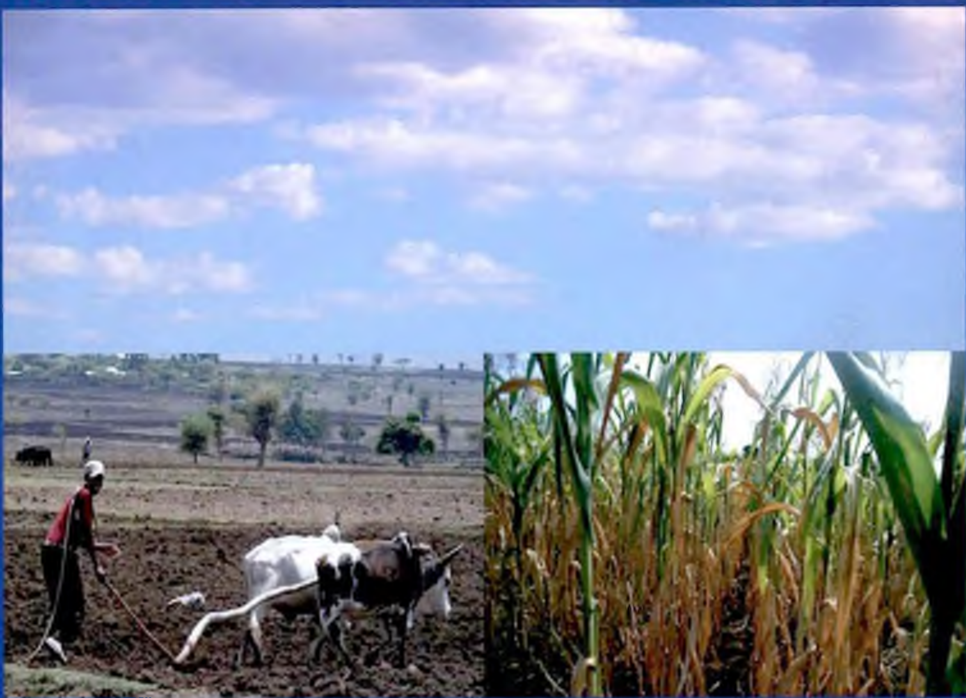
Climate variability and change in Ethiopia: Exploring impacts and adaptation options for cereal production



Belay Tseganeh Kassie

00214

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Thesis
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Propositions

1. Projections of future climate change are subject to uncertainty; however, that does not reduce the high certainty about the need of adapting to climate change.
   (this thesis)
2. The current land tenure system in Ethiopia (the so-called state-owned public property) limits farmers' motivation to deal with and invest in adaptation strategies.
   (this thesis)
3. Agricultural research in Ethiopia needs to change from a *descriptive* to *systems analytical approach* if it aims to significantly contribute to the improvement of agriculture.
4. The current selling or leasing agrarian land to foreign investors in Ethiopia, which is considered a development opportunity, will lead to a counter-productive development in the long-term.
5. Commercializing genetically modified crops to achieve food security is an unaffordable solution for Africa; it may even hinder exploitation of local genetic diversity.
6. In pursuing a PhD, "self-motivation, imagination and intuition" is more important than gathering knowledge.
7. One of the factors contributing to relatively low adaptive capacity in Africa is foreign "food-aid".

Propositions belong to the PhD thesis entitled as: Climate variability and change in Ethiopia: Exploring impacts and adaptation options for cereal production
Belay Tseganeh Kassie
Wageningen, 11 March 2014

Abstract

Smallholder farmers in Ethiopia have been facing severe climate related hazards, in particular highly variable rainfall and severe droughts that negatively affect their livelihoods. Anticipated climate change is expected to aggravate some of the existing challenges and impose new risks beyond the range of current experiences. This study aimed at understanding current climate variability and future climate change and associated impacts, and providing insights on current climate risk management strategies and future adaptation options for adapting agriculture, in particular maize production. The study was conducted in the Central Rift Valley, which represents major cereal-based farming systems of the semi-arid environments of Ethiopia. A second case study area, Kobo Valley was also used for additional analysis in part of the study. Empirical statistical analyses, field survey methods, and a systems analytical approach, using field experimental data in combination with crop-climate simulation modelling were used to achieve the objectives of the study. Crop growth simulation modelling was carried out using two well-accepted crop models, which is an innovative feature of the methodology used in this thesis.

The analysis revealed that rainfall exhibited high inter-annual variability (coefficient of variation 15-40%) during the period 1977-2007 in the CRV. The mean annual temperature significantly increased with 0.12 to 0.54 °C per decade during 1977-2007. Projections for future climate suggested that annual rainfall will change by -40 to +10% and the annual temperature is expected to increase in the range of 1.4 to 4.1 °C by 2080s. Simulated water-limited yields are characterized by high inter-annual variability (coefficient of variation 36%) and about 60% of this variability is explained by the variation in growing season rainfall. Actual yields of maize in the CRV are only 28-30% of the simulated water-limited yield. Analysis of climate change scenarios showed that maize yield will decrease on average by 20% in the 2050s relative to a baseline climate due to an increase in temperature and a decrease in growing season rainfall. The negative impact of climate change is very likely, however, the extent of the negative impact has some uncertainties ranging from -2 to -29% depending on crop model and climate change scenario. From the selection of models used, it was concluded that General Circulation Models to assess future climate are the most important source of uncertainty in this study.

In response to perceived impacts, farm households are implementing various coping and adaptation strategies. The most important current adaptive strategies include crop selection, adjusting planting time, *in situ* moisture conservation and income diversification. Lack of affordable technologies, high costs for agricultural inputs, lack of reliable information on weather forecasts, and insecure land tenure systems were identified as limiting factors of farmers' adaptive capacity. The crop model-based evaluation of future adaptation options indicates that increasing nitrogen fertilization, use of

irrigation and changes in planting dates can compensate for some of the negative impacts of climate change on maize production. Developing more heat tolerant and high yielding new cultivars is critical to sustain crop production under future climate change. It was clear from the study that enabling strategies targeted at agricultural inputs, credit supply, market access and strengthening of local knowledge and information services need to become an integral part of government policies to assist farmers in adapting to the impacts of current climate variability and future climate change.

Key words: Climate change, Adaptation, Crop modelling, Uncertainty, Maize (Zea mays), Central Rift Valley.

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CHAPTER 1

General introduction

1.1. Background

Climate variability and change are among the major environmental challenges of the 21st century. Successive reports of the Intergovernmental Panel on Climate Change (e.g. IPCC, 2007) and various other studies (e.g. Leemans and Eickhout, 2004; Morton, 2007; Cooper et al., 2009; Schlenker and Lobell, 2010; Thornton et al., 2011) show that climate change is having multifaceted effects on human societies and the environment. Scientific evidence indicates that anthropogenic factors are the major contributors to the prevailing global climate change (Forster et al., 2007). The atmospheric concentration of greenhouse gases (GHGs) such as carbon dioxide, methane and nitrous oxide has substantially increased over time. For example, the carbon dioxide concentration has increased from 280 ppm (pre-industrial level) to about 394 ppm in 2012; a 41% increase (www.epa.gov/climatechange/indicators) due to human activities. The global average temperature has increased by 0.74 °C in the last century and is projected to increase with 1.1-5.8 °C by the end of this century and the rainfall patterns will change with an increased frequency of extreme events (Meehl et al., 2007; IPCC, 2012).

Climate variability and change impacts directly or indirectly on all economic sectors to some degree, but agriculture is among the sectors most sensitive and inherently vulnerable to climate variability (Boko et al., 2007; Müller et al., 2011; Wheeler and Braun, 2013), and climate change is most likely to increase this vulnerability (Haile, 2005; Challinor et al., 2007b; Cooper et al., 2008; Thornton et al., 2010). The impacts of increased temperature from global warming and changes in rainfall patterns resulting from climate change are expected to reduce agricultural production and put further pressure on marginal land (Lobell and Field, 2007; Van de Steeg et al., 2009). Many studies (e.g. Challinor et al., 2007b; Hellmuth, 2007; IPCC, 2007; Jones and Thornton, 2009; Müller et al., 2011) conclude that the strongest impact of climate change on the economic output of agriculture is expected for Sub-Saharan Africa, which implies that the challenge to deal with the negative impacts of climate change will be largest in the poorest and already most food insecure regions. Smallholder farmers in Sub-Saharan Africa are already challenged by the current climate variability (Cooper et al., 2008) and with a business-as-usual development, climate change is expected to pose challenges beyond the current experiences (Cairns et al., 2013).

Despite growing efforts to reduce GHG emissions, more frequent climatic extremes are now inevitable (IPCC, 2012) and put agricultural adaptation and risk management strategies in the spotlight. Because agricultural production remains the main source of income for most rural communities, particularly in developing nations, adaptation of the agricultural sector to the adverse effects of change will be imperative to protect the livelihoods of the poor and to ensure food security. Adaptation can greatly reduce climate vulnerability of rural communiteis by making them better able to adjust to climate variability and change and helping them cope with adverse consequences (Adger et al., 2007; Hellmuth, 2007; Bryan et al., 2009; IPCC, 2012). Thus, adaptation research needs to be enhanced from local to global scales to identify appropriate adaptation strategies and to support the adaptation process through policies guided by scientific evidence.

1.2. Overview of Ethiopian agriculture and climate

This thesis focuses on Ethiopia, located between 3°30' and 14°50' northern latitude and 32°42' and 48°12' eastern longitude in north-eastern Africa. Its total area is about 1.13 million km^2 with elevations ranging from 125 m below sea level (Danakil depression) to 4,620 meters above sea level (mount Ras Dejen). While the total population of Ethiopia was about 18 million in 1950, currently it is about 93 million and still grows annually by 3.2% (CIA, 2013). According to the 2012 revision of the UN's world population prospects, the population of Ethiopia is projected to be around 150 million by 2050 (UN, 2013). Agriculture is the main source of livelihood for about 85% of Ethiopia's population, contributes 50% of the GDP and generates more than 80% of the foreign exchange earnings (Deressa and Hassan, 2009). It is dominated by small scale crop-livestock mixed farming systems and cereals are the most important food crops occupying about 77% of the total cultivated area. Production technologies are predominantly characterized by low agricultural inputs (fertilizer, improved seeds, pesticides) using traditional farming techniques (Arndt et al., 2011).

Ethiopia is characterized by diverse climatic conditions ranging from humid to semi-arid environments. Its climate system is largely determined by the seasonal migration of the inter-tropical convergence zone (ITCZ) and a complex topography (NMA 2001). Mean annual rainfall distribution ranges from a maximum of more than 2,000 mm over the south-western highlands to a minimum of less than 300 mm over the south-eastern and north-western lowlands. The south-west and western areas of the country are characterized by a uni-modal pattern whereas the remaining parts exhibit a bi-modal rainfall pattern (World Bank 2006). The mean annual temperature varies widely, from lower than 15°C in the highlands (>1500 m.a.s.l.) to more than 25°C in the lowlands (< 1500 m.a.s.l.).

Ethiopian agriculture and in general the economy, and climate are highly intertwined. Figure 1.1 shows the correlation between rainfall variability and the overall performance of the country's GDP: years of poor rainfall were associated with low, whereas years with high rainfall were associated with high country's total and agricultural GDP (World Bank, 2006). Climate variability, particularly rainfall variability and associated droughts have been causes for food insecurity in Ethiopia (Seleshi and Zanke, 2004; Rosell, 2011). Climate change is expected to pose more challenges and to further reduce the performance of the economy (Arndt et al., 2011). A study on mapping poverty and vulnerability in Africa identified Ethiopia as one of the countries most vulnerable to climate variability and change (Thornton et al., 2006).

