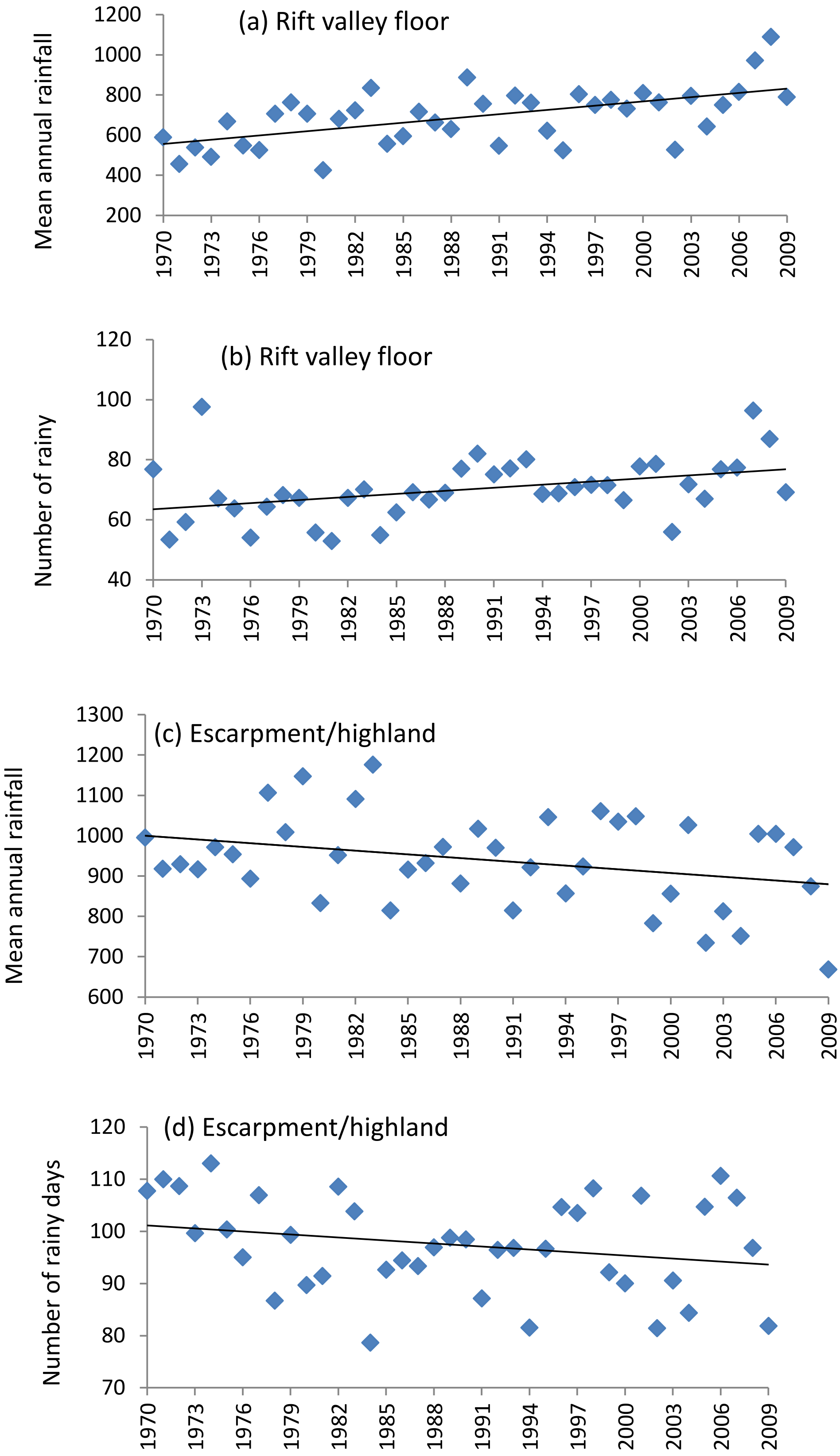


Figure 6.3 Time series analysis of annual rainfall and number of rainy days for the rift valley floor and escarpments/highlands of the CRV using simple linear regression from the mean of 5 stations in the rift valley floor and 11 stations in the escarpment (Thin straight lines indicate the linear fitting of the series for the period 1970-2009)

Table 6.3 Trends in annual maximum and minimum temperature for the Ethiopian CRV region, rift valley floor and escarpments/highland.

Landscape unit	Station	Tmax		Tmin	
		Trend (°C/Decade)	p-value	Trend (°C/Decade)	p-value
Highland	Assela	0.33	0.216	0.34	0.095
	Kulumsa	0.00	1.000	-0.52	0.032*
	Butajira	0.20	0.013*	-1.25	0.004*
For highland landscape unit		0.19	0.0307*	-0.4	0.0523
Valley floor	Ziway	0.44	0.000*	0.22	0.275
	Langano	1.20	0.001*	1.00	0.011*
	Adami Tulu	0.56	0.000*	0.03	0.866
For rift valley floor landscape unit		0.63	0.0000*	0.2	0.0447*
Regional(CRV)	Regional	0.4	0.000*	0.00	0.96

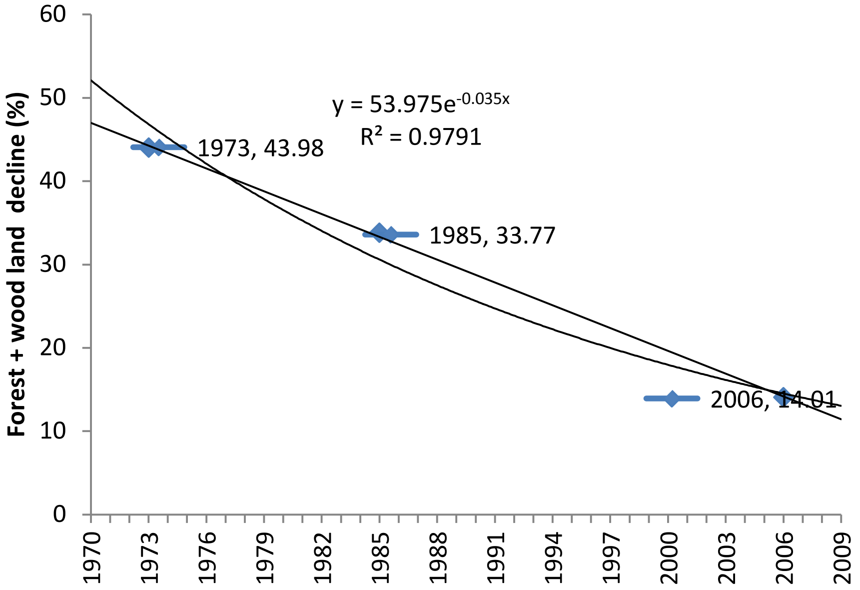
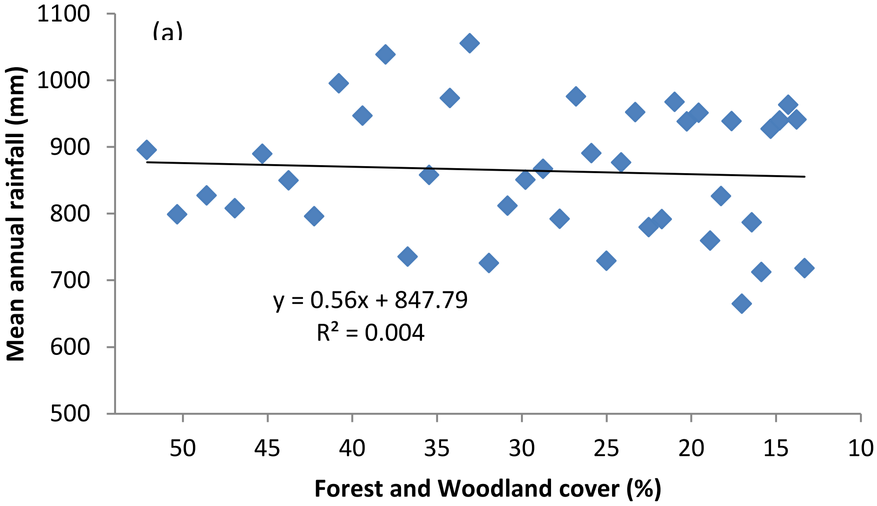


Figure 6.4 Forest cover over time (curved line) after exponential interpolation between actual data obtained from satellite remote-sensing images interpretation (dots).



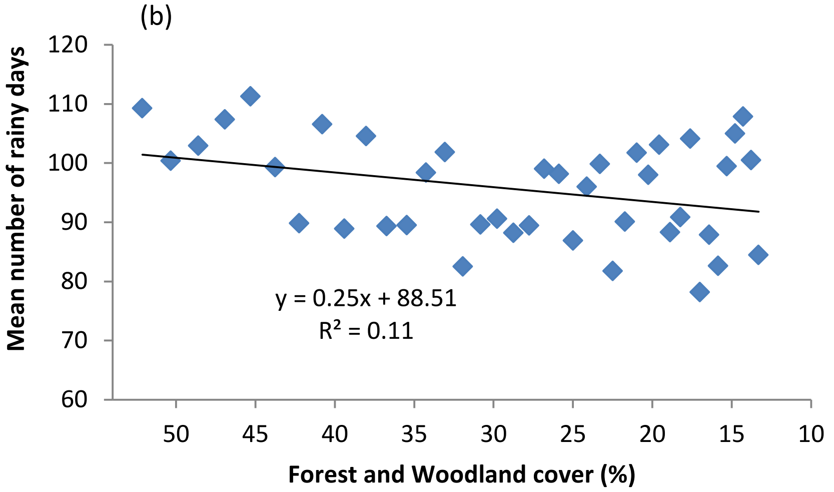


Figure 6.5 Simple linear regression (a) between annual rainfall and forest and woodland cover (%) (b) number of rainy days and forest and woodland cover (%) over long term data (40 years) across the Ethiopian CRV

Effect of deforestation on long term rainfall pattern

The continuous decline of forest and woodland for four decades was weakly correlated with mean annual rainfall and number of rainy days across the 16 stations in the CRV, but slightly more highly correlated with number of rainy days (Figure 6.5).

Annual rainfall and number of rainy days over the 40 years increased on the valley floor but the forest and woodland cover continuously decreased. If this change in land cover plays a major role in rainfall distribution, then rainfall should have decreased on the valley floor as in the escarpments/highlands, because more of the degraded areas are on the valley floor (Figure 6.2), and the valley floor has a lower actual annual evapotranspiration (656 mm) than the escarpments (892 mm) and highlands (917 mm), because it is mostly covered with bare lacustrine soils (Ayenew, 2003). The potential evaporation, however, ranges from >2500 mm on the valley floor to <1000 mm in the highlands (Le Turdu et al. 1999). The continuous degradation of the vegetation, intensive cultivation, and low actual evapotranspiration (Meshesha et al., 2012) pose a question: why is rainfall increasing on the valley floor? We offer three possible explanations.

(i) The increasing temperature on the valley floor over the last 40 years has increased evaporation, mainly from the four lakes (Ziway, Langano, Abiyata, and Shala) that occupy roughly 11% of the total area of the CRV (Ayenew 2003), to the extent that the increased evaporation could significantly alter the water cycle and lead to an increase in rainfall. The five stations that recorded increasing rainfalls (Langano, Bulbula, Ziway, Adami Tulu, and Meki) are also close to the lakes (within 7 km, Figure 6.1). Large inland lakes together with highly variable topography and vegetation can cause significant spatial variability in the rainfall pattern in eastern Africa (Nicholson, 1996). Similarly, Nieuwolt (1977) reported that Lakes Abaya and Chamo on the valley floor farther south in the rift valley produce large amounts of water vapour and also create local disturbances that are conducive to the production of rain. The construction of artificial lakes augmented rainfall in semi-arid Mexico (Jauregui, 1991). Haile *et al*. (2009) reported the development of high and thick clouds over Lake Tana in northwestern Ethiopia and frequent rains heavier than 10 mm/h at stations relatively close to the lake. Lauwaet *et al*. (2012) found differences in rainfall patterns with distance from Lake Chad, but large-scale atmospheric processes were not affected.