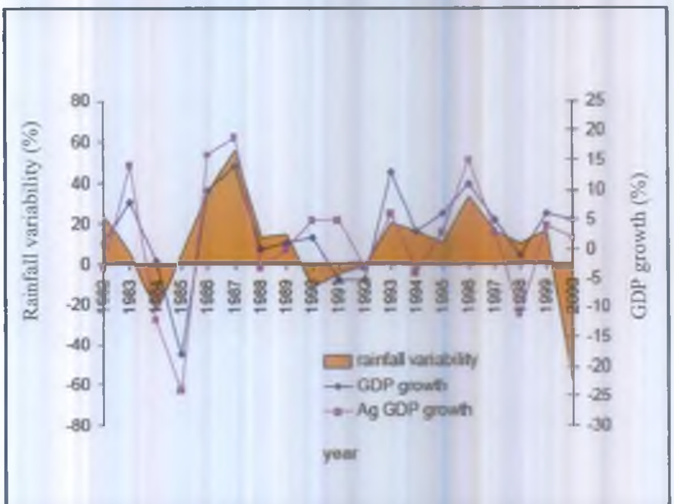

Fig. 1.1. Effect of rainfall variability on total and agricultural GDP in Ethiopia
(Adapted from World Bank, 2006)

Recognizing adaptation as a critical response to the impacts of climate variability and change, Ethiopia developed a national adaptation program for action (NAPA) in 2007 (NMA, 2007). The NAPA identified priority projects broadly focusing on institutional capacity building, improving natural resources management, enhancing irrigation agriculture and water harvesting, and strengthening weather early warning systems. Recently, Ethiopia published its vision for a climate-resilient economy (see EPA, 2011). Despite these policy efforts, studies on climate change impacts and adaptation options are scarce, which may limit policy formulation and decision making in terms of planning adaptation strategies. Some studies assessed impacts of climate change on Ethiopian economy (e.g. Dercon, 2004; Block et al., 2008; Deressa and Hassan, 2009; Mideksa, 2010; Arndt et al., 2011; Robinson et al., 2012) and few studies also empirically examine household vulnerability to climate change (e.g.Yesuf and Bluffstone, 2007; Deressa et al., 2008) and determinants of farmers choice for adaptation practices (e.g. Deressa et al., 2009). However, little evidence is available on bio-physical impacts (e.g. changes in crop yields) and adaptation options under various climate change scenarios, which is vital to inform and support farmers' decisions under a changing climate. A quantitative understanding of current climate variability, its impacts and how farmers respond to this, is an essential step for adapting agricultural systems to future climate change. Moreover, anticipating impacts of future climate change and evaluating potential adaptation options for various climate change scenarios is highly relevant for Ethiopia's agricultural production and improving food security.

1.3. Methodological perspectives on adapting agriculture to climate variability and change

A number of different approaches such as agro-climatic indices, empirical field survey methods, econometric models, statistical models and process based-crop simulation models have been used to assess the impacts of climate variability and change on agriculture (Feenstra et al., 1998; White et al., 2011). Agro-climatic indices are mostly used to characterize current climate variability and extreme events as indicators for climate induced risks. Studies focusing on understanding community perceptions on climate variability and change, and on assessing coping and adaptation strategies at farm households' level usually employ field survey methods. Econometric models are based on the concept that the long-term productivity of land is reflected in its asset values and hence, the impacts of climate on land value can be estimated econometrically using cross-sectional data (Gbetibouo and Hassan, 2005). Such models are, thus, often used to assess impacts of climate change on socio-economic components.

Prior to the development of dynamic simulation models, application of simple correlation and regression analysis (statistical models) contributed to the qualitative understanding of the interactions among environmental variables and crop production processes (Oteng-Darko et al., 2012). With the advancement in computer technology and increased knowledge on processes underlying crop production, it became possible to integrate this process-based knowledge in quantitative crop growth models. Crop models are bio-physical representations of crop growth processes and interactions of the soil-crop-climate components that determine crop growth and development (Van Ittersum et al., 2003; White et al., 2011).They are important tools for understanding the impacts of climate variability and change on crop production systems and to evaluate improved crop management options (White et al., 2011; Matthews et al., 2012). Crop modelling has been extensively used in various impact and adaptation studies (see e.g. Alexandrov and Hoogenboom, 2000; Cuculeanu et al., 2002; Žalud and Dubrovský, 2002; Challinor et al., 2007a; Meza and Silva, 2009; Laux et al., 2010; Rötter et al., 2011b; Cammarano et al., 2012; Berg et al., 2013; Lobell et al., 2013; Ruane et al., 2013).

Climate change impact assessments using crop modelling involve simulation and analysis of cropping systems (e.g. measuring crop yield changes) in relation to plausible climate change scenarios. Three basic approaches are used for creating climate change scenarios in climate change impact studies: (1) General Circulation Models (GCMs); (2) analogue (historical), and (3) synthetic or incremental changes in climate variables. Among these, GCMs are the most advanced tools to create climate change scenarios, which are widely used in climate change impact studies (e.g. Jones and Thornton, 2003; Ceglar and Kajfež-Bogataj, 2012; Rötter et al., 2012a; Cairns et al., 2013). The major advantage of using GCMs as the basis for creating climate change scenarios is that they estimate changes in climate due to increased GHG in a physically consistent manner (Benioff et al., 1996; White et al., 2011). The sensitivity of climate to GHG concentrations and societal development is represented with emission scenarios driven by assumptions on economic, demographic and technological developments (Nakicenovic et al., 2000), which are in turn used as inputs for GCMs to create climate change scenarios. Recently, the Coupled Model Inter-comparison Project Phase 5 (CMIP5) generated new representative concentration pathways (RCPs), which represent scenarios of trajectories for greenhouse gas emissions (Moss et al., 2010; Knutti and Sedláček, 2012). These new generation of RCPs are used in the IPCC Fifth Assessment Report and expected to be the basis for climate change impact studies over the coming few decades (Ramirez-Villegas et al., 2013).

Impact assessments are subject to uncertainties related to the GCMs, emission scenarios, downscaling techniques and crop models (Challinor et al., 2005; Monod et al., 2006; Ceglar and Kajfež-Bogataj, 2012; Rötter et al., 2012a). Quantifying uncertainty is an important effort in climate impact studies (Challinor et al., 2005; Yao et al., 2011), however, there is no consensus in the literature on how best to quantify these uncertainties (Challinor et al., 2005). The recommended approach by IPCC (Meehl, 2007) is to use ranges of multiple model simulations. While using multiple climate models, following the IPCC recommendation, is a common approach in climate risk studies for estimating uncertainties (Tebaldi and Knutti, 2007), most agricultural impact studies (e.g. Jones and Thornton, 2003; Luo et al., 2009; Cairns et al., 2013) applied a single crop model. Crop growth is, however, a very complex process involving a series of interactions of crop, weather and soil, and uncertainty as to how these interactions are captured adequately in deterministic crop models is unavoidable (Challinor et al., 2005; Kersebaum et al., 2007; Eitzinger et al., 2008; Palosuo et al., 2011; Rötter et al., 2011a;). Uncertainties exist in the crop response to climate, in the crop model structure and procedures as well as input parameters of the models (Yao et al., 2011). Outputs from a single crop model simulation do by definition not capture uncertainties in terms of ranges of possible outcomes (Rosenzweig et al., 2013b). One way to improve information from crop modelling is using the ranges of multiple crop-model simulation output (Challinor et al., 2009a; Tao et al., 2009; Rötter et al., 2011a). A multiple model crop simulation approach enables to better quantify uncertainties (Challinor and Wheeler, 2008b), and multi-model means/medians showed to be likely better predictors than any best model across a wide range of environments (Rötter et al., 2012b; Asseng et al., 2013). A pre-requisite for this is that the models used are suitable in their design for the objective of the study, and are tested for the study area. The need of such a multi-model simulation approach has been suggested in response to crop model inter-comparisons performed in the framework of the European COST action "Impacts of climate variability and change on European agriculture" (COST 734) (Palosuo et al., 2011; Eitzinger et al., 2012; Rötter et al., 2012b). This need has been recognized and is further being examined for climate change studies in the Agricultural Model Inter-comparison and Improvement Project (AgMIP, www.agmip.org) and in Modelling Europian Agriculture with Climate Change for Food Security (MACSUR, www.mascur.eu) knowledge hub. Both initiatives aim to improve the description of crop-climate interactions in models and to promote the application of multiple crop models in climate impact assessments with special emphasis on assessing uncertainty in crop simulation models (Asseng et al., 2013; Rosenzweig et al., 2013b; Rötter et al., 2013b). Thus, using not only multiple climate models but also multiple crop models in impact and adaptation studies seems a logical approach needed to improve the reliability of impact projections and provide better scientific basis for decision making in adaptation planning.

1.4. Definition of key concepts used in this thesis

The following sub-section briefly explains key concepts used in this thesis. More detailed explanations can be found in IPCC (2001) and Nakicenovic et al. (2000).

Climate variability: variation in the mean state and other statistics (such as standard deviations, occurrence of extremes, etc.) of climate on temporal and spatial scales beyond that of individual weather events. Variability may be due to natural processes within the climate system (internal variability), or due to anthropogenic forcing (external variability).

Climate change: A change in the state of the climate that can be identified by changes in the mean and/or the variability of its properties and that persists for an extended period, typically decades or longer. Climate change may be due to natural internal processes or external forcing or to persistent anthropogenic changes in the composition of the atmosphere or in land use systems.

Climate scenarios: Plausible and often simplified representations of the future climate based on an internally consistent set of climatological relationships, that have been constructed for explicit use in investigating the potential consequences of anthropogenic climate change. The difference between a climate scenario and the current climate provides a *climate change scenario.*

Emission scenarios/Representative concentration pathways. Plausible representation of the future development of emissions of greenhouse gas concentrations based on coherent and internally consistent set of assumptions about driving forces (such as demographic and socio-economic development, technological change) and their likely relationships.

*Crop growth simulation: S*implified representation of the complex relation between crop growth and environmental factors (climate, soil and management). Crop growth modelling involves model calibration and model evaluation. *Model calibration* refers to adjustment of parameters of a model so that simulated results reach a predetermined level, usually that of an observation whereas *model evaluation* involves comparison of outputs of a calibrated model with an independent data set and determination of suitability for an intended purpose.

Uncertainty: An expression of the degree to which a value (e.g., the future state of the climate system or its impact) is unknown.

Vulnerability: The degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes.

Adaptation: adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harmful impacts and exploit beneficial opportunities.

1.5. The study areas

The study was conducted in the Rift Valley of Ethiopia, which is part of the great East African Rift Valley system and divides Ethiopia into north-western and south-eastern highlands (Fig. 1.1). The study reported in this thesis (Chapters 2 to 5) was conducted in the central part of the rift valley (CRV), however, a second case study area, Kobo valley was also considered for additional analysis on farmers' perceptions and current adaptation practices (Chapter 4). These two case study areas were selected because they represent major cereal-based farming systems of the semi-arid environments of Ethiopia and are hotspots for climate induced risks.

CRV is located between 38° 15' and 39° 25'E and 7° 10' and 8° 30'S at about 120 kilometers south of Addis Ababa. The CRV is characterized by an alternating topography with a central valley floor at 1500-1700 meters above sea level (m.a.s.l) and bounded by a western and eastern escarpment with highest altitudes of over 4000 m.a.s.l. (Jansen et al., 2007). Based on annual rainfall distribution, CRV is characterized by a bi-modal rainfall pattern, which is a typical characteristic for the central, eastern and north-eastern parts of Ethiopia. Its valley floor receives 175-358 mm rainfall during a short rainy season (March-May) and 420-680 mm during the main rainy season (June to September). The CRV was previously a pastoral area covered by dense woodlands and there was no permanent cultivated land before the 1950s (Garedew et al., 2009; Biazin and Sterk, 2013). In recent decades, much of the land has been converted into mixed farming system. Over the last few decades, the cultivated land area increased threefold while the dense woodland coverage declined from 42% in 1965 to 9% in 2010 (Biazin and Sterk, 2013). Generally, it is characterized as one of the regions in Ethiopia with high competition for scarce land and water resources with increasing environmental risks (Ayenew, 2004; Jansen et al., 2007). Kobo valley is located between 39° 22' and 39° 48' E and 11° 5' and 12° 11' N at about 600 km north of the capital Addis Ababa, at the northern most range of the Ethiopian Rift Valley. The valley is surrounded both on the east and west by high mountains, some over 4000 m high, whereas the valley itself is 1300 m.a.s.l. Kobo is generally characterized by high rainfall variability and high temperatures and is vulnerable to frequent drought episodes that often lead to crop failure and associated acute famines. This area was one of the most severely affected parts of Ethiopia during the famine of 1983–84 and it still faces minor famines almost every three years (Bewket, 2008). It has a long history of agriculture, which is dominated by cereal-based farming systems.

Maize (Zea mays L.) is the second most important cereal, next to teff (*Eragrostis tef*) in area of production in Ethiopia. It is produced on an average area of about 2.0 million hectares of land (17% of the total grain crop area). In terms of volume of production, it is the leading crop constituting 26% of the total grain production (CSA, 2013). Maize has a significant role in the livelihoods of smallholders in the study areas (Biazin and Stroosnijder, 2012).

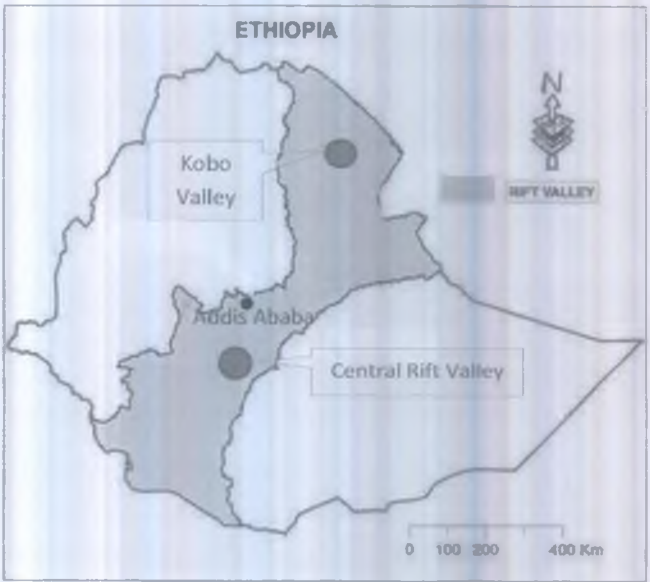

Fig.1.2. Location of study areas, Central Rift Valley and Kobo Valley in the Rift Valley of Ethiopia

1.6. Objectives of the study

The general objectives of the study were to quantify climate induced risks for rainfed crop production with emphasis on maize-based farming and to examine existing and explore future adaptation options that reduce vulnerability of agriculture to climate variability and change. The study investigated current climatic trends and how crop production is affected by current climate variability and how crop production might be affected by anticipated climate change. It also analyzed current adaptive practices and alternative options to adapt to projected changes. The specific research objectives were:

- To characterize trends, variability and changes in agro-climatic conditions of the Central Rift Valley;
- To quantify climate induced yield variability and yield gaps for rainfed maize production in the Central Rift Valley;
- To analyze farmers' perceptions on climate variability and change and to identify current climate risk management strategies and barriers for successful adaptation in the Central Rift Valley and Kobo Valley;
- To explore impacts and adaptation options under different climate change scenarios for maize production systems in the Central Rift Valley.

The above objectives were addressed with crop growth simulation modelling and GCMs-based climate change scenario approach in combination with empirical field survey methods and agro-climatic index analysis. Temporal variability and extreme values of selected rainfall and temperature indices were analyzed. Projected changes in rainfall and temperature were assessed based on four General Circulation Models (GCMs) and two emission scenarios. The analysis for imapcts of climate change on maize productivity and adaptation options was carried out using recent datasets of three GCMs in combination with two representative concentration pathways (RCPs) and two crop models. The use of multiple climate change scenarios and two crop models allowed indicating possible ranges of outcomes as estimates for some of the uncertainties, to better inform adaptation planning and policy making. In general, this study aims to contribute to increased understanding of the impacts of climate variability and changes thereby supporting adaptation planning and interventions aimed at increasing food security and improving rural livelihoods.

1.7. Outline of the thesis

The objectives defined in section 1.6 are addressed in four complementary research chapters (Chapter 2 to 5), which are followed by general discussion and conclusions (Chapter 6). Chapter 2 aims at understanding and characterizing agro-climatic variability as well as changes and associated risks with respect to implications for rainfed crop production in the Central Rift Valley (CRV). Temporal variability and extreme values of selected rainfall and temperature indices were analysed and trends were evaluated. Projected future changes in rainfall and temperature for the 2080s relative to the 1971-1990 baseline period were determined based on four General Circulation Models (CSIRO2, CGCM2, HadCM3 and

PCM) and two emission scenarios (SRES, A2 and B1). The analyses provide an overview of current and future climate trends and indications of climate induced risks on rainfed crop production.

Chapter 3 presents yield variability and yield gaps in the CRV of Ethiopia. A multi-model crop growth simulation approach using two crop models, i.e. Decision Support System for Agro-Technology (DSSAT) and WOrld FOod STudies (WOFOST) was applied to characterize climate-induced variability and yield gaps of maize. The models were calibrated and evaluated with experimental data and subsequently, a simulation experiment was carried out with an early maturing and late maturing cultivars using historical weather data of three locations in the CRV. The analysis provided quantified information on climate induced yield variability and existing yield gaps. It also discusses some of the uncertainties related to the different approaches of crop models used in simulating crop-climate interactions and the need of multiple modelling approaches in such studies. Chapter 4 presents farmers' perceptions on current climate variability and long term changes and their adaptation practices. The study was based on a household questionnaire, interviews with key stakeholders and focus group discussions in two selected case study areas, i.e., Central Rift and Kobo valleys, both representing semi-arid vulnerable regions with some contrasting agricultural potential. First, farmers' perceptions on climate variability and change are investigated and then their perceptions are compared with observed climate trends and potential sources of divergence are highlighted. Then, current climate risk management practices are explored and scopes and limitations are explained. In addition, farmers needs for future adaptation, and barriers for successful adaptation are identified and discussed. Chapter 5 addresses projected climate change impacts and potential adaptation options for maize production in the CRV. Impacts and adaptation are assessed using two crop models (DSSAT,v4.5 and WOFOST,v7.1) and three GCMs (CanESM2, CSIRO-MK3 and HadGEM2) in combination with two recently released Representative Concentration Pathways (RCP4.5, RCP8.5) for the period 2050s. It provides indications on magnitude and direction of climate change impact on maize production and assessed adaptation options to reduce projected negative impacts of climate change. It also discusses some of the uncertainties involved in projection of impacts and adaptation options by using multiple climate and crop model simulation outputs.

Chapter 6 synthesizes and discusses key findings and implications from all the chapters. It provides methodological outlooks and discusses the integration of main topics of the thesis such as climate variability and change, impacts, adaptation strategies and uncertainties. Finally, scientific insights and implications for climate risk management and pertinent issues for further research are described.

CHAPTER 2

Climate variability and change in the Central Rift Valley of Ethiopia: Challenges for rainfed crop production

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Abstract

Ethiopia is one of the countries most vulnerable to the impacts of climate variability and change on agriculture. This study aims at understanding and characterizing agro-climatic variability and changes and associated risks with respect to implications for rainfed crop production in the Central Rift Valley (CRV). Temporal variability and extreme values of selected rainfall and temperature indices were analyzed and trends were evaluated using Sen's slope estimator and Mann-Kendall trend test methods. Projected future changes in rainfall and temperature for the 2080s relative to the 1971-1990 baseline period were determined based on four General Circulation Models (GCMs) and two emission scenarios (SRES, A2 and B1).

The analysis for current climate showed that in the short rainy season (March to May), total mean rainfall varies spatially from 178 to 358 mm with a coefficient of variation of 32-50%. In the main (long) rainy season (June - September) total mean rainfall ranges between 420 and 680 mm with a coefficient of variation of 15-40%. During the period 1977-2007, total rainfall decreased, but statistically not significant. Also, there was a decrease in the number of rainy days associated with an increase in the intensity per rainfall event for the main rainy season, which can have implications for soil and nutrient losses through erosion and run-off. The reduced number of rainy days increased the length of intermediate dry spells by 0.8 days per decade leading to crop moisture stress during the growing season. There is also a large inter-annual variability of the length of growing season, ranging from 76 to 239 days. The mean annual temperature has exhibited a significant warming trend of 0.12-0.54°C per decade. Projections from GCM's suggest that future annual rainfall will change by -40 to +10% to by 2080. Rainfall will increase during November-December – outside the growing season, but will decline during the crop seasons. Also the length of the growing season is expected to be reduced by 12-35%. The annual mean temperature is expected to increase in the range of 1.4-4.1°C by 2080. The past and future climate trends, especially in terms of rainfall and its variability pose major risks to rainfed agriculture. Specific adaptation strategies are needed for the Central Rift Valley to cope with the risks, sustain farming and improve food security.

Key words: *Length of growing season, dry spells, agro-climatic characterization, climate change impact, Central Rift Valley, Ethiopia, rainfall, temperature*

2.1. Introduction

In its fourth assessment report, the intergovernmental panel on climate change (IPCC, 2007) concluded that climate change is already happening with multi-facetted effects on human societies and the environment. There is also an emerging consensus that Eastern Africa, and particularly Ethiopia, is one of the most vulnerable regions regarding the impacts of climate variability and change (Slingo et al., 2005; Boko et al., 2007; Challinor et al., 2007b; Thornton et al., 2011). Several studies on precipitation and temperature change indicated that the African continent is now warmer than it was 100 years ago and the rainfall exhibited higher inter-annual and intra-seasonal variability (Boko et al., 2007; Challinor et al., 2007b; Cooper et al., 2009; Cooper and Coe, 2011; Rosell, 2011). Climate variability over the last three decades of the 20th century resulted in droughts and famine in several countries of Africa (Conway and Schipper, 2011; Dixit et al., 2011).

Ethiopia is among the most vulnerable countries in Africa due to its great reliance on climate sensitive sectors, particularly agriculture (Thornton et al., 2006; World Bank, 2006; Hellmuth, 2007; NMA, 2007; Conway and Schipper, 2011; Rosell, 2011). Historically, strong links have been observed between climate variability and the overall performance of Ethiopia's economy, reflected by high correlation between rainfall and GDP fluctuations (World Bank, 2006). Climate variability, particularly rainfall variability and associated droughts have been major causes of food insecurity and famine in Ethiopia (Conway, 2000; Hulme et al., 2001; Seleshi and Zanke, 2004; Thornton et al., 2006; NMA, 2007; Conway and Schipper, 2011; Demeke et al., 2011; Rosell, 2011; World Bank, 2006). For instance, Seleshi and Zanke (2004) reported that the 1984 famine, the worst disaster Ethiopia has experienced in the 20th century, was the result of failure of the main rainfall season which resulted in reduction of the GDP by 9.7% and agricultural outputs by 21% (World Bank, 2006). The 1984 famine was an extreme event, but crop failure or reduced yields due to water shortage during the growing season is a common risk, particularly for the rainfed cropping systems in semi-arid Ethiopia. Various studies indicate that future climate change will lead to an increase in climate variability and in the frequency and intensity of extreme events (Boko et al., 2007; Stern, 2007). The changing rainfall pattern in combination with warming trends could make rainfed agriculture more risky and aggravate food insecurity in Ethiopia. Van de Steeg et al. (2008), for instance, indicate that the growing season in some parts of Ethiopia could be 20% shorter by 2050s relative to the current baseline period (1960-1990) which would have negative repercussions on food production.