(ii) Deforestation in areas close to water bodies such as lakes leads to lake breezes that in turn are favourable for moisture transport and increased rainfall (Mawalagedara and Oglesby, 2011).

(iii) The expansion of irrigation in the study area since 1973, particularly around the lakes, could likely have contributed to increased evapotranspiration, which may have contributed to the rainfall increase. Segal *et al.* (1998) found that irrigation did indeed alter rainfall in a mesoscale model.

In any case, our findings suggest that increasing temperatures and the presence of lakes affect rainfall distribution more strongly than vegetative cover on the valley floor. A similar argument was suggested by Meher-Homji (1980) in India, where coastal stations did not record declining rainfall despite high deforestation in the area. The stations in the escarpments/highlands in our study are thus likely to be affected more strongly by large-scale weather drivers such as monsoons due to ITCZ migration than by local-scale factors. The rainfall decline in the escarpments/highlands coincided with decreasing rainfall in recent decades (1980-2009) in most parts of Ethiopia due to rapid warming of the Indian Ocean that suppressed convection over tropical eastern Africa (Williams and Funk, 2010).

Effect of deforestation on temperature trend

Deforestation can produce two competing effects, warming due to a reduction in evapotranspiration and a cooling due to an increase in surface albedo, but the warming is much greater than the cooling, resulting in warmer conditions (Zhang et. al., 1996; Oglesby et al., 2010). The decrease in transpiration combined with a reduction of surface roughness due to deforestation suppresses the flux of sensible heat from the surface that in turn will increase the surface temperature. If surface albedo is not increased appreciably by deforestation, moisture-flux convergence driven by the increase in surface temperature can offset the other effects, and average precipitation can increase (Dirmeyer and Shukla,1994; Garcia-Carreras and Parker 2011). Modelling studies of deforestation have similarly predicted that reductions in evaporative cooling associated with the loss of vegetation will increase regional air temperatures (Snyder 2010).

The influence of forests and topographical variables to spatial rainfall distribution based on long term rainfall (1970-2009)

Slope was the best predictor of total annual rainfall, explaining 29% of the rainfall variability in the CRV (Table 6.4). Steeper slopes provide stronger orographic lifting and hence higher rainfall (Buytaert *et al*., 2006). Slopes may have a considerable effect on the lifting of air over montane barriers in orographic precipitation. Elevation greatly influences the climate of Ethiopia but explained less of the spatial variability of total annual rainfall in the CRV. The pattern of increasing rainfall associated with increasing altitude in the CRV is modified at high altitudes by the influence of the high mountains, which may cause either rain shadows or areas of heavy orographic rainfall (Makin *et al.*, 1975). The orographic effect on the spatial distribution of rainfall over the area is substantial. Drier pockets occur in rain shadows. Areas close to the eastern highlands receive more rain annually than areas farther from the mountainous region even if the latter are higher. For example, Assela (2390 m) receives a mean annual rainfall of 1118 mm, but Kulumsa (2200 m), just 11 km to the north, receives only 810 mm, and Sagure (2480 m) south of Assela receives only 776 mm (Makin et al., 1975). Topographical variables such as slope and aspect and characteristics of the dominant air masses in the highlands of Ethiopia are generally more important than elevation in explaining the variability of annual rainfall (Krauer, 1988). For the annual number of rainy days, slope and elevation explained most (60%) of the variability in the multiple regression model (Table 6.4).

The absence of significant correlations of distance from forest (effect of forest) with long-term annual rainfall and number of rainy days may partly be attributable to the non-systematic location of the meteorological stations relative to the remnant forest (Munessa-Shashemene forest). Most of the stations are not near this forest. Furthermore, the meteorological stations in this study are distributed across different climatic zones (semi-arid, sub-humid, and humid climates), but the remnant forest mostly has a sub-humid climate.

Table 6.4 Best regression models based on stepwise regression showing relationship between mean annual rainfall and N<u>o</u> of rainy days (1970-2009) as dependent variables and slope and elevation as explanatory variables in the CRV, Ethiopia

40 years (1970-2009)			
Dependent variables	Model	R^2	P-value
Annual rainfall (mm)	Rainfall=50.47*slope+756.16	0.29	0.03
Annual N<u>o</u> of rainy days	Number of rain days = 0.048*elevation + 6.60*slope-13	0.60	Slope=0.048 Elevation=0.006
2 years (2012-2013**)**			
Annual rainfall (mm)	Y=0.69 Elevation-529.94	0.26	0.05
Annual N<u>o</u> of rainy days	Y=-1.77 distance to forest +173.49	0.40	0.01

R^2 = coefficient of multiple determination

The influence of forests and topographical variables to spatial rainfall distribution based on two years observed rainfall (2012-2013)

For a better understanding of the effect of remnant forests on local rainfall distribution, 15 tipping bucket rain gauges were installed systematically along a transect away from the forest where the rainfall data were collected for two subsequent years. All gauges were in the same climatic zone (sub-humid) as that of the remnant forest. The annual rainfall and number of rainy days from the short-term data were explained by elevation and distance from the remnant forest (R^2 of 0.26 and 0.40 respectively, Table 6.4). Distance from the forest was not significantly correlated with total annual rainfall, but both total annual rainfall and number of rainy days were negatively correlated with distance from the forest (Figure 6.6), indicating that both total annual rainfall and number of rainy days increased closer to the forest. Forests were thus good predictors of the short-term annual number of rainy days, consistent with the findings of other studies that found better correlations of rainy days with forests than with total rainfall (Brooks 1928, Meher-Homji 1980, 1991; Wilk *et al.* 2001).

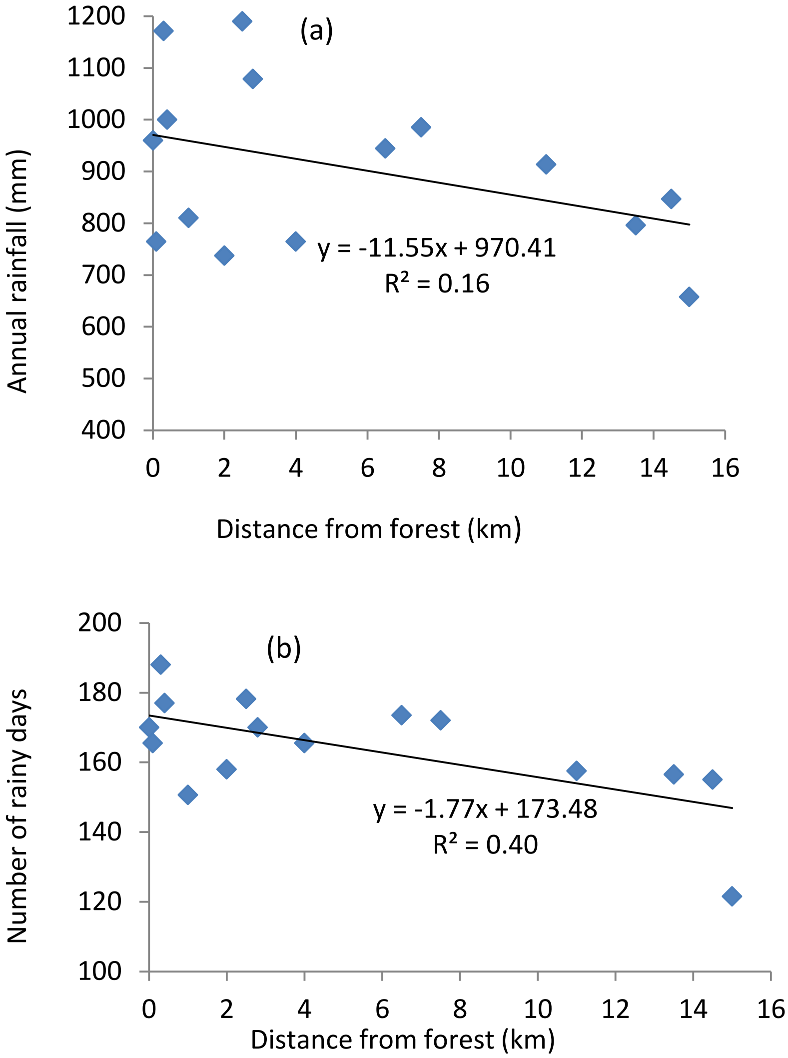


Figure 6.6 Simple linear relationship between (a) annual rainfall and distance from forest and, (b) number of rainy days and distance from forest for the two years rainfall data (2012-2013) in the CRV, Ethiopia.

6.4 Conclusions

A continuous decline in forest and woodland cover (deforestation) increased the temperature on the valley floor in the Ethiopian CRV. This increase in temperature combined with the presence of lakes played an important role in an increase in rainfall. This study did not find a significant correlation between long-term rainfall and decline in forest and woodland cover in the CRV. The total annual rainfall and number of rainy days in the escarpments/highlands of the CRV, however, has significantly decreased, which may be due more to a change in the large-scale regional pattern of atmospheric circulation caused by rapid warming of the Indian Ocean than to a decrease in forest and woodland cover. Slope was important in explaining long-term rainfall spatial variability in the CRV. Elevation had little effect on rainfall variability in the escarpments/highlands of the CRV due to the effects of the rain shadow from the mountains. The short-term (two years) rainfall data indicated that the existing forest cover had little influence on the spatial distribution of rainfall but significantly affected the number of rainy days.

Chapter 7

Synthesis

Synthesis

7.1 Introduction

In this introduction we briefly describe the course of the thesis research as it follows from the research questions posed in the general introduction (Chapter 1) and the subsequent choice of methodology.

The Central Rift Valley (CRV) represents major cereal based farming systems of the semi-arid environment of Ethiopia and is a hot spot for climate induced risks such as droughts and long dry spells. Rainfall variability results in high risk of drought and intra-seasonal dry spells, leading to low crop yields and sometimes total crop failure (Tesfaye and Walker, 2004; Tilahun, 2006; Kim et al., 2014). Maize is the staple food crop which is sensitive to moisture stress in different growth stages (Ransom et al., 1997). Due to risks of crop failure by erratic rainfall and long dry spells, farmers are reluctant to use soil nutrients and related production enhancing inputs **(**Hilhost and Muchena, 2000**;** Rockström et al., 2002**;** Hulst, 2012). This lack of investment in productive inputs means that even in a year when rainfall is favourable, the yield is not as large as it could be. For example, actual farmers' maize yield in the CRV is about 2.3 t ha^{-1} which is only about 30 % of simulated attainable yield under rainfed conditions. This implies a large potential to increase yields with improved agricultural inputs, especially nitrogen fertilizer (Kassie et al., 2014). Hence, reducing water-related risks through appropriate management techniques can encourage farmers to invest in soil improvements and other productivity enhancement techniques (Rockström et al., 2010).

An additional risk is that, with the climate already changing and further change in climate highly likely to happen (IPCC, 2007), existing problems and increased food insecurity in the region it is expected to exacerbate. In the face of climate change and variability and recurrent climatic extreme events, farmers in Ethiopia already employ different risk-management and coping strategies such as changing crops/varieties, soil and water conservation measures, water harvesting, adjustment of cropping calendar and tree planting (Bryan et al., 2009; Di Falco et al., 2011; Birhanu and Sterk, 2013; Shiferau et al., 2014; Kassie et al., 2014). However, indications are that these existing coping mechanisms may not be sufficient to meet the projected changes (Melka et al., 2013). Therefore, how existing techniques could effectively be used in the future and what new techniques do exist needs research.

Despite their global reputation, large scale climate models have little local and regional specificity and have failed to address the regional and local impacts and to identify the local abilities to adapt to climate change impacts (Yarnal, 1998; Smit and Pilifosova, 2003). Thus, regional and local scale estimates of the timing and magnitude of climate change is important in order to address the problems of subsistent farmer households. Understanding impacts of climate change is a critical step in being able to address effectively the effects of climate variability and extreme events on food security (Thornton et al., 2014). Understanding the potential for adaptation to climate change is critical in determining how such changes will affect food security and addressing climate change issue (Hertel and Lobell, 2014).

The main focus of this study was, therefore, to asses changes in current and future growing season rainfall characteristics including climate extremes and to quantify their impacts with the intention of developing potential adaptation options in the drought-prone CRV of Ethiopia. For the assumed role of landscapes and seasons for the variation in rainfall characteristics, the CRV was divided into three landscape units: the valley floor, the escarpments, and the highlands all of which are considered in our data analysis. The analysis also considered the two important growing seasons in the study area: the *Belg* (March-May) and *Kiremt* (June-September) seasons. To detect any changes in the rainfall behaviour, this study commenced by investigating rainfall based on 10 rainfall indices over a period of 40 years (1970-2009) using 14 meteorological stations in the CRV.

To assess the behaviour of growing season rainfall characteristics in the future, the study continued by downscaling climate change data into finer spatial and temporal scales useable at the regional and local scale. The changes in the amount of seasonal rainfall, the onset and cessation of rainfall, length of growing season and dry spells for the current and future climate change scenarios were investigated using statistical methods. The impact of climate change and assumed yield-enhancing effect of elevated atmospheric CO_2 on maize and wheat yield was investigated using current and downscaled model predictions of climatic data and a crop production model.

Through 2 years of field experimentation it was possible to investigate whether maize intensification using supplemental irrigation with optimum plant density under optimum fertilizer is a viable option to significantly improve crop yield and water productivity in Ethiopia's CRV. Furthermore, for long-term effect and climate change scenarios it was possible to test, using the validated FAO's AquaCrop model, the effect of supplemental irrigation, optimum plant density, adjusting sowing time under optimum fertilizer as a viable option to offset negative impacts of climate change in Ethiopia's CRV.

The relationships between existing remnant forests and deforestation and rainfall amount and number of rainy days was investigated using 15 newly installed rain gages along a 60 km transect line that traverses forest areas and open areas and 16 existing meteorological stations over the CRV. Furthermore, the relationships between rainfall and topographic factors: elevation, slope and slope aspect was explored.

7.2 Brief answers to the research questions

1: Do extreme rainfall events changed over the past 40 years (1970-2009) annually and seasonally in the Ethiopian CRV? (Chapter 2)

On an annual basis, our analysis indicates that in both *Belg* and *Kiremt* no significant change in extreme rainfall indices has occurred during the last 40 years. However, there are seasonal and spatial differences. During *Belg* there was a significant change in Cumulative Dry Days (CDD) in all landscape units of the CRV. Other extreme rainfall events showed a general decreasing trend during *Belg* (though mostly not significant). Similarly, during *Kiremt* most extreme rainfall indices did not show significant change but show a decreasing tendensy.

Spatially, different results at each landscape unit were found. In the rift valley floor, annual rainfall and extreme rainfall events showed an increasing trend while the western and eastern escarpments showed a tendency towards decreasing trend (though not significant).

2: How are growing season rainfall characteristics likely to change during Belg and Kiremt seasons in the semi-arid and sub-humid/humid part of the CRV? (Chapter 3)

Generally, the growing season agriculturally relevant rainfall characteristics will be changed favorably for sub-humid and humid parts of the CRV, while the semi-arid part of the CRV changes unfavorably for crops. The *Belg* season total rainfall is likely to decline, while the *Kiremt* season total rainfall is likely to increase. Projected dry spells during critical maize growing stage (60-90 DAS) increase during *Belg* and decrease during *Kiremt*. The projected mean Length of Growing Period (LGP) shortens in the semi-arid zone, whereas it slightly increases in the sub-humid/humid zone. The projected onset of rainfall in the *Belg* will be earlier for humid zone and will be delayed in the semi-arid zone. The mean cessation date will be extended at humid part and comes early at semi-arid zone. For wheat, during the first 90 days of crop growth there is no continuous dry spell longer than 10 days during the baseline or future climate scenarios. The projected onset of rainfall for wheat is likely to come earlier, while the cessation is likely to be late as compared to the baseline period. Therefore, the projected LGP for wheat is likely to increase for projected climate change conditions.

3: How will the change in climate and elevated atmospheric CO_2 affect maize and wheat yield in the CRV? (Chapter 3)

Overall, the predicted changes in climate and elevated CO_2 (rainfall, temperature, evapotranspiration and CO_2) are expected to increase medium and long cycle maize yield in the sub-humid/humid parts of the CRV. Whereas, the predicted changes in climate and elevated CO_2 is likely to decrease long cycle maize yield in semi-arid parts of the CRV. The short cycle wheat that grows only during *Kiremt* season mostly in sub-humid/humid part of the CRV was not affected by climate projections, because water is not a limiting factor for wheat grown during *Kiremt* under the baseline climate, thus attainable yield is already obtained during the baseline climate. However, when CO_2 level increased from 369 ppm to 779 ppm for future climate the yield of wheat can increase with 40%.

4: Is maize intensification using supplemental irrigation and optimum plant density under optimum fertilizer a viable option for bridging dry spells in the Ethiopia's CRV? (Chapter 4)

The maize grain yield from our on-farm experiments under rainfed condition, low plant density (30,000 plants ha^{-1}) and 150% of recommended fertilizer was 81% higher than farmers yield under similar condition but with only 50% of recommended fertilizer use. Therefore, the main factor for this yield difference between farmers practice and on-farm experiment could be attributed to the amount of fertilizer applied. In a moderate drought year (when there is < 10 days of dry spells during critical growth stages of maize) the grain yield difference between rainfed and supplemental irrigation (SI) (applied when moisture depletion reached below 20 % maximum available water) was 12 %. In a similar year under the same SI the grain yield difference between a plant density of 45,000 plants ha^{-1} and 75,000 plants ha^{-1} was only 18 %. In spite of these significant effects the investment in supplemental irrigation is probably not worth the effort for normal and moderately dry years. However, in years with critical dry spells SI may provide food where otherwise total crop failure will cause famine.

5: Is maize intensification through supplemental irrigation, optimum plant density and adjusting sowing date under optimum fertilizer a viable option for adaptation to climate change in the Ethiopia's CRV? (Chapter 5)

Based on AquaCrop model simulation, the effect of above management factors on long term climate and climate change scenarios were assessed. By simulating 30 years of baseline climate, SI increased maize grain yield by 20 % as compared to rainfed simulated yield. On the other hand, using 94-111 mm of water, SI can avoid total crop failure in drought years. The shifting of sowing period of maize from the current *Belg* season (mostly April or May) to the first month of *Kiremt* season (June) can offset the predicted yield reduction caused by climate change.

6: Do forests affect rainfall and what other local factors affect rainfall distribution in the CRV of Ethiopia? (Chapter 6)

Based on two-years of rainfall data (2012-2013), both total rainfall and number of rainy days decreased as we move away from the forest, indicating the effect of forests on rainfall pattern. However, only number of rainy days was significantly ($R^2 = 0.40$) explained by forest cover (distance from forest). Though it was not statistically significant, as we move away from forests the rainfall amount also decreased ($R^2 = 0.26$).

7: Do deforestation induce temperature increase? (Chapter 6)

Deforestation significantly increased the maximum temperature. This increase in surface temperature is likely attributed to Lake Breeze which subsequently increased rainfall in the rift valley floor where a chain of lakes are located.

7.3 Emerging issues

During the evolution of this thesis work and combining results from various chapters a number of emerging issues became obvious. The most important ones are described below.

The need to scale down climate change projections

Many have already argued against using large spatial domains, such as the national scale, to develop adaptation options in regions with large variations in topography. This, because it overlooks effects of local features that contribute to high local variability in the climate (Thornton et al., 2009; Moore et al., 2012). For studying trends in spatial and temporal distribution of rainfall in Ethiopia, defining study regions in an objective and geographically meaningful manner is important (Cheung et al., 2008). The Ethiopian rift valley is a typical example of the complex topography of Ethiopia manifested by abrupt changes in rainfall over the region with pockets of humid climates alternating with arid ones within a few tens of kilometers (Nicholson, 1996).

Also, in an area with large seasonal rainfall variation, changes in rainfall on an annual basis often mask significant inter-seasonal variations (Garnaut, 2008). Thus, spatial and temporal aggregation over such diverse climates and seasons often give contrasting results of trend in rainfall (Easterling et al., 2000; Seleshi and Zanke, 2004; Bewket and Conway, 2007; McSweeney et al., 2010). Cognizant of this fact, the CRV was stratified into three landscape units: rift valley floor, escarpment and highlands and in to two cropping seasons *Belg* and *Kiremt*. Our analysis of rainfall changes at the annual and regional scale often did not show significant trends. However, analysis of rainfall in different chapters of this thesis show notable contrasts across the landscape units and seasons. In Chapter 2 we found a difference between rift valley floor and highlands in annual total wet-day rainfall and other extreme rainfall events. Similarly, the trend analysis of 10 extreme rainfall indices for the last 40 years was quite different during the *Belg* and *Kiremt* as compared with the annual trend. For example, the *Belg* season showed a significant increasing trend in CDD whereas; the annual and *Kiremt* season analysis showed no such significant trend in CDD (Chapter 2, Table 2.4). Similarly, for projected rainfall analysis, there was a consistent decrease of rainfall during *Belg* and consistent increase of rainfall during *Kiremt* (Chapter 3).

From Chapter 3 through 5 there is a major similarity in projecting the drying of *Belg* and declining crop yield mostly in dry sub-humid and semi-arid part of the CRV (Rift valley floor). Even for the current climate, ecologically arid, semi-arid and dry sub-humid parts of Ethiopia are known to be most vulnerable to drought (Tadeg, 2007). So, it shows that current risks may be exacerbated by the projected climate change in the semi-arid and dry sub-humid areas of the CRV of Ethiopia. Such studies are crucial in indicating areas that need priority in adapting to climate change. The variation of current and projected rainfall and yield in such a small spatial area and seasons demonstrated the importance of climate assessment that consider ecological differences (landscape unit) and cropping season rainfall variability (*Belg* and *Kiremt*). Thus, we advocate climate analysis to be conducted at such fine spatial and temporal scales.

Seasonal shift from Belg (dryer) to Kiremt (wetter)

In Chapter 2, the *Belg* season rainfall showed consistent increase in the maximum number of consecutive dry days (CDD) over the past 40 years (1970-2009) in the CRV. Similarly, annual total wet day rainfall showed a declining tendency. Projections of future climate show a further decline of *Belg* rainfall across the CRV (Chapters 3 and 5). Thus, our results reinforce the general agreement that the *Belg* season rainfall in east African region including Ethiopia is declining since the second half of the 20th century (Funk et al., 2005; Funk et al., 2008; Williams and Funk, 2011; Lyon and DeWitt, 2012). Many studies attributed the decrease in *Belg* rainfall to the warming of Indian Ocean Sea Surface Temperature (for example; Camberlin, 1998; Lyon and DeWitt, 2012). Since the *Belg* rain is mainly caused by easterly winds from the Indian Ocean (Rosell, 2011).