Understanding the variability and expected future changes of climatic conditions, particularly characteristics of rainfall, temperature and evapotranspiration (which is co-determined by temperature) is therefore crucial for planning and designing appropriate adaptation strategies. This study aims at understanding and characterizing variability and changes of agro-climatic conditions and associated risks for rainfed crop production in Ethiopia. We use the Central Rift Valley as a case study area. It is one of the environmentally vulnerable regions in Ethiopia, where rainfed crop production has expanded rapidly over recent decades (Jansen et al., 2007).

2.2. Materials and Methods

2.2.1. Description of the study area

The Central Rift Valley (CRV) of Ethiopia (Fig. 2.1) is part of the great East African Rift Valley system. The center of CRV (about 10,000 km^2) is located 120 kilometers south of Addis Ababa and it is characterized by an alternating topography with a central valley floor at 1500-1700 meters above sea level (m.a.s.l) and bounded by a western and eastern escarpment with highest altitudes of over 4000 m.a.s.l. (Jansen et al., 2007). Based on annual rainfall distribution, CRV is characterized by a bi-modal rainfall pattern, which is a typical characteristic for the central, eastern and north-eastern parts of Ethiopia. Its valley floor receives 175-358 mm rainfall during a short rainy season (March to April), locally known as *Belg* and 420-680 mm during the main rainy season (June to September), locally known as *Kiremt*. The *Belg* rainfall is caused by humid easterly and south-easterly winds from the Indian Ocean, and *Kiremt* rainfall is a result of convergence in low-pressure systems associated with the Inter Tropical Convergence Zone (Conway, 2000; Seleshi and Zanke, 2004; NMA, 2007). Crop production, mainly rainfed cereal-based production systems and modest livestock rearing are the mainstays of livelihoods for households in the Central Rift Valley. The major crops are cereals, mainly teff (*Eragrostis tef*), maize (*Zea mays*), and wheat (*Triticum aestivum*).

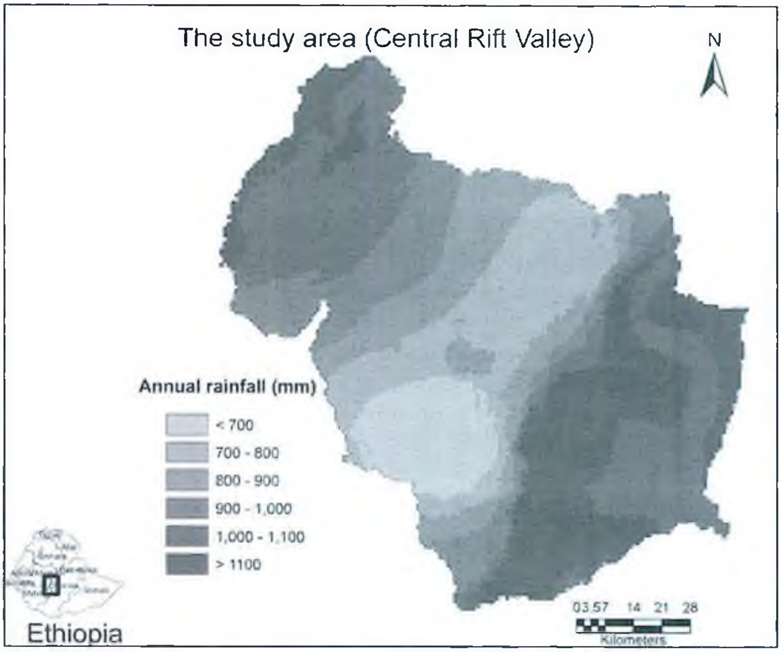

Fig. 2.1. Location map of the study area (Central Rift Valley) in Ethiopia with spatial distribution of its annual rainfall. The annual rainfall map is obtained from WorldClim Global climate data set (Hijmans et al., 2005).

2.2.2. Data sources and data quality assessment

Daily meteorological data for 24 stations was obtained from the National Meteorological Agency (NMA) of Ethiopia. We selected 16 stations (Table 2.1) which have relatively long periods of data records (at least 30 years) and have no more than 10% missing values (Seleshi and Zanke, 2004; Rosell, 2011). The daily time series from each station and for each year were plotted to identify obvious outliers, which were removed from the data series. Outliers were detected using the Turkey fence approach (Tukey, 1977). The rules of this approach are that inner fences are located at a distance 1.5 times interquartile range below the lower and above the upper quartiles and outer fences are located a distance 3 times the interquartile range below the lower and above the upper quartiles. Values outside the turkey fences are considered as outliers. Negative daily rainfall records were also removed and maximum and minimum temperature values were set to missing values if the daily maximum value was less than the daily minimum value. With this procedure, two daily rainfall records at Langano and three daily rainfall records at Hombol have been removed and only one maximum temperature record at Butajira was set to a missing value. The data series was also examined for homogeneity and no heterogeneity was detected. Missing data in time series were filled with data from neighboring stations using statistical regression techniques as described in detail in Allen et al. (1998) and applied in various studies (Seleshi and Zanke, 2004; Vergni and Todisco, 2011).

2.2.3. Data analysis

The temporal variability and occurrence of various rainfall and temperature indices were evaluated at selected weather stations based on the analysis of a set of indicators defining variation and extreme conditions, following Stern et al. (1982); Trnka et al. (2011) and Vergni and Todisco (2011). The rainfall indices include values of accumulated rainfall (monthly, annual and seasonal), number of rainy days, mean daily rainfall intensity, precipitation concentration index (PCI) (section 2.2.4), normalized rainfall anomaly (section 2.4), start of the growing season (SOS), end of the growing season (EOS), length of growing season (LGS), dry spells, and crop water requirement satisfaction index (WRSI). The temperature indices were the annual minimum and maximum temperature, mean annual temperature, minima and maxima of daily minimum and maximum temperature, number of days with daily maximum temperature exceeding 25°C (summer days). Trends were assessed using Mann-Kendall trend test (Mann, 1945; Kendall, 1975) and Sen's slope estimator (Sen, 1968). The Mann-Kendall test is a non-parametric approach, widely applied in various trend detection studies (Alexander and Arblaster, 2009; Kizza et al., 2009; Karaburun et al., 2011). Statistical analyses and other computations were performed with INSTAT v3.36 statistical software (Stern et al., 2006).

2.2.4. Analysis of rainfall and temperature variability

Spatial distribution of the mean annual rainfall was obtained from the WorldClim global climate data set (Hijmans et al., 2005). The temporal rainfall variability for representative meteorological stations was determined by calculating the coefficient of variation (CV) as the ratio of the standard deviation to the mean rainfall in a given period (CV%, when expressed as a percentage). Heterogeneity of monthly rainfall amount was investigated using the precipitation concentration index (Bewket, 2008; Vergni and Todisco, 2011). The precipitation concentration index used for characterizing the monthly rainfall distribution is given by Oliver (1980):

$$PCI = 100 * \frac{\sum P_i^2}{(\sum P_i)^2} \quad (1)$$

Where, P_i is the rainfall amount of the i^{th} month. PCI values of less than 10 indicate uniform monthly rainfall distribution in the year, whereas values from 11 to 20 denote seasonality in rainfall distribution. PCI values above 20 correspond to substantial monthly variability in rainfall amounts. Inter-annual variability was evaluated using standardized anomalies for rainfall with respect to the long-term normal conditions for a specific time scale. The normalized rainfall anomaly (RA) for a given station was computed as:

$$RA_{ij} = \frac{P_t - P_m}{\sigma} \quad (2)$$

Where, RA_{ij} is normalized rainfall total for station i during a year (or season) j; P_t is the annual rainfall in year t ; P_m is long term mean annual rainfall over the period of observation; and σ is the standard deviation of annual rainfall. Positive normalized rainfall anomalies indicate greater than long-term mean rainfall, while negative anomalies indicate less than the mean rainfall. When averaged over several stations, the normalized rainfall anomaly yields a normalized rainfall anomaly index. For temperature trend analysis, daily temperature data sets of five representative stations with high quality data records (Table 2.1) were examined on annual and seasonal basis.

2.2.5. Analyzing the growing season characteristics

Start and end of the growing season

According to Stern et al. (1982) the start of the rainy season can be defined as the first occurrence of at least 'X' mm rainfall totaled over 't' consecutive days. This potential start can be a false start if an event, F, occurs afterwards, where F is defined as a dry-spell of 'n' or more days in the next 'm' days. We adopt this approach and define the earliest start of the growing season as the first occasion when the rainfall accumulated within a 3 days period is 20 mm or more. Various authors used similar criteria in assessing the start of the growing season (Stern et al., 1982; Barron et al., 2003; Mamo, 2005). Since the study area exhibits a bimodal rainfall pattern (short rain during March to May and long rains during June to September), March 1 was picked as the earliest possible planting date for the study area (Mamo, 2005). Accordingly, the potential starting date of the growing season was defined as the 1st occasion from 1st March that has at least 20 mm within a three day period. The risk of crop failure of early planting was assessed by adding a caveat, i.e. the potential starting date of the growing season was not followed by a dry spell of 10 or more days in the first 30 days after planting. The end of the growing season is mainly dictated by stored soil water and its availability to the crop after the rainfall stops. Stern et al. (1982) defined the end of the season as the first date on which soil water is depleted. In this study, the end of the rainfall season was defined as any day after the first of September, when the soil water balance reaches zero.

Table 2.1. Rainfall and temperature data for representative stations in and around the Central Rift Valley, Ethiopia.

				Rainfall data		Temperature data	
Station	Latitude	Longitude	Elevation (m.a.s.l)	Period	Missing (%)	Period	Missing (%)
Arata	7°97'	39°05'	1850	1976-2009	8.8		
Assela	8°24'	39°19'	2350	1966-2007	1.7		
Awassa	7°05'	38°29'	1750	1973-2009	0.5	1972-2009	0.0
Bulbula	8°09'	38°22'	1700	1968-2008	0.0		
Butajira	8°09'	38°49'	2000	1969-2009	9.7	1975-2009	8.6
Debre Zeit	8°01'	38°32'	1860	1951-2009	6.7	1951-2009	0.5
Hombol	8°37'	38°77'	2000	1976-2008	9.0		
Kulumssa	8°08'	39°08'	2200	1959-2008	0.0	1961-2008	0.0
Langano	7°43'	38°48'	1700	1970-2009	7.5		
Meki	7°36'	38°58'	1680	1967-2008	0.1		
Melkassa	8°24'	39°19'	1550	1977-2007	3.1		
Mojo	8°37'	39°07'	1870	1963-2009	2.5		
Nazreth	8°33'	39°17'	1622	1976-2007	3.9		
Ogocholo	7°15'	38°40'	2020	1976-2007	8.3		
Sagure	7°13'	38°58'	2800	1977-2008	1.0		
Ziway	7°05'	38°29'	1640	1970-2009	0.2	1971-2009	0.4

Dry spell analysis

Daily rainfall data for each meteorological station were fitted to a simple Markov chain model. We assessed the chance of rain given the previous day is dry, i.e. the chance that a dry spell continues, and also the chance of rain given the previous day is rainy, i.e. the chance that a rain spell continues, which is known as a Markov chain (Stern et al., 2006; Stern and Cooper, 2011). The probability of dry spell lengths of 5, 7, 10 and 15 days during the growing season were determined from the Markov chain model to get an overview of dry spell risks during the crop growing period.