During the current climate analysis (1970-2009), the *Kiremt* rainfall showed a decreasing tendency in most parts of the CRV (Chapter 2). However, in Chapter 3 the *Kiremt* rainfall is projected to increase for climate change scenarios. Also the duration of *Kiremt* which is from June-September for the current climate is expected to increase in the future and will extend the cessation of the *Kiremt* season rainfall by 1–2 months (Chapter 3, Table 3.5). There are studies that associate the delayed *Kiremt* cessation and hence prolonged rain to the warming of SSTs in the Indian Ocean and Arabian Sea (Tessema and Lamb, 2003).

Even under current climate the *Kiremt* rain is more reliable than the *Belg* rains. Dry spells greater than 10 days are not common over most of the major *Kiremt* regions in Ethiopia, mostly limited to the lowland areas of extreme western and north-eastern Ethiopia (Segele and Lamb, 2005). Thus, our results conform to existing literature which states that in the Ethiopian highlands, climate change may extend the agricultural growing seasons as a result of increased temperatures and rainfall changes (Thornton et al., 2006; Boko et al., 2007). Therefore, both long cycle crops which grow during *Belg* and *Kiremt* and the short cycle crops like wheat which grows entirely during *Kiremt* season, are likely to benefit from the projected increase of the *Kiremt* rainfall (Chapters 3 and 5).

Challenges of future maize cropping in semi-arid CRV

In Chapter 5, under current climate, maize yield is very low and sometimes there is total crop failure under rainfed condition when there is severe drought from long dry spells during critical growth stages. In Chapters 3 and 5, future impact assessment studies suggest that without adaptation the long cycle maize yield is likely to face even more challenges from a continuous drying of *Belg* season rainfall and increasing dry spells. The projected maize yield at different parts of the CRV was identified using point level climate data from the MarkSimGCM climate downscaler and daily weather generator using AquaCrop model simulations. Based on this, maize yield is projected to decrease in the dry land parts of the CRV (dry sub-humid and semi-arid part), while it is likely to increase in the sub-humid/humid part of the CRV (Chapter 3). The projected maize yield decrease in drylands part of the CRV was attributed to the change in growing season rainfall characteristics. The first change is the onset of the *Belg*, the season used for sowing long cycle maize, that is projected to be delayed by up to 2-9 weeks (Chapter 3, Table 3.5). The second important factor is the persistent increase of dry spells in the semi-arid climate during the *Belg* season (Chapters 2 and 5). This leads us to look into options that help subsistence small holder farmers to cope with the current climate variability and future climate change scenarios. In Chapter 4 and 5, through field experiment and AquaCrop model simulation we showed the possibility of minimizing the current climate variability and future climate change challenge by using different coping and adaptation options.

In Chapter 4, we show through on farm field experiment how Supplementary Irrigation (SI) using water harvesting ponds together with increased fertilizer use and optimum plant density can increase maize yield. In a moderate dry year the grain yield increase attributed to SI was 12%. However, a grain yield increase attributed to fertilizer use was 101%. This large increase in grain yield is contributed to the higher use of (150% recommended) of fertilizer against the current use (50% or less) by adjacent farmers. Thus, the fertilizer effect is larger than the water (SI) effect.

When plant density increases from 30000 to 75000 the yield increase was statistically significant. So, we recommended 75000 plants ha^{-1}. The combination of SI, fertilizer and optimum plant density each plays their own role in ensuring water availability and increasing yield. In Chapter 5 we showed the critical role of SI in bridging critical dry spells that lead to significant yield decline or crop failure. Increased fertilizer use is essential in significantly increasing yield and minimizing yield gap. In Chapter 4, based on long term onset and dry spell analysis of current climate, we recommended a later onset of maize during the month of May which is the last month of *Belg* season. In the semi-arid part of CRV, when the local maize is planted in May, the flowering and grain-filling stages (the critical growth stages) will coincide with the months of lower probability of long dry spells between mid-July and mid-August. In Chapter 5 for projected climate we recommended a further shift of sowing period of maize from the current *Belg* season (mostly April or May) to the first month of *Kiremt* season (June), i.e shifting the future sowing of maize out of the *Belg* season. We consider planting time an important water management instrument (Ngigi et al., 2005), that makes it possible to reduce crop failure by delaying sowing dates.

7.4 Contribution to science

Aims of our research were to downscale climate change models, to analyze details of climate change induced changes in rainfall and compare these with current rainfall variability, to determine the impact of these changes in relation to possible other crop production limiting factors and to develop options for crop intensification that reduce the impact of climate change and increase food security in the CRV. After a literature screening on these issue we formulated a number of hypotheses. We can now make up the balance; are the hypotheses confirmed or rejected and what did this thesis added to our body of science with respect to the issues mentioned.

Our first hypothesis related to climate change models. We assumed that we can find methods that can downscale reputed models to the regional scale of the CRV in Ethiopia.

This hypothesis is confirmed. For this study, we used the ECHAM5 GCM and ensemble mean of six GCMs under two emission scenarios. The future climate data generated and used were for two different time periods: 2020-2049 and 2066-2095 with (1966-1995) as baseline period. The ECHAM5 model is known for its good performance in east Africa. On the other hand, multi-model ensemble means are believed to be better reliable in climate projections. For our study we required information at finer spatial and temporal scales than the typical GCM grid resolutions. To generate daily rainfall and temperature (maximum and minimum) data, the web-based MarkSimGCM module with a user interface in Google Earth was used. The third-order markov rainfall generator, MarkSim takes the outputs of the original resolution of each GCM and interpolates to 0.5 latitude–longitudes. MarkSim has been widely used in East Africa and reportedly provides a realistic simulation of daily precipitation and temperature. In this study, we made a comparison of MarkSimGCM simulations with historical data from 6 rainfall stations. For each station, a MarkSimGCM was run for current climate to produce 30 years of simulated daily data, and monthly mean rainfall, annual totals, and variances. Overall, the MarkSimGCM simulated monthly and annual means adequately close to the historical values on most stations in the CRV. Hence, we consider MarkSimGCM capable of downscaling.

Our second hypothesis was that due to current rainfall variability crop production is limited by drought stress, notably by long dry spells in critical crop growth stages.

This hypothesis is mostly rejected. From the field experiment with SI it appeared that the main factor for the yield gap between farmers practice and attainable yield is not the factor water but the amount of fertilizer applied. Of course there is a strong difference between years. In normal/good rainfall years farmers yield is strongly limited by lack of fertilizer. In dry years or years with dry spells during critical growth stages the effect is much less and water can be a limiting factor. Soil fertility is considered as one of the principal factors that limit maize productivity in maize growing areas of Ethiopia (Abebayehu et al., 2011; Wondosene and Sheleme, 2011). Applying below recommended rates and failure to use the two nutrients (Urea and DAP) in proper combination have marginal effect on yield (Endale, 2010). Despite reports of increased use of fertilizer in Ethiopia in recent years, there is ample evidence that most farmers are not adequately compensating for the loss of soil nutrients caused by more intensive cultivation (Mulat, 1996; Endale, 2010). In Chapter 4 from the field experiment study we showed that, farmers who used half less than the recommended fertilizer obtained only 28 % maize yield as compared to yield obtained under non-limiting soil fertility level both under rainfed condition. Similarly, Kassie et al. (2014) from their yield gap analysis study in the CRV reported only about 30 % farmers' actual maize yield as compared to simulated yield attainable underwater-limited conditions with recommended fertilizer level. The major factor for this huge yield gap was attributed to limited use of fertilizer.

Addressing this yield gap is important in improving food security. For example, de Fraiture et al. (2009) estimated that 80 % of the gap between actual and potentially obtainable yields in the current rainfed agriculture land area can be bridged by using adequate fertilizer to meet about 85 % of the projected global food demand by 2050.

Our third hypothesis was that the effect of climate change on crop production can only be studied if we can obtain insight in the details of changes in rainfall characteristics and in the prediction of the occurrence of extreme events like long dry spells.

This hypothesis is confirmed. As demonstrated in Chapter 2, the detailed investigation that included 10 rainfall indices over a period of 40 years (1970-2009) using 14 meteorological stations from the three landscape units and for the two seasons enables to detect any changes in the behaviour of extreme rainfall indices locally and seasonally. Overall, during the last 40 years, on annual basis and on both *Belg* and *Kiremt* seasons no significant change in extreme rainfall indices except CDD has occurred on most parts of the CRV. Our results contradict with the majority of global and regional studies that reported significant increase in extreme precipitation trends of observed changes since the beginning of the twentieth century in many areas (Easterling et al., 2000; Rosenzweig et al., 2001; Karl and Trenberth, 2003; Cheung et al., 2008; Donat et al., 2013). However, local scale studies are rare. In Ethiopia, this is the first study with long term analysis of changes in daily rainfall and extreme events at the landscape and seasonal scales that can provide information whether there is a continuous significant change in extreme rainfall indices. Where such important climate information is available locally, it helps to understand local-scale consequences of climate change and thereby to the design of locally-specific adaptation interventions.

Our fourth hypothesis was that we can use a crop growth model and long term rainfall data to predict effects in a statistically sound way.

This hypothesis is confirmed. The AquaCrop model that was chosen for our crop modelling was able to simulate the soil water, canopy cover and crop yields well under both rainfed condition and different levels of SI with conservative crop parameters and user specific crop parameters obtained in a field experiment carried out in the CRV using maize BH540 cultivar. The values of RMSE, NRMSE and percent deviation for the model validation were all in acceptable ranges. Due to its simplicity, accuracy, and robustness, AquaCrop is becoming a widely used crop model for estimating crop yield for climate change scenarios and to test different adaptation options.

Our fifth hypothesis was that adaptation measures must aim at improving the water supply to the crop so that investments in crop intensification are worth the effort.

This hypothesis is confirmed with a lot of restrictions. Using SI from farm ponds for staple crops is justified if used in a very precise manner. This is because the amount of water is limited and should be used for critical dry spells only. In the CRV, as a means of coping water scarcity, rainwater harvesting in the form of individual farm ponds is practiced and mainly used for small-scale vegetable cropping, chat, livestock and household. At the same time, the staple crop that is grown for household consumption is maize and is important crop for achieving food security. Maize has been selected as one of the national commodity crops to satisfy the food self-sufficiency program of the country (Kebede et al., 1993). However, the failure of the unreliable *Belg* rains at a critical stage of crop growth most often caused widespread damage to maize. Farmers assume that WH may not be sufficient for staple field crops and are puzzled what to do to bridge dry spells for staple cropping like maize. Results from this study indicate that SI from individual water harvesting ponds can be used for maize cropping by bridging dry spells that can cause total crop failure.

To adopt water harvesting technology for staple crops farmers need to know the optimum level of SI and whether that optimum level water could be harvested from existing farm ponds. Based on farm field experiment and crop modelling we determined the optimum level of SI as application of irrigation water when the percentage of soil water depletion reached 75 % of the maximum available water in the root zone and is sufficient to save maize yield from crop failure and increase crop yield (Chapters 4 and 5). Under this level of SI, using 94-111 mm of SI during sensitive growth stages can avoid total crop failure in drought years. We proved that this amount of SI is available from existing farm ponds, even in drought years. Thus, farmers' notion that WH may not be sufficient for staple field crops is not supported by this study.

Our sixth hypothesis was that crop intensification is only worth the effort if not only the water supply is improved but also other production limiting factors, such as fertility, are improved.

This hypothesis is confirmed. In this study, we proved that such intensification of SI using water harvesting ponds and with higher maize plant density (75,000 plants ha^{-1}) under optimum fertilizer is an option to adapt to climate change in the Rift Valley dry lands of Ethiopia.

Our seventh hypothesis is that farmers are right in their idea that small scale forest have a beneficial effect of rainfall and one of the recommended impact reducing strategies therefore is the protection and plantation of small forests.