Crop water satisfaction index

Water requirement satisfaction index (WRSI) is an indicator of crop performance based on the availability of water to the crop during a growing season. It is crop specific and indicates the extent to which the water requirements of a given crop have been satisfied during the growing stages. The water requirement of a crop during the growing season is calculated by multiplying the potential evapotranspiration (PET) and a crop-specific coefficient (Kc). PET is calculated from temperature, relative humidity, wind speed and sunshine hours using the FAO Penman-Monteith equation (Allen et al., 1998). The water requirement satisfaction index (WRSI) was then determined using a water balance approach (Frere and Popov, 1979; Stern et al., 1982). The WRSI starts with a value of 100% at the start of the growing season, while water deficit and water excess reduce WSRI. Initial soil water could contribute to the WSRI at the beginning of the season, but such information is often not available. The WSRI decreases in two ways (Stern et al., 2006). First, if there is water surplus of more than 100 mm, then the index is reduced by 3 units (a surplus poses negative influence on the crop performance by 3% for each 100 mm of excess water). Second, if there is a deficit, the index is reduced by the percentage of this deficit in relation to the total water requirements for the season. Values of WRSI between 50-100% imply conditions ranging from severe stress (on the lower end) to conditions with adequate moisture to avoid crop stress. Whereas values of WRSI below 50% indicate crop failure due to severe moisture stress (Martin et al., 2000).

2.2.6. Future climate scenario analysis

Projected changes in rainfall and temperature were analyzed based on eight combinations of four general circulation models (GCMs) and two IPCC SRES emission scenarios, A2 and B1. The A2 represents one of the high emission scenarios, while B1 belongs to the low emission variants (Nakicenovic et al., 2000). The GCMs used were the Hadley Centre Coupled Model Version 3 (HadCM3), Commonwealth Scientific and Industrial Research Organization Global Climate Model mark 2 (CSIRO2), the Canadian Global Climate Model Version 2 (CGCM2) and Parallel Climate Model (PCM). Climate change scenario data of these GCM-SRES combinations was extracted from the TYN CY 3.0 data set of the Tyndall Centre for Climate Change (Mitchell et al., 2004). The Tyndall Centre for climate change offers country basis data on changes per month (precipitation in mm, temperature in °C) at the end of the 21st century (2071-2100) relative to a baseline period (1961-1990). Future climate time series were constructed using the delta change method (Fowler et al., 2007). The delta change method involves perturbing observed climate time series by mean changes (differences or ratios of changes) simulated with GCMs. We have used the delta method for each specific month for rainfall and temperature, to consider seasonal differences in climate change. For temperature, the same delta was applied to minimum and maximum temperatures. Changes in rainfall and temperature for the 2080s relative to the current baseline period (1971-1990) have then been determined based on outputs from the GCMs and the observed climate data of the meteorological stations used for this analysis.

2.3. Results

2.3.1. Rainfall variability and trends

The spatial distribution of rainfall in the Central Rift Valley is shown in Fig. 2.1. A large part of the valley floor receives less than 800 mm per year. The North West and south east escarpments receive over 1100 mm per year. The annual weighted average rainfall in the CRV is 894 mm with a standard deviation of 98 mm. The mean annual rainfall across the sixteen stations ranged from 660 mm (Langano) to 1113 mm (Butajira) (Table 2.2). Most of the stations showed moderate variation in annual rainfall (CV% 20-30%) except for two stations (Langano and Hombol), which have higher variations (CV% >30%). The precipitation concentration index (PCI) value is more than 11% for most of the stations and highlights the seasonality in rainfall distribution. Normalized rainfall anomaly index calculated for a period of 31 years (1977-2007) for all stations (not shown here) also indicate that the annual rainfall of CRV, generally exhibit cyclic wet and dry conditions with negative anomalies for 35% of the years.

Ziway station was selected as an example to illustrate the monthly rainfall distribution (Fig. 2.2). The mean monthly rainfall for this station varies from 2.3 mm for the driest month (November) to 155.3 mm for the wettest month (July). About 60% of the total annual rainfall at Ziway is received during four months (from June to September) and 37% of this amount is concentrated in July and August. The normalized rainfall anomaly (RA) calculated for Ziway station indicates that 55% of the years during the past 40 years' exhibited negative anomalies and the frequency of negative anomalies increased during recent years.

Analyses for the seasonal rainfall of the selected stations indicate that growing season rainfall of CRV generally exhibits high intra-seasonal variability. In the *Belg* season total rainfall varies from 175 to 358 mm (CV% 32-55). The *Kiremt* season has a total rainfall varies between 420 and 680 mm (CV% 15-40). Both the *Belg* and *Kiremt* rainfall show either no or just a slight, non-significant decline in rainfall over time (e.g. Figs. 2.3a and 2.3c for Ziway). When analyzing the number of rainy days and the daily rainfall intensity index (mean rainfall per rainy days), the result indicates that in the *Kiremt* season rainy days vary from 29 to 68 days with an average of 51 days per season (CV% 17). In the *Belg* season the number of rainy days varies from 7 to 37 days per season with an average of 22 days (CV% 33). The daily rainfall intensity (mean rainfall per rainy days) in the *Kiremt* ranges from 5.9-17.1 mm day^{-1} with an average of 9.7 mm day^{-1} (e.g. see Fig.2.3b and 2.3d for Ziway station).

Table 2.2. Annual and seasonal rainfall (mm), coefficient of variation (CV %) and precipitation concentration index (PCI) for representative meteorological stations in and around the Central Rift Valley in Ethiopia. *Kiremt* season refers to June to September while *Belg* refers to March to May.

Station	**Annual**		***Kiremt season***		***Belg season***		**PCI**
	Mean	CV	Mean	CV	Mean	CV	
Arata	734	19.4	446	17.8	219	35.6	12.3
Assela	1091	21.7	681	19.2	339	32.0	11.9
Awassa	959	15.1	470	22.6	294	27.7	10.3
Bulbula	728	29.6	425	38.4	191	47.4	11.9
Butajira	1113	26.5	587	29.2	358	43.3	11.2
Debre Zeit	852	24.2	633	24.1	164	50.2	17.2
Hombol	801	40.3	612	39.8	181	48.3	16.4
Kulumssa	818	12.6	444	14.7	250	37.5	11.2
Langano	660	35.7	431	36.7	175	41.6	12.6
Meki	729	29.6	425	38.4	191	47.4	13.8
Melkassa	796	19	525	21.6	167	45.7	14.5
Mojo	901	21.9	668	23.4	166	55.1	17.2
Nazreth	859	17.1	614	20.4	181	44.7	16.6
Ogocholo	700	28.1	421	38.1	195	34.8	12.7
Sagure	772	18.7	464	23.9	215	36.5	12.7
Ziway	751	21.7	449	24.6	208	46.3	12.4

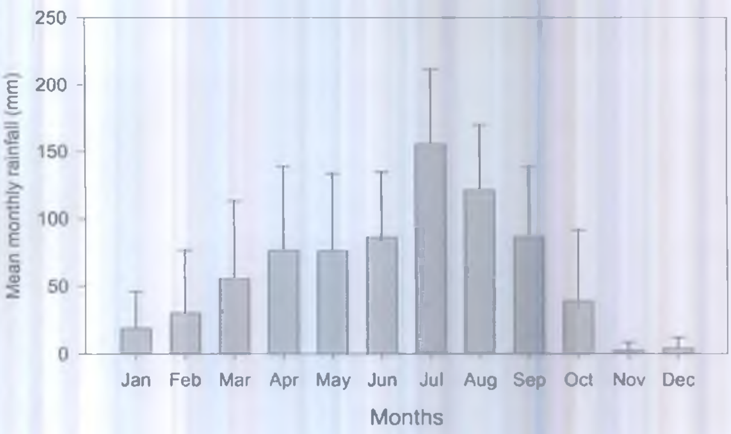

Fig. 2.2. Monthly rainfall distribution with standard deviations for the period 1970-2009 at Ziway station in the Central Rift Valley.

The daily rainfall intensity during the *Belg* varies from 4.5 to 16.4 mm day^{-1} with an average value of 10 mm day^{-1}. The daily rainfall intensity showed a slight increase over time during the *Kiremt* (e.g. see Fig. 2.3b for Ziway) while it decreases during the *Belg* (Fig. 2.3d) but both trends were not significant.

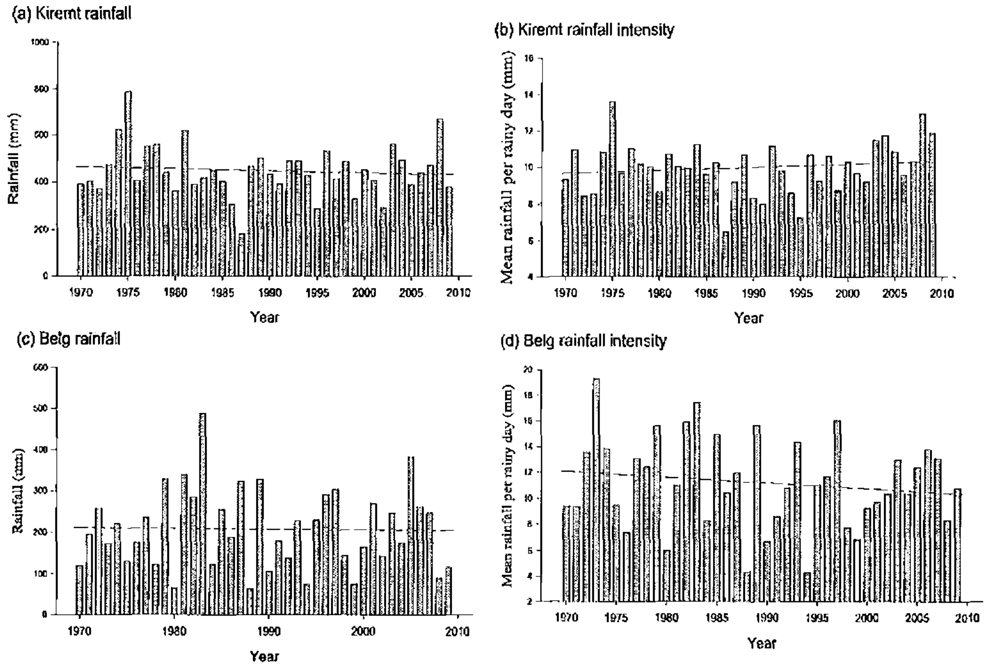

Fig. 2.3. Seasonal rainfall variability and trends for the period 1970-2009 at Ziway station, Central Rift valley, Ethiopia: (a) the mean annual rainfall for the *Kiremt* (June to September) season; (b) the mean rainfall per rainy day (daily rainfall intensity) for the *Kiremt*; (c) the mean annual rainfall for the *Belg* (March to May) season; (d) the mean rainfall per rainy day (daily rainfall intensity) for the *Belg* season. Both seasons show a slight decline in rainfall amount but trends are not statistically significant at 0.05 level of significance. The mean daily rainfall intensity is increasing for the *Kiremt* and decreasing for the *Belg*.

Table 2.3 presents Sen's slope estimates and Mann-Kendall trend test results for the annual and seasonal rainfall of representative stations in the Central Rift Valley. The annual rainfall shows negative trends in seven and positive trends in nine out of the sixteen stations. The *Belg* rainfall exhibits negative trends in five stations and positive trends in eleven of the sixteen stations. The *Kiremt* rainfall shows negative trends in nine stations and positive trends in six stations. However, the Mann-Kendall trend test result showed that for most of the stations, trends of the annual and seasonal rainfall are not statistically significant ($p > 0.05$). The area weighted mean annual rainfall (not shown here) also indicates an insignificant declining trend during the period 1977 to 2007 (trend=-0.4).

Table 2.3. Mann-Kendall trend test result for the annual and seasonal rainfall of representative stations of the Central Rift Valley, Ethiopia. The seasonal rainfall refers to the short rainy season locally known as *Belg* (March to May) season and the main rainy season known as *Kiremt* (June to September).

Station	Annual rainfall		*Belg* rainfall		*Kiremt* rainfall	
	Trend (mm/year)	P-value	Trend (mm/year)	P-value	Trend (mm/year)	P-value
Arata	2.54	0.34	0.56	0.64	0.44	0.76
Assela	-3.93	0.20	-0.73	0.54	-6.31	0.00
Awassa	0.56	0.89	1.28	0.45	-1.83	0.16
Bulbula	5.78	0.06	0.74	0.29	2.15	0.11
Butajira	0.01	1.00	-1.53	0.47	1.95	0.34
Debre Zeit	0.02	0.98	0.68	0.26	-0.34	0.69
Hombol	-10.32	0.05	-1.31	0.54	-3.81	0.37
Kulumssa	-0.17	0.92	0.24	0.84	-0.19	0.96
Langano	4.55	0.11	1.26	0.22	2.54	0.17
Meki	5.78	0.06	0.74	0.29	2.15	0.11
Melkassa	2.27	0.40	0.61	0.66	0.11	0.92
Mojo	2.55	0.25	0.33	0.71	2.00	0.23
Nazreth	-0.65	0.62	0.15	0.93	-0.33	0.92
Ogocholo	-1.83	0.43	-1.08	0.60	-0.45	0.78
Sagure	-3.40	0.28	0.91	0.72	-0.17	0.93
Ziway	-0.64	0.79	-0.03	0.99	-0.13	0.92

2.3.2. Temperature variability and trends

The annual mean temperature in the CRV is 18.9°C. The annual mean minimum and maximum temperatures are 12°C and 26°C, respectively. For the *Belg*, the minimum temperature ranges between 11 and 15°C and the maximum temperature varies between 25 and 29°C. The *Kiremt* season has minimum temperatures of 10-14°C and maximum temperatures of 22-26°C. Temperature characteristics are illustrated for Ziway station in Fig.2. 4.

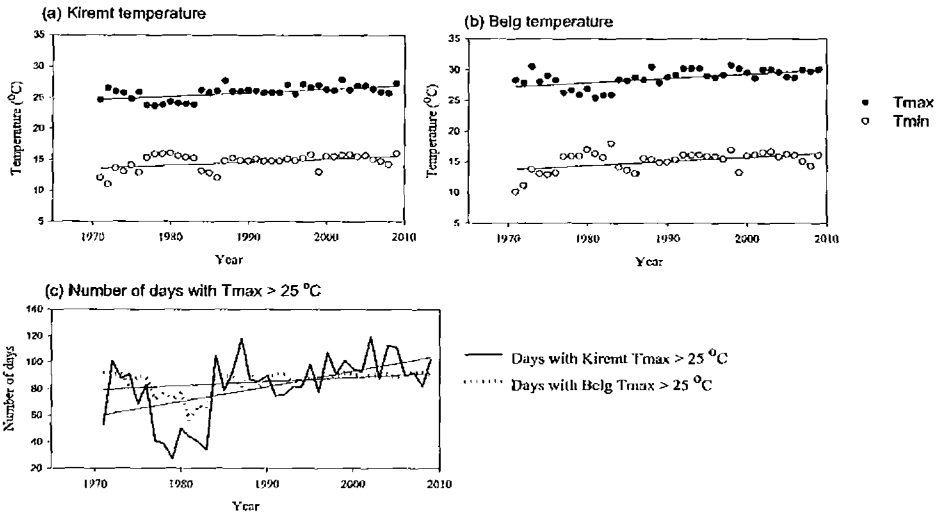

Fig. 2.4. Time series and trends for minimum and maximum temperatures during the *Kiremt* (June to September) and *Belg* (March to May) at Ziway, Central Rift Valley, Ethiopia: (a) the daily minimum (Tmin) and maximum (Tmax) temperatures for the *Kiremt*; (b) the daily minimum (Tmin) and maximum (Tmax) temperatures of the *Belg*; (c) the number of days with daily maximum temperature (Tmax) exceeding 25°C (summer days) for both seasons.

Trends of annual minimum, maximum and mean temperature and Mann-Kendall test results are presented for five representative stations in Table 2.4. The annual minimum temperature significantly increases in Awassa and Debre Zeit and the maximum temperature significantly increases in Awassa, Debre Zeit, Butajira and Ziway. The mean annual temperature generally shows a warming trend ranging from 0.12 to 0.54°C per decade. On a seasonal basis, the *Belg* minimum temperature increases with 0.1-0.5°C and the maximum temperature with 0.1-0.6°C per decade. Trends are statistically significant in Awassa and Ziway ($P<0.05$). The *Kiremt* minimum temperature increased with 0.2-0.4°C per decade and its maximum temperature with 0.2-0.5°C per decade. Extreme temperature events, i.e. lowest and highest daily minimum and maximum temperatures indicate a significant increase (results not shown). The number of days with maximum temperature greater than 25°C (summer days) did increase (see e.g. Fig. 2.4c for Ziway station).

Table 2.4. Trends of annual minimum, maximum and mean temperature and Mann-Kendall test result for trends at reference stations in the Central Rift Valley, Ethiopia. Positive values of normalized test statistics (Z) indicate an increasing trend and negative Z values indicate decreasing trends.

Station	Trend (°C/decade)	Normalized test statistics (Z)	Probability
Annual minimum temperature			
Awassa	0.35	4.3	0.000*
Butajira	-0.12	-0.3	0.744
Debre Zeit	0.11	2.5	0.013*
Kulumsa	-0.3	-1.6	0.121
Ziway	0.43	1.6	0.100
Annual maximum temperature			
Awassa	0.45	4.9	0.000*
Butajira	0.44	3.8	0.000*
Debre Zeit	0.12	3.8	0.000*
Kulumsa	0.14	1.2	0.230
Ziway	0.47	4.3	0.000*
Mean annual temperature			
Awassa	0.41	5.8	0.000*
Butajira	0.18	0.8	0.426
Debre Zeit	0.12	3.6	0.000*
Kulumsa	-0.13	-1.4	0.155
Ziway	0.54	5.1	0.000*

* *Statistically significant at 0.05*

2.3.3. Characteristics of the growing season

Start and end of the growing season

Figures 2.5a and 2.5b present the inter-annual variability of the start and end of the growing season for six stations in the Central Rift Valley. The mean potential onset date of the growing season in the CRV ranged from Julian day number 86 to 101 (i.e. 26 March to 10 April). The coefficient of variation for the start of the season (SOS) ranged from 24 to 33%. The earliest potential onset date of the growing season is day 66 (6 March) and the latest is day 184 (2 July). The mean end date of the growing season (EOS) for the study area ranged from day 253-286 (9 September to 12 October) with a coefficient of variation of 5-7%. The earliest possible end date of the growing season is day 245 (1 September). Analysis for the risk of failure in early planting due to false start of the rainfall season (not shown here) indicates that at Ziway, the first planting was not successful in 65% of the 40 years. The extra time before a successful planting had a mean of 26 days with a standard deviation of 27 days.

Length of growing season (LGS)

The mean length of growing season of six stations in the study area ranged from 161 to 197 days (CV% 13-21%) (Fig. 2.5c, d). The standard deviation for the length of the growing season is 24-35 days. The inter-annual variability of LGS is illustrated for Ziway station in Fig.2.5d. Some of the years in Ziway had a short growing season and some have extended growing season. Statistically, it varies from a minimum of 76 days to maximum of 239 days. The length of growing season is highly correlated with the starting date of the growing season ($R = 0.7$ to 0.9). For instance, 77% of the variability in length of the growing season at Ziway is explained by the starting time of the growing season (Fig. 2.5e). Weak correlations exist between start and end date of the season as well as between length of growing season and end date of the season ($R < 0.5$).

Crop water requirement satisfaction index

Figures 2.6a and 2.6b present the seasonal water requirement satisfaction index for a 90-day and 120-day maize cultivar at Ziway between 1970 and 2009. The WRSI for a 90-day-maize cultivar varies from 76 to 100% except for three years (1970, 1986 and 1987). The exceptional low values in the three years were due to the early termination of rain and long dry spells during the growing season. The index was less than 100% in 55% of all analyzed seasons. For a 120-days maize cultivar, the index varies from 64 to 100% and in 83% of the seasons the WRSI was less than 100%. Index values lower than 100% generally indicate inadequate rainfall during the growing season.

Dry spells during the growing season

For three selected stations, the probability of occurrence of longer dry spells (longer than 15 days) is 0.2 in March and decreases to 0 from middle to the end of June and increases again after the end of August (Fig. 2.7). The probability of dry spells of 5 and 7 days is 1 during the earlier months. All dry spell probability curves converge to their minimum during the peak rain season (Day 184 -244) and increase again around September (Day 245-274) signaling the end of the growing season. In general, the *Belg* has higher probability of dry spells than the *Kiremt*.

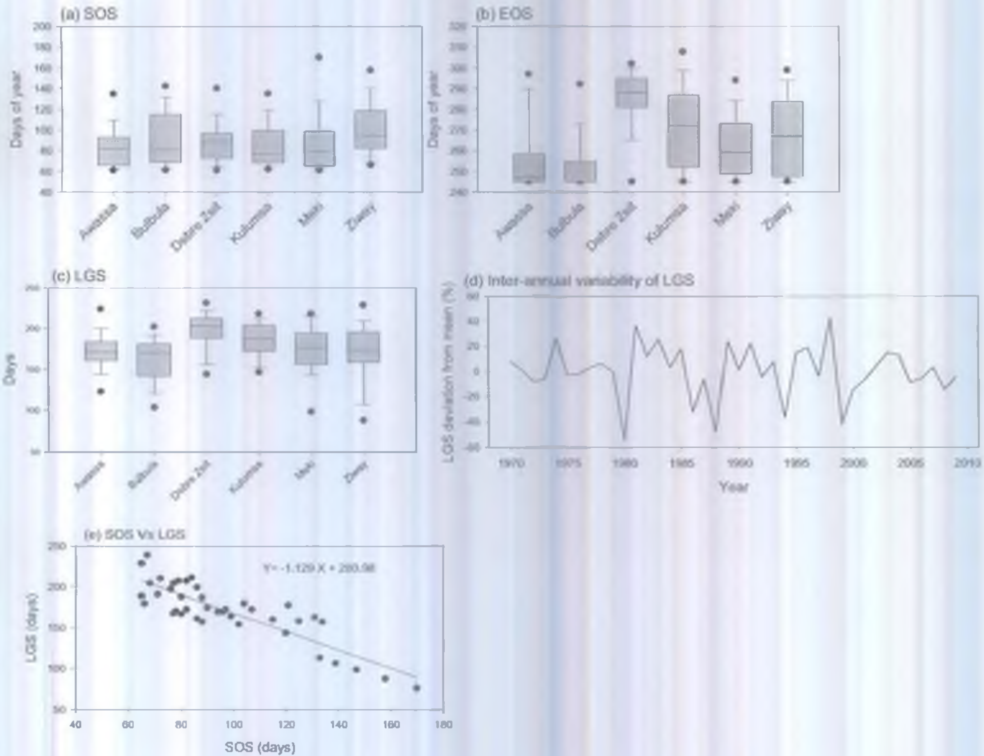

Fig. 2.5. Characteristics of the growing season at the Central Rift Valley. The Box and whisker plots in a, b and c depict the start of the season (SOS), end of the season (EOS) and length of the season (LGS); respectively for representative stations (Awassa, Bulbula, Debre Zeit, Kulumsa, Meki and Ziway). Boxes indicate the lower and upper quartiles. The solid line within the box is the median. Whiskers indicate the minimum and maximum values and dots are outliers; (d) shows the year to year variability of length of growing season at Ziway presented in terms of percentage of deviation from the mean (anomalies); (e) indicates the relation between length of growing season and start of the season for Ziway station.