This hypothesis could not be fully confirmed because of the complication of the presence of lakes in the CRV. Local people in many regions believe that forests attract rain, but climatologists; based on large scale models, claim that a small forest can have no effect on rainfall. Stroosnijder (2012) in his farewell address upon retirement referred it as one of the popular myths that needs to be unmasked. Stigter (2010) described farmers' strong believe that local forests attract rain as "I have heard these believes expressed myself regularly in Africa and Asia when having discussions with local farmers. I could only answer that there was no theory to explain this, particularly not as a local scale effect".

In Ethiopia, despite interest and farmers' belief that forests attract rain, to the best of our knowledge no research has ever been conducted in a country about this issue. This study, as demonstrated in Chapter 6, was conducted in two ways: First, the effect of existing remnant forests on rainfall at the landscape scale was studied by installing automatic rain gages in forests and open areas following a transect line. Second, long term relationship between the long term deforestation and rainfall and temperature pattern change was studied to determine the effect of deforestation on climate.

From our two years observation, forests were found to be a significant predictor to annual rainy days. Despite the fact that the relation between distance from forest and annual total rainfall was not statistically significant, both annual rainfall total and number of rainy days showed inverse relationship with distance from forest. In general our results support farmers' perceptions of forests attract rain.

7.5 Reflections

When looking at the various chapters as a whole, some issues came up that are not directly related to the research questions or the hypothesis but are worth mentioning although we not tested the relevance for all. Especially issues related to management options to optimize the use of water are of interest since the scientific evidence gathered in this thesis was meant for improving the livelihood of farmers in the CRV of Ethiopia.

Adapting cropping calendar to seasonal shift

From this thesis it is apparent that the two important cropping seasons (*Belg* and *Kiremt*) are likely to shift in the future in the CRV of Ethiopia. The *Belg* season rainfall is occurring very late or failing altogether for the current climate and continues to decrease during the rest of this century which makes the prospect of future *Belg* crop growing very difficult. Since the *Belg* season is important for planting long-cycle cereal crops like maize and sorghum and growing *Belg* crops, anomalously short *Belg* rainy seasons in recent years (2000–2004) have led to recent food shortages in southern

Ethiopia (Verdin et al., 2005). On the other hand, the *Kiremt* season rainfall is likely to increase and extended in the future. Therefore, if no changes in cropping practices are made to adapt to the future climatic conditions as shown in this thesis, following seasonal shifts maize production will be at risk in the CRV (Chapters 4 and 5).

In recent times, due to the shifting of seasons, farmers have started to use the reliable *Kiremt* season for most of the crops (Sime and Aune, 2014). In most of the semi-arid regions of Ethiopia farmers are gradually replacing long cycle, *Belg* and *Kiremt* season crops such as maize and sorghum by other early maturing *Kiremt* season crops such as teff (Mahoo et al., 2013). Other coping mechanisms of farmers are shifting to short cycle crops during reliable *Kiremt*. The disadvantage of shifting to short cycle crops is that they have lower yield capacity than long cycle crops. Long cycle crops, if sufficient agricultural inputs could be made available, are often substantially more productive than short cycle varieties planted during the *Kiremt* season (Meza et al., 2009).

In our thesis we showed two possible adaptation options in a condition of seasonal shift due to climate change: the first adaptation option is shifting of maize cropping from *Belg* and *Kiremt* to only *Kiremt* season. This means the productive long cycle crops that were sown during *Belg* and harvested during *Kiremt* for the current climate can shift to only *Kiremt* season crop for future climate. This cropping shift would not compromise the length of growing period because the cessation date of *Kiremt* rainfall is likely to be extended in the future, which could help farmers grow long cycle maize crop by adjusting their cropping calendars. The second option is to continue using both *Belg* and *Kiremt* seasons for maize cropping by using supplemental irrigation through water harvesting ponds to bridge long cycle dry spells that occurred during drying *Belg* due to climate change.

Feasibility of farm water harvesting for staple crops' SI

Despite its great potential, the application of rain water harvesting (RWH) technologies is still low in Ethiopia. RWH in Ethiopia was originally meant for improving moisture availability for field crop production; however, it is mostly limited to vegetable production at home backyards (Getnet and MacAlister, 2012). It is common believe that SI for staple crops is not realistic. For instance, in the CRV, RWH in the form of individual farm ponds is commonly practiced as a means of coping with water scarcity. However, the water of these ponds is mainly used for high value small-scale crops such as for vegetable cropping, chat, livestock and household. Similarly, Pachpute et al. (2009) in Tanzania reported that, the stored water from individual water harvesting with storage size of 320 m^3 per household is not used for crop production but it is suitable for domestic uses and watering of livestock.

On the other hand there are several reported successes stories of SI for rainfed agriculture in reducing the risk of total crop failure due to dry spells and increase crop yields (Oweis et al., 1999; Fox and Rockstrom, 2002; Biazin et al., 2011). In the Ethiopian CRV, it is possible to use SI for 0.3-0.8 ha of maize using water harvesting ponds with the capacity of 350 m^3 (Chapter 2). In Chapter 4 we showed the potential of sufficient runoff that can be harvested in the farm ponds, even in dry years, and used for SI for maize cropping in the Rift Valley dry lands of Ethiopia. However, SI can be successful and efficacy when it is part of an integrated package which includes non-water inputs (Oweis and Hachum, 2012). In our thesis we showed that using SI together with improved soil fertility and optimum plant density it is possible to grow maize even during periods of extreme dry spells.

The overall success of RWH is determined not only from technical issues but also from economic issues. The financial feasibility of RWH ponds for SI was assessed by Hartog (2012) in the CRV of

Ethiopia. The analysis includes the initial investment for constructing farm ponds, maintenance costs, and a drip kit for irrigation. The analysis showed that if the productivity of maize can increase 2.5 times higher than current yields (2.15 t ha^{-1}) construction of farm ponds and irrigating maize could be financially feasible for farmers. In our experiments yields with improved fertilizer are about 3.5 times higher (Chapter 4, Table 4.7).

Optimum use of SI at sensitive stages of crop growth during critical dry spells

Since SI is a "limited" type of irrigation, the timing of water application is critical. Identifying the critical growth stages where water deficits can severely affect yield is of great importance. According to Kang et al. (2000) and Oweis and Hachum (2012) shortage of soil moisture during the most sensitive stages of crop growth, i.e. flowering and grain filling can severely affect plant growth and yield and application of SI during these critical crop growth stages – can substantially increase yield and water productivity.

Literature provides varying lenghts of dry spells that causes harmful effect to yield, for instance, Barron et al. (2003) consider a 10-day dry spell as damaging to a maize crop due to water deficit in Kenya and Tanzania. Similarly, in north-eastern Ethiopia, consecutive 10 days length of dry spell causes crop failure (Segele and Lamb, 2005, Araya et al., 2010). Another study in the semi-arid part of the CRV by Biazin and Sterk (2013) found that dry spells longer than 30 days occurring in the first 60 days after onset, or longer than 20 days in the 60-90 DAS period were critical and caused total crop failure for maize crops. This difference in dry spell lengths in different regions can be attributed to soil's water holding capacity (Stroosnijder, 2008) which implies the need to identify critical dry spells for different soils and regions.

So, in this thesis we further contributed to the existing literature in identifying the sensitive stages of maize crop and the critical dry spell lengths that lead to total crop failure or significantly minimize yield for the CRV region. In Chapter 5, we showed that the sensitive growth stages of maize was 60-90 days after sowing (DAS) which coincides with flowering stage of maize and 30-60 DAS. A dry spell of > 30 days that occurred during 60-90 DAS and a dry spell of > 20 days that occurred both during 30-60 and 60-90 DAS periods were critical dry spells which resulted in total crop failure. Finally, it was possible to show how SI saved maize crop during those severe drought periods by increasing the maize grain yield from total crop failure to 6.8 t ha^{-1}. However, a dry spell of only < 5 days during the critical growth stage (60-90 DAS) has minimal effect on yield and gives optimum yield. Under this condition, the effect of SI on yield was marginal (2.5% increase) with the amount of SI water used also very minimal (1.7 mm).

RWH can reduce risk of fertilizer use

Farmers in semi-arid East Africa always prioritize drought as their major productivity-reducing problem (Stroosnijder, 2008; Slegers, 2008). This makes farmers hesitate to invest in fertilizer due to risk of crop failure from erratic rainfall and long dry spells (Bindraban et al., 1999; Hilhost and Muchena, 2000**;** Rockström et al., 2002; Fox et al., 2005; Cooper et al., 2008; Dercon and Christiaensen, 2011). Therefore, uncertain rainfall and very low levels of irrigation make intensive cultivation with improved seeds and fertilizer risky (McCann 1995). So, there is a question of what to do to minimize risk of crop failure under rainfed conditions and increase farmers' confidence of using inputs? Oweis et al. (1999) suggest that risk-averse farmers can be expected to use farm inputs and technology if they perceive that the increased risk is compensated by the increased returns. For example, the certainty of income generation through sustainable RWH can increase opportunities for crop intensification and investments in smallholder farming (Pachpute et al., 2009). Because, the available harvested water from water harvesting ponds, besides directly providing water for crop growth convinces farmers that fertilizer can be applied effectively and at low risk (Fox et al., 2005; Wakeyo and Gardebroek, 2013). Therefore, confidence of farmers to have reliable water and subsequent risk reduction of harvest failure as well as economic benefit for the household encourages farmers to make more investment in agriculture and adopt new technologies (Fox et al., 2005). Wakeyo and Gardebroek (2013) also reported that water harvesting increases the probability of using fertilizer in Ethiopia.

In this thesis we contribute to this proposition by showing that using SI from water harvesting ponds it is possible to avoid total crop failure during drought years and improve maize yield in the Rift Valley dry lands of Ethiopia. Our results demonstrate the possibility of minimizing the risk of crop failure from dry spells and improving yield by using SI and fertilizer as complementary inputs. This in turn can reduce farmers' fears that the crop either totally fails or might give very minimum yield. In India, McGuirk and Mundlak (1991) recommended high levels of fertilizer input and irrigation as complementary inputs for adoption of high yielding varieties and to realize the yield potential. In the Ethiopian CRV, we further proved that the high risk associated with fertilizer application under rainfed farming conditions could be minimized or avoided if use of fertilizer is combined with RWH. Thus, we believe fertilizer and water availability are complementary inputs for sustainable and reliable yield increase. However, agronomists most often emphasize the role of water only in terms of its direct effect on crop yield and argue that the low fertility of the soils is often much more a limiting factor than the low and irregular rainfall (Penning de Vries and Djiteye, 1982; Tittonell and Giller, 2013). But, the role of water should not be underestimated, because water availability in addition to its direct effect on crops is also a key factor in determining risk perceptions of harvest loss among farmers and then affects the decision to invest in fertiliser (Fox et al., 2005).

The effect of forests and deforestation on climate

The effect of forests and deforestation on climate continues to be a point of argument (Sheil and Murdiyarso, 2009; van der Ent et al., 2012). However, most observational and modelling studies have indicated that deforestation can cause indirect impacts to local and regional rainfall patterns and surface temperatures (Pielke, 2001; Duriex et al., 2003; Ray et al., 2006). For example, the most recent study by Gourdij et al. (2015) found a day time temperature increase of 0.4 ^{O}C per decade in areas that have experienced rapid deforestation within 50 km radius since 1983 a rate which is about three times the global average increase, whereas night time minimum temperature increases 0.18 ^{O}C per decade, a rate consistent with global average temperature increase. Generally, there is a consensus on the idea that the day time temperature increase is always associated with local deforestation (Casitillo and Gurney, 2013, Houspanosssian et al., 2013).

In Chapter 6, our result shows that in the Ethiopian CRV the temperature has significantly increased over the past four decades which is consistent with persistent deforestation mostly in the rift valley floor of the area. Especially the increase in the maximum daily temperature in the rift valley floor was higher than the highlands (Chapter 6, Table 6.3). In the past four decades (between 1973 and 2006), there was a consistent forest/woodland degradation which increased degraded land by 200 % in the CRV (Meshesha et al., 2010).