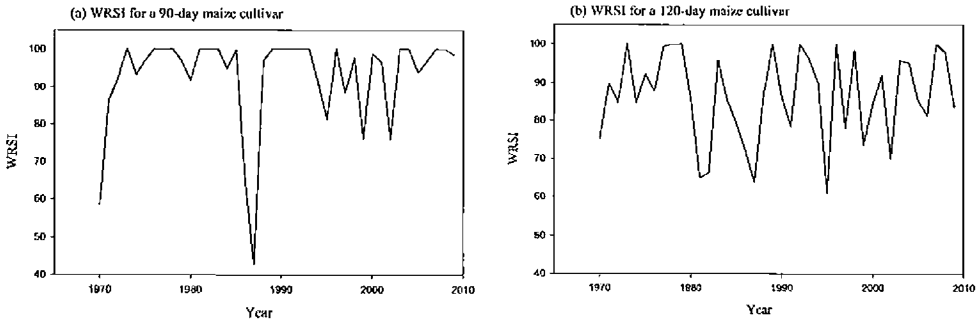

Fig. 2.6. Water requirement satisfaction index: (a) for a 90-day maize cultivar and (b) for a 120-day maize cultivar at Ziway in the Central Rift Valley of Ethiopia. The WRSI index indicates the extent to which the water requirements of a given crop have been satisfied during its growth cycle.

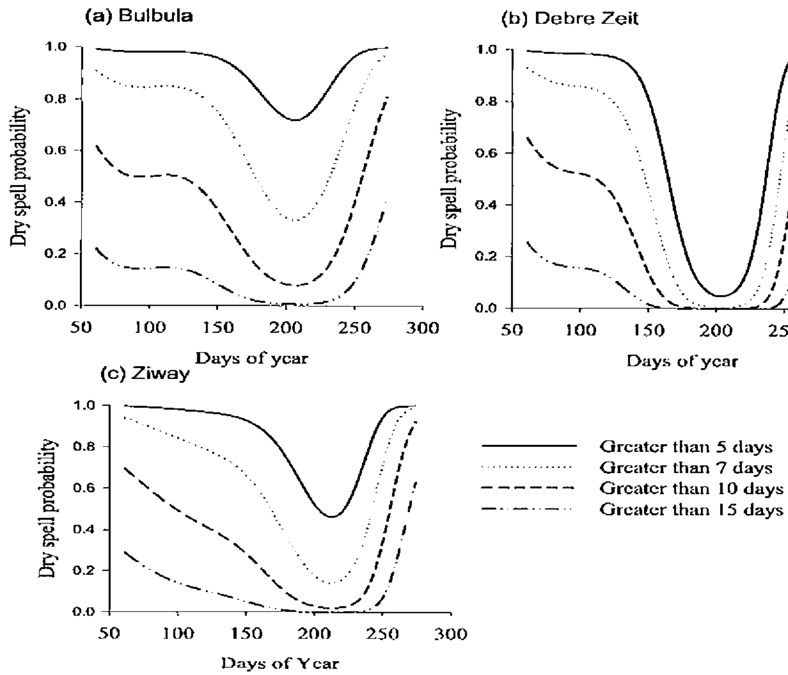

Fig. 2.7. Probability of dry spells longer than 5, 7, 10 and 15 days length during the growing season for three stations (Bulbula, Debre Zeit and Ziway) of the Central Rift Valley.

2.3.4. Future climate scenarios

Projected changes in rainfall

Projections based on eight combinations, i.e. four general circulation models (GCMs) with two IPCC emission scenarios, suggested that the annual and seasonal rainfall will most likely decline by the 2080s relative to the current baseline (1971-1990). The range of projected rainfall changes is presented for Ziway station in Table 2.5. The change in annual rainfall range from +10% (by HadCM3A2) to -40% (by CGCM2A2). The most relevant months from the point of view of rainfed crop production (i.e. March to September) showed declining rainfall in most projections. The *Kiremt* rainfall shows an extremely wide range of projected changes from -20% (by CSIRO2) to -68% (by CGCM2A2). The rainfall change for the *Belg* season is also extremely wide from -18% (by HadCM3) to -65% (by CGCM2). A substantial increase in rainfall is expected for agriculturally less relevant months (November to December). The GCM projections suggest that the length of growing season will vary in the range of +16 to -35% by 2080s relative to the current climatic conditions (Table 2.6). Highest changes are projected by the CGCM2 model for A2 emission scenario, showing a decline of the length of growing season by 22% at Ziway, 35% at Debre Zeit and 12% at Kulumsa.

Projected changes in temperature

All four GCMs under the two emission scenarios suggested an increasing trend in temperature. For Ziway, the *Kiremt* maximum temperature is expected to increase in the range of 2-4°C under the A2 scenario and 1.3-2.5°C for the B1 scenario (Fig. 2.8). The *Kiremt* minimum temperature is also expected to increase by 2-4°C under A2 scenario and by 1.2-2.4°C under the B1 scenario. For the *Belg*, the maximum temperature is expected to increase by 2.3-4.2°C under the A2 scenario and 1.8-2.7°C under B1 scenario and the minimum temperature is expected to increase by 2.3-4.2°C (A2 scenario) and 1.4-2.7°C (B1 scenario).

Table 2.5. Ranges of percentage changes in monthly and annual rainfall as projected by different General Climate Models (GCMs) for two emission scenarios for the 2080s relative to the baseline period (1971-1990) at Ziway station, CRV, Ethiopia. Note, the combination CGCM2A2, for example is composed of the GCM named CGCM2 and emission scenario A2.

	HadCM3 A2	HadCM3 B1	CSIRO2 A2	CSIRO2 B1	CGCM2 A2	CGCM2 B1	PCM A2	PCM B1
January	32	18	14	-4	11	4	1	0
February	15	2	9	-7	10	6	0	1
March	19	-5	-8	-4	0	11	15	3
April	34	16	-11	-14	-46	-18	-2	-2
May	-18	1	-5	-8	-65	-45	7	1
June	-14	-16	-20	-16	-68	-42	-1	2
July	7	2	-12	-8	-38	-17	0	-5
August	14	8	-13	-7	-50	-21	4	2
September	7	0	1	3	-44	-29	-1	0
October	33	-11	27	18	-40	-49	61	35
November	191	9	38	26	238	191	2	21
December	139	73	9	37	195	102	44	55
Annual	10	2	-6	-6	-40	-22	5	2

Table 2.6. Projected percentage change in length of the growing season (LGS) for three representative stations of the Central Rift Valley, Ethiopia, based on the combination of four GCMs and two emission scenarios by the 2080s relative to the current baseline period (1971-1990); GCM-emission scenario combinations as in Table 2.5.

	LGS changes (%) under different scenarios							
	CGCM2	CSIRO2	HadCM3	PCM	CGCM2	CSIRO2	HadCM3	PCM
Stations	A2	A2	A2	A2	B1	B1	B1	B1
Ziway	-22	-11	16	4	-13	-3	7	2
Debre Zeit	-35	-7	-3	2	-18	-6	-4	1
Kulumssa	-12	2	12	13	-7	8	10	11

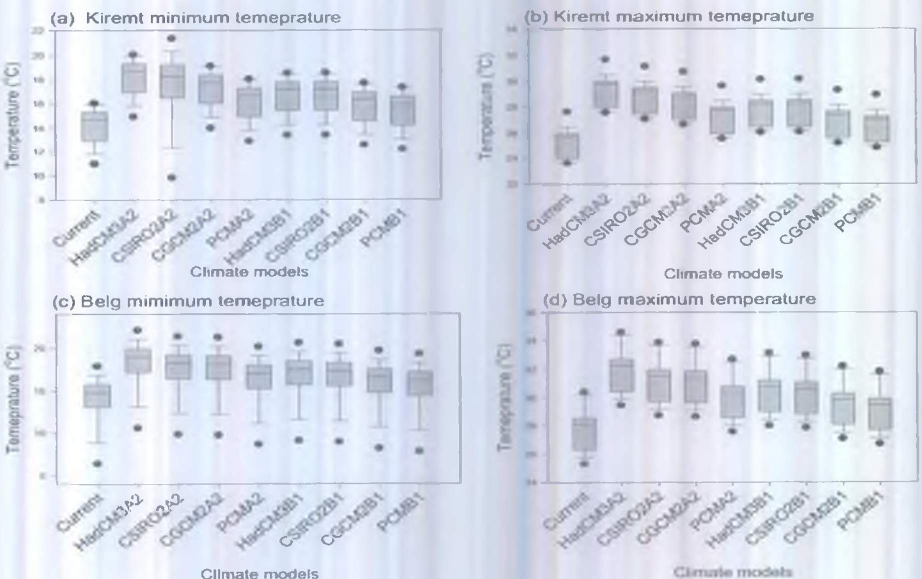

Fig. 2.8. Box-and-whiskers plots of the minimum and maximum temperatures projected under the A2 and B1 emission scenario and four climate models by the end of the century relative to the current base period (1971-1990). Lower and upper boundaries of the boxes indicate the 25th and 75th percentiles; respectively. A line within the box marks the median. Whiskers above and below the box indicate the 90th percentiles. Dots are outliers with criteria of 5th and 95th percentiles. GCM2 is a climate model from the Canadian Center for Climate Modelling and Analysis, Canada; CISRO2 is the

Australian Common Wealth Scientific and Industrial Organization, Australia; HadCM3 is the Hadley Center for Climate Prediction and Research, UK; PCM is Parallel climate model of the National Center for the Atmospheric Research, USA. A2 and B1 indicate the mid-range and low emission scenarios of the IPCC (Mitchell et al., 2004; Meehl et al., 2007). The models represent moderate (+2.5°C) to high (+4°C) global warming estimates for the end of the century.

2.4. Discussion

2.4.1. Current climate and its implication for rainfed crop production

The analysis on long term rainfall data for the CRV showed large inter-annual and season to season variation in the amount and distribution of rainfall. Our analysis on trends revealed that the growing season rainfall generally exhibited a slight, but statistically insignificant decline. A decrease in the number of rainy days with an increase in the mean rainfall per rainy day has been observed over the past few decades, signifying an increase in the intensity of rainfall, particularly for the *Kiremt*. The trends observed are, however, not statistically significant. This result is in agreement with other studies in parts of the country. For instance, Cheung et al. (2008) found a decline in the *Kiremt* rainfall for watersheds located in the south western and central parts of the country, but also their observed changes were not statistically significant for any of the watersheds examined. Osman and Sauerborn (2002) also found negative anomalies with *Kiremt* rainfall frequently being lower than the long-term average for the north central highlands of Ethiopia. Despite the absence of significant trends in rainfall patterns, the high inter-annual variability and season to season variation implies a challenge to rainfed agriculture. The declining trend in *Kiremt* rainfall and increase in daily rainfall intensity disadvantages rainfed crop production. Various studies indicate that the amount and temporal distribution of rainfall is generally the most important determinant of inter-annual fluctuations in crop production in Ethiopia and has reported to have significant effects on the country's economy and food production for the last three decades (World Bank, 2006; Bewket and Conway, 2007; Hellmuth, 2007; Araya and Stroosnijder, 2011; Conway and Schipper, 2011; Demeke et al., 2011). Large variability of *Belg* rainfall already makes this season unsuitable for rainfed agriculture (Rosell, 2011). Higher rainfall intensities during the main rainy season could increase the rate of erosion and loss of nutrients from arable soils, thereby reducing soil fertility (Yengoh et al., 2010) and consequently impacting crop productivity.