Despite deforestation is considered as a contributing factor to declining rainfall in various regions (e.g. Chan, 1986; Zhang, 1986), our results in Chapters 2 and 6 indicate a consistent increase in the mean annual and seasonal rainfall over the past four decades in the rift valley floor. However, there are similar arguments in previous studies which states that when deforestation is in an area close to a water body such as lakes, the local and/or regional circulations (Lake Breeze) are favourable for moisture transport and increased rainfall (Mawalagedara and Oglesby, 2011). But, when deforestation is in a region such as the Amazon basin, where 50 % of the moisture available for precipitation comes from local evapotranspiration, rainfall would decrease (Lean and Warrilow, 1989).

Effect of elevated CO_2 concentration on maize

Despite a general consensus towards the positive impact of elevated atmospheric CO_2 concentration on crops, there is no agreement on how much elevated CO_2 concentration could increase crop yield. The effect is more debatable when it is on C4 plants like maize where photosynthesis is almost CO_2-saturated at present levels of ambient CO_2 (approximately 355 ppm) (Rotter and Van de Geijn, 1999). Thus, some have serious doubt on projections that rising CO_2 will fully offset losses due to negative effects of future projected changes in temperature and precipitation on crop yields (for example, Long et al., 2006). Others strongly argue against the weak response of CO_2 fertilization, and rather argue that CO_2 effect on crop growth and yield is too strong (for example, Tubiello et al., 2007).

In Chapters 3 and 5, we found that the magnitude of maize (a C4 crop) yield increase was 7 % during 2020-2049 period, where the CO_2 level increased from the reference 369 ppm concentration to 559 ppm (Chapter 3). But, the projected maize yield reduction under climate change during 2020-2049 was 11 % in semi-arid CRV (Chapter 2) and 16 % in dry sub-humid CRV (Chapter 5). Therefore, in our thesis the projected lower maize yield due to climate change is only partly compensated by the expected increase in CO_2 concentration and its subsequent yield enhancing effect.

7.6 Limitation of the study

Although this thesis used robust methodologies such as rainfall analysis, field experimentation and modeling; there are limitations of scope, temporal and spatial nature. For example, in this thesis adaptation options are only studied for one site. As we have witnessed in this thesis, it is realistic to assume that effects can be different in other locations in other climates so do adaptation options. So it is inappropriate to extrapolate the recommendations of the study to other agro climates and regions of the country.

Field experiments were conducted over only two seasons and three farms in dry sub-humid area of the CRV, Ethiopia. Long-term experiments in a wider area on more farms could have provided more insights. Specially, since experiments were conducted over only two seasons (a dry and wet year); irrigation being used only in the dry year, many years of such on farm field experiments could have provided more convincing and robust result than crop modeling that we used to support our field experiment.

In our study, the meteorological stations that showed increasing rainfall are within 7 km radius of the four lakes that exist in the rift valley floor (Chapter 6). Thus, we can argue that those lakes within 7 km radius to the meteorological stations could likely contribute to the increase in rainfall due to transport of moisture from the lakes to the nearby land surface (Lake Breeze). The long term observed significant temperature increase in the rift valley floor (Chapter 6) might also arguably contributed to Lake Breeze that increased the rainfall of the rift valley floor. Observed lake influence distance have been reported in previous studies to be as much as 10 km to 45 km (e.g. Moroz, 1967; Lyons, 1972; Estoque et al., 1976; Ryznar and Touma, 1981; Gálvez et al., 2006). In general the major inland lakes in east African rift valley region are believed to have an important influence on rainfall in the surrounding area (Ba and Nicholson, 1998). For example, Nieuwolt (1977) reported that Lakes Abaya and Chamo, Ethiopian southern rift valley lakes, which are located in the valley floor, produce large amounts of water vapor and also create local disturbances that are conducive to rainfall formation. Similarly a study by Haile et al. (2009) in the Ethiopian Blue Nile Basin near Lake Tana reported the development of high and thick clouds over the lake and heavy rainfall events of higher than 10 mm h^{-1} at stations relatively close to Lake Tana.

The analysis of the role of lakes for increasing rainfall in the surrounding area and also the role of deforestation in increasing day time temperature was carried out by indirect method and revising existing literature. However, the limits of our dataset prevent any further analysis to draw a robust conclusion about the role of these lakes in affecting the surrounding rainfall pattern and the role of deforestation in aggravating local warming.

7.7 Institutional, policy and research implications

Notwithstanding the above-mentioned limitations, this thesis is a step toward improving our understanding of risks of cropping under the current and future climate change scenarios at the sub regional scale in Ethiopia and assesses options of reducing the existing and expected risks. Thus, the findings could assist farmers to make informed decisions in coping climate variability and adapting future climate change at farm level. It also helps policy makers to identify priority areas for climate change adaptation planning and implementation.

Amongst the major findings that farmers need to apply to their farming system is the complementary use of water harvesting and fertilizer. Water harvesting ponds and fertilizer use need to be recommended as a package and need to be well integrated into the farming system since it provides the advantage of reducing crop failure, increase crop yield and reduces farmers' fear of dry spell crop failure.

In order that individual water harvesting ponds can be effectively used for food crops, other types of water harvesting ponds need to be used; for example, communal water harvesting ponds should be encouraged for livestock use so that the burden of using water for livestock from individual water harvesting farm ponds could be reduced and farm ponds can specifically be used for staple crops. The other advantage is that communal ponds can collect water from larger catchments than farm ponds so that they can collect more water for livestock. Using deep boreholes for home consumption can further increase the amount of water available for staple crops. Beyond that, farm ponds are not clean for home consumption and may expose farmers to water borne diseases and lead to reduce farmers' productivity.

The *Belg* is already unreliable and drying and it will become more dry whereas the *Kiremt* is predicted to become wetter and extended, therefore, farmers need to adapt to this seasonal shift. In our thesis based on long term current and future climate analysis in the CRV, we recommended late sowing (month of May for current climate and June for future climate) to reduces the occurrence of dry spells and risk of crop failure for maize cropping; therefore, farmers need to be advised and well informed to choose the most successful onset period.

7.8 Recommendations for further research

Climate change affects the growth and development of crops through various direct and indirect processes. Most research on the climate change impacts to crops have focused on the direct impacts of climatic factors such as, increased temperature, changing on rainfall patterns, increased drought and changes in CO_2 concentration, yet indirect effects of climate change that can affect crop production like pests, diseases, and the severity of soil erosion are rarely taken in to account (Adams et al., 1998). For instance, in this study large rainfall occurrence during the months of June and August (Chapter 3, Figures 3.3a and 3.3b) from heavy rain events could result in high runoff. A similar study has also predicted the increase in the number of extreme wet days over the Ethiopian Highlands by 50-90 % during the mid-twenty-first-century (Vizy and Cook, 2012). IPCC (2007) also projected increasing intensity of precipitation events under future climate scenarios, particularly more intense wet season is expected in east African countries (Shongwe et al., 2011) which likely increase soil erosion. Increased soil erosion affects crop yield in different ways like by removing plant nutrients, reducing water availability etc. On the other hand the impact of pests and diseases affect crop yield. Some studies suggest that pests and diseases can reduce productivity of major crops by up to 50 % (Oerke, 2006). Thus, for holistic assessment of the effect of crop production in a changing climate a fully integrated model that incorporates all those factors is required, currently non-existent.

In this thesis we conducted field experimentation on adaptation options for two years in one agro-climatic area but we believe that long term research is required in different agro-climatic environments such as in dry sub-humid and semi-arid environments. Furthermore, a thorough assessment of socio-economic feasibility study of SI through water harvesting ponds for staple crops could increase farmers confidence that SI through RWH a viable option both technically and economically.

Our findings imply that lakes can play a positive role in increasing surrounding rainfall. This can be used as an entry point for further research on the effect of lakes on rainfall using robust methodology. Since there is a chain of more than seven lakes in the Ethiopian rift valley, studying their role for the surrounding climate could be important in the face of climate change. Thus, we recommended further research to determine the effect of the rift valley lakes on the climate of the surrounding area.

Similarly, more research is required to determine the effect of forest cover and deforestation at different parts of the country where there are wide remnant of forests and wider deforestation in the country. Deforestation inducing local warming need to be studied by including albedo and evapotranspiration.

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Summary

Ethiopia's rain-fed agriculture based economy is highly sensitive to climate fluctuations. Strong correlation of rainfall variability with fluctuations in both GDP and agricultural GDP indicates that rainfall variability has been significantly affecting the country's agriculture dependent economy and food production. Climate change and variability poses the most serious threat to agricultural production and food security in the country. The food security situation of the country is greatly influenced by the performance of rain-fed cropping systems. In Ethiopia, Climate change induced rainfall variability and drought is likely to exacerbate the challenge of increasing agricultural production and economic growth. The Central Rift Valley (CRV) is a food producing area in Ethiopia and yet one of the most drought prone areas in the country. Interannual variability of seasonal rain fall in terms of dry spells, late onset, early cessation of rainfall and total lack of rainfall are the major causes of crop failure. Hence, there is a need to analyze details of changes in rainfall and compare these with current rainfall variability, to determine the impact of these changes in relation to possible other crop production limiting factors and to develop options for crop intensification that reduce the impact of climate change and increase food security in the CRV.

Chapter 2 investigated trends in 10 extreme rainfall indices over a period of 40 years (1970-2009) in the CRV using 14 meteorological stations to detect any changes in the rainfall behaviour. The analysis was conducted on three landscape units: the valley floor, the escarpments, and the highlands and on the two seasons: the *Belg* (March-May) and *Kiremt* (June-September) seasons. The RClimDex software developed by the Expert Team on Climate Change Detection, Monitoring and Indices (ETCCDMI) was used for data quality and homogeneity test. Then the trends of the rainfall indices were detected using the Mann-Kendall non-parametric test. In the annual time series analysis, most of the stations in the rift valley floor showed increasing trends in total precipitation (PRCPTOT) and extreme rainfall indices. The *Belg* and *Kiremt season* analysis of the extreme rainfall indices during the last 40 years indicates that less than 30% of the stations in the escarpment and highland part of the CRV showed significant decreasing trend. However, the maximum number of consecutive dry days (CDD) showed consistent increase at almost all stations in the whole of the CRV, with 50% of them significantly increasing and none with a decreasing trend. Spatially, the rift valley floor received increasing annual rainfall while the escarpments and the highlands received decreasing annual rainfall over the last 40 years. The difference in results obtained from daily rainfall and extreme rainfall events for landscape units and seasons indicates the importance of climate assessment at the local and seasonal scales.

Chapter 3 assessed how Belg and Kiremt growing seasons rainfall characteristics is likely to change in the future and to evaluate potential impacts of these changes and elevated atmospheric CO_2 concentration on maize and wheat yield in the Ethiopian CRV. AquaCrop model for yield simulations and MarkSimGCM module for obtaining daily climate data from ECHAM5 model and six ensemble mean of model projections under A2 (high) and B1 (low) emission scenarios were used. The result indicated that the projected rainfall during Kiremt will likely increase by about 12-69% whereas the Belg rainfall will decrease by about 20-68%. Though, the onset of the Belg rainfall season for maize crop is projected to be late by about 2-9 weeks, the mean cessation date for future climate is expected to extended by more than a month, which extended the projected mean LGP for long cycle crop (maize) by up to a month. But, Adama station in the semi-arid climate showed late onset and

early cessation. During Belg and Kiremt seasons, the subsequent 90 days of maize and wheat growing periods will not have dry spell lasting longer than 10 consecutive days except at Adama where there could be greater than 15 days of dry spell. Yield simulation under projected rainfall showed that maize yield will increase by up 30%. The yield of wheat was almost level between the baseline and projected climate. Though there was an increase of Kiremt rainfall, wheat yield did not show yield increment because for Kiremt growing wheat crop water was not a limiting factor, even under baseline climate. Therefore, the only yield difference for wheat was obtained from CO_2 fertilization that showed a yield increase of from 17% to 40% during 2020-2049 and 2066-2095 respectively under A2 emission scenario, when the level of CO_2 increases from 369.41 ppm to 779.22 ppm. Similarly, maize has also shown yield increase from elevated CO_2 by up to 14% when the level of CO_2 increases from 369.41 ppm to 779.22 ppm. In terms of maize response to the overall climate change, at Assela (humid climate) maize yield was projected to increase by 33-37% between 2020 and 2049 periods and by 60-70% between 2066 and 2095 whereas Adama despite the projected yield increase from rainfall change and elevated CO_2, the overall climate change impact is likely to bring a yield decline ranging between 11%-46%.

Chapter 4 tested experimentally the hypothesis that supplemental irrigation in combination with increased plant density under optimum fertilizer use would bridge dry spells, reduced risk of crop failure and increase grain yield. During 2012 (dry) and 2013 (wet) on-farm field research was conducted with 10 combinations of supplemental irrigation and plant density. The simplest combination was rainfed farming with 30,000 plants ha^{-1}. The most advanced combination was no water stress and 75,000 plants ha^{-1}. Fertilizer effect was assessed by comparing maize yield between on-farm research and neighbouring farmers. For technical feasibility of supplemental irrigation (SI) from water harvesting ponds (RWH), we first estimated the availability of sufficient runoff in dry years. The result shows that in March there is hardly enough water in the ponds. Starting from April there is more available runoff water from a 2.2 ha catchment that is sufficient for 0.5 ha maize area crop water requirement. So, in the CRV, we recommend a later sowing of maize (mostly May) when there is more runoff from RWH ponds. Despite significant maize yield differences between rainfed and SI levels, the investment in supplemental irrigation during non-critical drought years is not worth the effort since it is not financially feasible. Increasing plant density from 30,000 plants ha^{-1} to 75,000 plants ha^{-1} significantly increased maize yield. The use of optimum fertilizer (150% recommended level) to on-farm research increased grain yield by 101% as compared to the current use of fertilizer by adjacent farmers (50% less or half less than recommended). Finally, this hypothesis could not be fully proven with our only 2 years experiment particularly in a critical drought condition.

Chapter 5 the hypothesis in chapter 4 was further tested for long term climate and climate change scenarios using modeling. The MarkSimGCM weather generator was used to generate projected daily rainfall and temperature data originally taken from the ECHAM5 general circulation model and ensemble mean of six models under A2 (high) and B1 (low) emission scenarios. We first assessed the change in the occurrence of long dry spells during maize growing season and the magnitude of the elevated CO_2 level in compensating negative climate change impact was also assessed for short term climate projection (2020-2049). After validating the FAO AquaCrop model, we used it to predict maize yields and explore three adaptation options: supplemental irrigation, increasing plant density and changing sowing date. The dry spell analysis result shows that the projected longest dry spell under both ECHAM5 and ensemble mean of models during March and April increased, whereas it decreased during June-October. In spite of grain yield increase by 7.5% when CO_2 concentration level increased from the reference 369.41 ppm to 518.88 ppm Under ECHAM5 on A2 scenario, it only partly compensate a negative climate effect on maize production. We recommend higher plant density (up to 75000 plants ha^{-1}) for farmers in the CRV, since our result shows s significant yield increase when the plant density increases from 30,000 plants ha^{-1} to 75,000 plants ha^{-1}. The optimum level of SI, in combination with the 30,000 plants ha^{-1} plant density, was application of irrigation water when the soil water depletion reached 75% of the total available water in the root zone. We also found that SI has a marginal effect in good rainfall years but using 94-111 mm of SI can avoid total crop failure in drought years. Hence, SI in combination with plant density and optimum fertilizer is a promising option to improve food security in the Rift Valley dry lands of Ethiopia. Our results also show that shifting the sowing period of maize from the current *Belg* season (mostly April or May) to the first month of *Kiremt* season (June) can offset the predicted yield reduction**.** In general, the present study showed that climate change will occur and without adaptation have negative effects. Use of SI with optimum fertilizer and plant density and shifting sowing date are viable options for adapting to the changes, stabilizing or increasing yield and therefore improving food security for the future.

Chapter 6 we investigate the forest-rainfall relationships in the environmentally hotspot area of the Central Rift Valley (CRV) of Ethiopia. Specifically, we evaluate long term rainfall (1970-2009) and temperature (1981-2009) trend and its relationship with long term deforestation and the relationship between existing remnant forests and topographical variables with spatial rainfall distribution. The study used 16 long term (40 years) and 15 short term (2 years) rainfall stations. The Mann-Kendall test and stepwise multiple regression methods were used. The results showed that despite a continuous decline of forest and woodland cover over the past 40 years (1970-2009), annual rainfall in the rift valley floor increased by 37.9 mm/decade. However, annual rainfall on the escarpment/highlands decreased by -29.8 mm/decade. There was also a significant warming observed in the rift valley floor that could be attributed to long term deforestation in the CRV. The existence of remnant forests showed significant effect ($R^2 = 0.4$) on number of rainy days spatial variability as indicated from systematically observed two-year's rainfall data (2012-2013).

Samenvatting

De economie in Ethiopië drijft voor een groot deel op door de regen gevoede landbouw. Omdat landbouw productie wordt beïnvloed door klimaatfluctuaties, is de economie ook afhankelijk ook een afhankelijk van het klimaat en fluctuaties in het klimaat. Met name de fluctuaties in neerslag hebben een sterke correlatie met de GDF en de landbouw GDP.

Klimaatverandering vormt derhalve ook een serieuze bedreiging voor de ontwikkeling van de landbouw en daarmee de voedselzekerheid in het Ethiopië. Omdat de landbouw nog altijd voor het overgrote deel niet-geïrrigeerde landbouw is, is het belangrijk te weten hoe klimaatverandering de klimaatvariabiliteit in Ethiopië zal veranderen omdat dit de voedselzekerheid in het land zal bepalen. De voorspelde klimaatverandering laat zien dat de variabiliteit in neerslag zal toenemen en dit betekend dat er meer kans zal zijn op droogtes en droge periodes in het groeiseizoen. Deze verandering in klimaat zal compromitterend zijn voor de voedselzekerheid.

Het centrale deel van de Rift vallei (CRV) is een gebied waar veel voedsel wordt verbouwd, maar is tegelijkertijd een gebied waar vaak droogtes en bijbehorende misoogsten voorkomen. Klimaat variabiliteit tussen verschillende jaren zoals droge periodes, late start of vroeg einde van de regens of verminderde totale neerslag zijn de hoofdredenen van misoogsten in het gebied. Derhalve is het belangrijk in detail te bestuderen hoe de neerslagkarakteristieken in het gebied zijn en hoe ze zich over de jaren hebben ontwikkeld, en hoe de klimaatverandering deze karakteristieken zal veranderen. Op basis hiervan kan een beoordeling worden gemaakt van de invloed die deze veranderende karakteristieken op de voedselproductie in het gebied. Met deze kennis kunnen plannen voor de intensivering van de landbouw in het gebied worden ontwikkeld die rekening houden met et veranderende klimaat, maar ook met andere limiterende factoren zoals sociale, economische, bodem fysische en hydrologische situatie in het gebied.

Hoofdstuk 2 bestudeerd de trends in 10 indices die de regenkarakteristieken beschrijven voor een periode van 40 jaar (1970-2009) voor 14 meteorologische stations in de CRV om eventuele veranderingen in de neerslag te detecteren. De studie is gedaan voor drie landschappelijke eenheden: de vallei, de steile hellingen en de hooglanden; en tevens is er onderscheid gemaakt voor de twee neerslag seizoenen in de CRV, de Belg (maart-mei) en Kiremt (juni-september). De RClimDex software dat ontwikkeld is door een team van klimaatdeskundigen (ETCCDMI) is gebruikt om de kwaliteit en homogeniteit van de data te testen en de trends in de neerslagkarakteristieken zijn achterhaald met behulp van de Mann-Kendall niet-parametrische test. In de jaarlijkse tijdreeks analyse, lieten de meeste van de stations in de Rift Vallei bodem een stijgende trend in de totale neerslag (PRCPTOT) en in de extreme regenval indices zien. De analyse van de extreme regenval indices van de Belg en Kiremt seizoenen van de laatste 40 jaar geeft aan dat minder dan 30% van de stations op de helling en hooglanden een significant dalende trend heeft. Echter, het maximum aantal opeenvolgende droge dagen (CDD) liet een stelselmatige toename zien in bijna alle stations in de gehele CRV, waarbij 50% van de stations een aanzienlijk stijging lieten zien en geen enkel station een dalende trend. Als men de ruimtelijke verdeling van de neerslag bekijkt, blijkt dat de vallei bodem een toenemende trend in neerslag laat zien, terwijl de hellingen en de hooglanden juist een afnemende jaarlijkse neerslag in de afgelopen 40 jaar vertonen. Het verschil in de resultaten in de trends van neerslag karakteristieken voor de verschillende landschappelijke eenheden en seizoenen geeft het belang aan van klimaat beoordeling op de lokale en seizoensgebonden schalen.

Hoofdstuk 3 bespreekt hoe de neerslagkarakteristieken van de Belg en Kiremt groeiseizoenen in de toekomst vermoedelijk zullen veranderen en hoe de potentiële effecten van deze veranderingen, en dan met name de verhoogde atmosferische CO2-concentratie, de opbrengst van maïs en tarwe zullen beïnvloeden in de CRV. Om dit te bestuderen zijn de resultaten van het AquaCrop model van FAO naar rendement simulaties, het MarkSimGCM module voor de dagelijkse klimaat gegevens van ECHAM5 model en zes samengestelde gemiddelden van model projecties onder A2 (hoog) en B1 (laag) emissiescenario's gebruikt. De resultaten gaven aan dat tijdens de Kiremt de verwachte neerslag waarschijnlijk zal toenemen met ongeveer 12-69%, maar dat de Belg neerslag zal afnemen met ongeveer 20-68%. Hoewel, de start van neerslag van het Belg seizoen voor mais naar verwachting met 2 tot 9 weken zal worden uitgesteld, zal de gemiddelde datum van het einde van het regenseizoen voor het toekomstige klimaat zal naar verwachting met meer dan een maand worden verlaat, derhalve zal de verwachte gemiddelde LGP met maximaal een maand worden verlengt. Hoewel dit voor de meeste stations kan worden verwacht, is de projectie voor het station Adama station in de semi-droge klimaat dat er zowel een verlate start als een vroeg einde van het regenseizoen wordt verwacht. Tijdens de Belg en Kiremt seizoenen komen in de daaropvolgende 90 dagen van de groeiperiodes van maïs en tarwe geen droge periodes van langer dan 10 opeenvolgende dagen voor, behalve in Adama waar sprake zou kunnen zijn van droge periodes van meer dan 15 dagen. Als de oogst wordt gesimuleerd voor de verwachte neerslag bleek dat de opbrengst van maïs tot maximaal 30% zal toenemen. De opbrengst van tarwe lag tussen het niveau berekend voor de baseline en het verwachte klimaat. Al was er een toename in neerslag voor Kiremt, laat de opbrengst van tarwe geen verhoging zien, omdat waterbeschikbaarheid niet de beperkende factor is voor tarwe, zelfs niet onder het baseline klimaat. Daarom is de enige verschil in opbrengst voor tarwe veroorzaakt door CO2-bemesting als gevolg van de klimaatverandering. De opbrengst kan stijgen van 17% tot 40% tijdens 2020-2049 en 2066-2095 respectievelijk onder A2 emissiescenario kan worden verwacht, wanneer het niveau van CO2 stijgt van 369,41 ppm tot 779,22 ppm. In het geval van maïs, werd ook een opbrengstverhoging als gevolg van de verhoogde CO2 worden verwacht tot 14% als het niveau van CO2 stijgt van 369,41 ppm naar 779,22 ppm. Over het geheel genomen laat deze analyse zien dat de reactie van maïs op de klimaatverandering afhangt van de locatie in de CRV. In Assela (vochtig klimaat) zal opbrengst van maïs naar verwachting met 33-37% stijgen tussen 2020 en 2049 en met 60-70% tussen 2066 en 2095, terwijl in Adama, ondanks de verwachte opbrengstverhoging van neerslag verandering en verhoogde CO2, de totale impact van klimaatverandering waarschijnlijk een rendement daling variërend tussen de 11% -46% zal sorteren. Dit toont duidelijk de noodzaak om variaties op korte afstand als gevolg van lokale omstandigheden in klimaatadaptatie plannen mee te nemen.

Hoofdstuk 4 testte met behulp van een veldexperiment de hypothese dat aanvullende irrigatie in combinatie met een verhoogde dichtheid van planten onder optimale gebruik van meststoffen, het risico op misoogsten zou verminderen en graanopbrengst zou moeten kunnen verhogen. In 2012 (droog jaar) en 2013 (nat jaar) is een veldonderzoek uitgevoerd op een boerenbedrijf in de CRV. Het veldonderzoek bestond uit met 10 combinaties van supplementaire irrigatie en plantdichtheid. De eenvoudigste combinatie was 30.000 planten ha-1 zonder irrigatie en de meest geavanceerde combinatie was geen water stress en 75.000 planten ha-1. Het effect van het gebruik van kunstmest werd bestudeerd door de opbrengst van maïs op het experimentele veld te vergelijken met die van de naburige boeren. Voor de technische haalbaarheid van aanvullende irrigatie (SI) met regenwater dat in overkapte bakken opgevangen is (ADV), is er eerst een schatting gemaakt van de hoeveelheid water die beschikbaarheid is in deze opvangbakken in de verschillende tijden van het jaar, voor droge en natte jaren. Hieruit bleek dat er in maart er nauwelijks genoeg water in de opvangbakken. Vanaf april is er meer water beschikbaar dat afstroomt in het naastgelegen stroomgebiedje van 2,2 ha. De hoeveelheid water die kan worden opgevangen is voldoende om 0,5 ha maïs te irrigeren. Derhalve adviseren wij mais later te zaaien (in mei) dan gebruikelijk gedaan wordt, zodat er voldoende water in de opvangbakken beschikbaar is om eventuele kort durende droge periodes te overbruggen. Ondanks de aanzienlijke opbrengst van maïs verschillen tussen niet en gedeeltelijk geïrrigeerde velden, is de investering in het irrigatie systeem tijdens niet-kritieke droogte jaar is niet de moeite waard omdat het financieel niet haalbaar. Toenemende plantdichtheid van 30000 planten ha-1 tot 75000 planten ha-1 liet de opbrengst van de mais aanzienlijk toenemen. Het gebruik van optimale kunstmest (150% aanbevolen niveau) op landbouwbedrijven onderzoek vergroot graanopbrengst met 101% ten opzichte van het huidige gebruik van meststof naburige landbouwers (50% of minder dan de helft aanbevolen hoeveelheid). Tenslotte moet gemeld worden dat deze hypothese niet volledig aangetoond kan worden, omdat het experiment slechts 2 jaar is uitgevoerd en in het tweede jaar zijn geen kritieke toestand droogte situaties voorgekomen.

Hoofdstuk 5: de hypothese in hoofdstuk 4 werd verder getest op lange termijn scenario’s van het klimaat van de afgelopen 30 jaar en de voorspelde klimaatverandering met behulp van modellering. De MarkSimGCM weer generator werd gebruikt voor het genereren geprojecteerde dagelijkse neerslag en temperatuur gegevens die oorspronkelijk afkomstig waren uit het ECHAM5 algemene circulatie model en het gemiddelde van zes modellen onder A2 (hoog) en B1 (laag) emissiescenario's. We hebben de eerst de verandering in het optreden van lange droge perioden tijdens maïs groeiseizoen en de omvang van de verhoogde CO2-gehalte in het compenseren van de negatieve gevolgen van klimaatverandering onderzocht. Tevens is dit ook beoordeeld voor het klimaat op korte termijn projectie (2020-2049). Na het valideren van het FAO AquaCrop model, hebben we het model gebruikt om het om opbrengsten van maïs te voorspellen en drie klimaatadaptatie opties te onderzoeken: aanvullende irrigatie, het verhogen van plantdichtheid en het veranderen van de zaai datum. De resultaten van de analyse van droge periodes laten zien dat de kans op lange droge periodes zowel onder ECHAM5 en het gemiddelde van alle modellen in maart en april zullen verhogen, terwijl de kans juist daalde in juni-oktober. Ondanks dat de graan opbrengst met 7,5% zal stijgen als gevolg van de gestegen CO2 concentratie van 369,41 ppm tot 518,88 ppm zoals wordt voorspeld door ECHAM5 met A2-scenario, kan dit slechts voor een deel de negatieve effecten op het klimaat op de productie van maïs te compenseren. We raden hogere plantdichtheid (tot 75.000 planten ha-1) voor de boeren in de CRV, aangezien onze resultaten aantonen dat er een significante toename opbrengst kan worden verwacht als de plantdichtheid van 30.000 planten ha-1 tot 75.000 planten ha-1 stijgt. Het optimale niveau van aanvullende irrigatie (SI), in combinatie met de 30.000 planten ha-1 plantdichtheid, was het de toedienen van irrigatiewater als de grond een verdroging bereikte 75% van de totale beschikbare water in de wortelzone. Onze resultaten gaven aan dat in goede neerslagjaren de SI een marginaal effect heeft, maar in droge jaren kan met toediening van 94-111 mm SI totale mislukking gewas worden voorkomen. Derhalve, zien wij SI in combinatie met plantdichtheid en optimale meststof is een veelbelovende optie om de voedselzekerheid in de Rift Valley droge gebieden van Ethiopië te verbeteren. Onze resultaten laten ook zien dat het verschuiven van de zaaitijd van maïs uit het huidige Belg seizoen (meestal april of mei) naar de eerste maand van Kiremt seizoen (juni) de voorspelde opbrengstreductie kan compenseren. In het algemeen is de onderhavige studie aangetoond dat zonder agronomische adaptatie de verwachte klimaatverandering negatieve effecten voor de voedselzekerheid zal hebben in de CRV. Het gebruik van SI met een optimale kunstmest en plantdichtheid en het verschuiven van de zaaidatum zijn haalbare opties voor de boeren in het gebied om zich aan te passen aan de verwachtte veranderingen. Met deze adaptatie opties kunnen de gewasopbrengsten worden gestabiliseerd of zelf verhoogd, waardoor van de voedselzekerheid voor de toekomst zal verbeteren.

Hoofdstuk 6 beschrijft het onderzoek dat we gedaan hebben naar de relatie tussen het voorkomen van bos en hoeveelheid neerslag in de CRV. Met name hebben we gekeken naar de langjarige neerslag (1970-2009) en de temperatuur (1981-2009) trends en de relatie die de gemeten neerslag heeft met de ontbossingsgeschiedenis en de relatie tussen de nog bestaande bossen en topografische variabelen met ruimtelijke regenval distributie. De studie gebruikte data van 16 lange jarige stations (40 jaar) en 15 neerslagstations waar slechts korte termijn data (2 jaar) van gemeten is. De Mann-Kendall-test en stapsgewijze multiple regressie methoden zijn gebruikt om de data statistisch te analyseren. De resultaten toonden aan dat ondanks de aanhoudende daling van het bos in de afgelopen 40 jaar (1970-2009), de jaarlijkse neerslag in de Rift Vallei bodem met 37,9 mm / decennium is gestegen. Echter, de jaarlijkse neerslag op de hellingen / hooglanden daalde met -29,8 mm / decennium. Tevens is er ook een significante opwarming waargenomen in de Rift Vallei bodem die kan worden toegeschreven aan de lange termijn ontbossing in de CRV. Het tweejarige (2012-2013) experiment om het effect van geïsoleerde bossen in de CRV op neerslag te bestuderen, toonde aan dat het voorkomen van geïsoleerde bossen in de vallei bleek een significant positief effect (R2 = 0,4) te hebben op de van het aantal regendagen.

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- Basic Statistics (2011)
- Environmental Research in Context (2011)
- Research in Context Activity: 'Co-organising Symposium on Adaptation to Climate Change for Water, Energy and Environment', Hawassa University (2013)

Other PhD and Advanced MSc Courses

- Adaptation to Climate Change in Developing Countries, Wageningen University (2011)
- Advanced Statistics-Design of experiments, Wageningen University (2014)
- Scientific and Professional Publishing on Environment and Sustainability, Open University (2014)

External training at a foreign research institute

- Training on TDR and Automated weather observing instruments, Eijkelkamp Agrisearch Equipment, The Netherlands (2011)

Management and Didactic Skills Training

- Supervision of MSc student with thesis entitled 'Rain on the menu: Rainwater harvesting for small-scale irrigation of maize in the Central Rift Valley, Ethiopia' (2012)
- Teaching for the MSc course 'Environmental Impact Assessment' (2012-2013)

Oral Presentations

- *Synthesis of Research on Land Use and Land Cover Dynamics in the Ethiopian Highlands.* European Geosciences Union General Assembly 2011, 03-08 April 2011, Vienna, Austria
- *Effect of forests and forest cover change on rainfall in the Central Rift Valley of Ethiopia*. International Conference on Climate Change and Global Warming, 11-12 December 2014, Melbourne, Australia

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Curriculum vitae

Alemayehu Muluneh Bitew was born on February 21, 1974 in Gojjam, Ethiopia. Alemayehu has obtained his BSc degree in Agricultural Engineering and Mechanization with distinction from Hawassa University (formerly Debub University) in July 2003. Right after his graduation, he was employed by Hawassa University in the department of Agricultural Engineering and Mechanization and served as a graduate assistant from August 2003 - August 2004.

In September 2004, he got a Wageningen University fellowship for the Master program and obtained a Master of Science (MSc) Degree in International Land and Water Management in June 2006. Between 2007 and 2010, he has been involved in lecturing and research activities at Hawassa University. He has been teaching courses like environmental impact assessment, soil and water conservation, hydrology and water harvesting technology. Alemayehu has also served as department head of Agricultural Engineering and Mechanization department from 2007-2008. Alemayehu attended a post-graduate training programme on Sustainable Land Management from the United Nations University - Land Restoration Training Programmes in Reykjavik,Iceland.

In January 2011, Alemayehu joined the Land Degradation and Development Group (currently named as Soil Physics and Land Management) of Wageningen University to pursue a PhD study. His PhD study was funded by NUFFIC. He was awarded with additional funding from international foundation for science (IFS) for his field research. During his PhD study period, he also supervised a M.Sc. student and presented research results at both international and national conferences.

Alemayehu Muluneh married Dagmawit Asfaw in April 2009 and has a baby girl. He would like to continue in research and teaching regarding on environmental change and natural resources management. His contact address is: muluneh96@yahoo.com

Publications

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Muluneh, A., Biazin,B., Stroosnijder, L., Bewket, W., Keesstra, S., 2014. Impact of predicted changes in rainfall and atmospheric carbon dioxide on maize and wheat yields in the Central Rift Valley of Ethiopia. Reg Environ Change, DOI 10.1007/s10113-014-0685-x

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