The length of the growing season and its reliability (Jaetzold and Kutsch, 1982) determines the suitability of crops and cultivars that can be cultivated in a given area and is an important indicator of yield potentials. The lengths of the growing season in the CRV exhibits a high inter annual variability with slight declining trend. The onset date of the growing season shows a trend towards late starting. With a high correlation between the starting date of the growing season and length of the growing season, delay of the onset implies shortened growing period leading to low crop productivity. Earlier studies also provided evidence that uncertainty of the growing season is one of the main challenges for rainfed crop production. World Bank (2006), for instance, reported that the late start of the *Kiremt* in 1997 caused a reduction in average yield of cereals by 10% across Ethiopia. Camberlin and Okoola (2003) observed a 25-30% maize yield reduction in Kenya due to a 20 day delay of the main rainfall season. The CRV is further characterized by intermittent dry spells with higher probabilities of occurrence during the growing season. Most of the crops cultivated in the CRV are most likely to be exposed to moisture stress. For instance, at Ziway, there is a chance of 26% of getting dry spells of longer than 7 days at the early growth stage of a crop and the probability is higher (92%) during the late development stage of the crop. Earlier studies by Segele and Lamb (2005) and Araya and Stroosnijder (2011) also indicate that dry spells of about 10 days length is one of the major causes of crop failure in rainfed farming systems of Ethiopia. The latter authors indicate that 20% of crop failure in drought prone parts of Ethiopia is due to dry spells during the growing season. In general, the *Belg* has higher probability of dry spells than the *Kiremt*. This may be because *Belg* rainfall is influenced much more by cyclonic activity than the Kiremt period and negative anomalies in sea surface temperature (SST) are strongly associated with rainfall deficiency in the Belg season (Seleshi and Camberlin, 2006).

The water requirement satisfaction index calculated for 90-day and 120-day cycled maize cultivars indicates that the effective rainfall available during the growing season is not sufficient for maximum production of the crops in most of the seasons. Crops, particularly long cycled varieties experience water stress during the growing season and farmers need to shift to short cycled crops as long as rainfall is the only source of water for crop production. The analysis provides an indication for the necessity of improved farm management practices to support production of short cycled varieties.

The inter-annual and intra-seasonal rainfall variability in the CRV is accompanied with a significant warming trend in temperature, which can add stress to crop growth during periods of already high temperatures. The mean annual temperature increased in the range of 0.12-0.54°C per decade during the study period. Previous studies also indicate that warming has occurred across Ethiopia (Conway, 2000; Boko et al., 2007; NMA, 2007), particularly since the 1970s at variable rates but broadly consistent with global and African trends. The latter authors indicated that between 1960 and 2006, the mean annual temperature has been increased at an average rate of 0.2°C per decade. The warming trend imposes its impact on crop production with raising the evaporative demand, particularly in regions like the CRV where rainfall is already scarce. Declined growing season rainfall with high evaporative demand will increase the risks of low yields in rainfed crop production.

2.4.2. Projected climate change and possible implications

Projection of future rainfall conditions suggest that annual and seasonal rainfall of the study area are most likely to decrease. Associated with the declining trends in seasonal rainfall, the length of growing season of CRV is also projected to be shortened. Other reports on future rainfall projections for Ethiopia support our result. For instance, Arndt et al. (2011) indicate that the *Kiremt* rainfall will decline by 20% and the *Belg* rainfall will decline by 5-6% by 2080s relative to the 1960-1990 period. Thornton et al. (2006) reported that in much of the regions across Africa including Ethiopia, there will be little to moderate reduction in the length of the growing period (< 20%) and in other parts the reduction will be more severe (>20%). Our analysis for future temperature also revealed that the warming trend will continue and the annual temperature is expected to increase in the range of 1.4-4.1°C by the end of this century. This result is consistent with reports for other countries as well as global projections. For Ethiopia, NMA (2007) reported that the annual temperature is expected to increase in the range of 2.7 to 3.4°C by the 2080s compared to the 1961-1990 base period. For global scale projection, the Fourth IPCC assessment report suggested an increasing trend of temperature in the range of 1.5 to 4.5°C by the end of the century (Meehl et al., 2007).

We used a delta change approach which assumes that the behavior of current climate variability stays the same in the future. However, such an assumption may not be true as climatic extremes (e.g. heat waves; high intensity rainfall) are expected to become more frequent and severe under a changing climate. On the other hand, climate models, be it GCMs or RCMs, still have a number of deficiencies that make projections, especially those on changes in variability quite uncertain, even in well-studied European regions as shown by (Boberg and Christensen, 2012). Future progress in dynamic downscaling combined with improvements of stochastic weather generators, calibrated for the region, and their application will allow showing what the effects of plausible changes in extreme events under future climates would be. Considering this limitation, the analysis on projected rainfall and temperature changes provides indication that rainfed crop production in the CRV, which is already affected by current climate variability, is most likely to be further challenged under the changing climate. The projected decline in growing season rainfall and the continuing warming trend will further increase moisture stress in the future. Several climate change impact studies revealed that there could be considerable yield reduction, particularly in Sub-Saharan countries including Ethiopia. Parry et al. (2004), for instance, reported that cereal yields in East Africa will be declined by 5-20% by 2080s and NMA (2001) reported a decrease in wheat yield of 24-33% in Ethiopia by 2080.

2.5. Conclusions

Past and future trends in inter-annual and inter-seasonal rainfall variability, declining rainfall amount, variability in the length of the growing seasons and in-season dry spells together with increasing temperature generally indicate an increasing risk for rainfed crop production in the CRV. However, the severity of risk varies spatially and depends on the climate change scenario, whereby some of them also show a reduced risk. Shorter growing seasons due to a delayed start of rainfall hampers soil preparation and exposes crops to increased terminal moisture stress during grain filling, reducing crop yields. Increased rainfall intensities can cause increased soil erosion and losses of nutrients from arable soils impacting crop production. The increasing temperature will increase the rate of evapotranspiration and crop water requirements, adding to the currently frequent water stress of crops. Rainfed crop production in the CRV, which is already impacted by the current climate variability, is likely to be further challenged with future climate change. As a consequence, specific impact-based adaptation strategies are essential to reduce the vulnerability of rainfed crop production in the CRV.

Acknowledgements

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CHAPTER 3

Climate-induced yield variability and yield gaps of maize (*Zea mays*) in the Central Rift Valley of Ethiopia

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Abstract

There is a high demand for quantitative information on impacts of climate on crop yields, yield gaps and their variability in Ethiopia, yet, quantitative studies that include an indication of uncertainties in the estimates are rare. A multi-model simulation approach using the two crop models, i.e. Decision Support System for Agro-Technology (DSSAT) and WOrld FOod STudies (WOFOST) was applied to characterize climate-induced variability and yield gaps of maize. The models were calibrated and evaluated with experimental data from the Central Rift Valley (CRV) in Ethiopia. Subsequently, a simulation experiment was carried out with an early maturing (Melkassa1) and a late maturing (BH540) cultivar using historical weather data (1984-2009) of three locations in the CRV. Yield gaps were computed as differences among simulated water-limited yield, on-farm trial yields and average actual farmers' yields.

The simulation experiment revealed that the potential yield (average across three sites and 1984-2009) is 8.2-9.2 and 6.8-7.1 Mg/ha for the late maturing and early maturing cultivars, respectively; ranges indicate mean differences between the two models. The simulated water-limited yield (averaged across three sites for 1984-2009) is 7.2-7.9 Mg/ha for the late maturing and 6.1 to 6.7 Mg/ha for the early maturing cultivar. The water-limited yield shows high inter-annual variability (CV 36%) and about 60% of this variability in yield is explained by the variation in growing season rainfall. The gap between average farmers yield and simulated water-limited yield ranges from 4.7 to 6.0 Mg/ha. The average farmers' yields were 2.0-2.3 Mg/ha, which is about 1.1 to 3.1 Mg/ha lower than on-farm trial yields. In relative terms, average farmers' yields are 28-30% of the water-limited yield and 44-65% of on-farm trial yields. Existing yield gaps indicate that there is scope for significantly increasing maize yield in the CRV and other, similar agro-ecological zones in Africa, through improved crop and climate risk management strategies. As crop models differ in detail of describing the complex, dynamic processes of crop growth, water use and soil water balances, a multi-model approach provides information on the uncertainty in simulating crop-climate interactions.

Key word: WOFOST, DSSAT, Crop simulation, Water-limited yield, Yield gap, Ethiopia

3.1. Introduction

Climate variability and change negatively affect agriculture in most parts of Africa especially the semi-arid areas in Sub-Saharan countries (Hellmuth et al., 2007; Cooper et al., 2008; Thornton et al., 2011), characterized by high rainfall variability (Haile, 2005). It is expected that climate change has already and will further increase climatic variability and the frequency and severity of extreme weather events in Africa as well as elsewhere (Cooper et al., 2008; Müller et al., 2011; Thornton et al., 2011; Coumou and Rahmstorf, 2012; IPCC, 2012). With the increasing climate induced risks, rainfed agriculture in many regions of Africa is projected to become further constrained. For instance, a study by Jones and Thornton (2009) indicated that crop yields in Sub-Saharan Africa may decline by 10-20% and some regions would be unsuitable for crop farming by the mid of this century. Some other studies are less pessimistic (Müller et al., 2011).

Ethiopia is among the most vulnerable countries in Sub-Saharan Africa due to its great reliance on climate sensitive sectors, particularly agriculture (Thornton et al., 2006; World Bank, 2006; Conway and Schipper, 2011; Rosell, 2011). Climate variability, particularly rainfall variability and associated droughts have been reported as major causes of food insecurity and famine in Ethiopia (Thornton et al., 2006; Conway and Schipper, 2011; Demeke et al., 2011; Rosell, 2011). Though climate risk has been suggested as the main source of uncertainty in crop production, quantified information on climate induced-yield variability and the magnitude of yield gaps (Van Ittersum and Rabbinge, 1997) due to water limitation and imperfect management is scarce across Africa. There is high demand to better quantify impacts of climate variability (as well as climate change) in Sub-Saharan Africa (Challinor et al., 2007b; Müller et al., 2011; Funk et al., 2012). The generation of new data through traditional agronomic field research methods is, however, not sufficient to meet these urgent needs (Jones et al., 2001). Traditional agronomic field experiments are conducted at particular points in time and space, making results site and season specific, time consuming and expensive. Application of advanced research tools such as crop simulation modelling approaches offer an effective alternative to develop climate risk management strategies (Hansen and Jones, 2000; Jones et al., 2001; Verdin et al., 2005; Cooper et al., 2008; Challinor et al., 2009a). Dynamic, process-based crop simulation techniques are important tools for understanding the impacts of climate variability and change on crop production systems and to evaluate climate risk management options (Alexandrov and Hoogenboom, 2000; Soler et al., 2007; Challinor et al., 2009a; Meza and Silva, 2009; Ventrella et al., 2012). However, such tools are not yet widely used in research and agricultural decision support in Africa.

While using multiple climate models has become a common approach in climate risk studies (Tebaldi and Knutti, 2007; Rosenzweig et al., 2013b), usually only single crop models have been applied in translating climate into agricultural impacts (see e.g. Žalud and Dubrovský, 2002; Soler et al., 2007; Meza and Silva, 2009; Liang et al., 2011). Crop growth is a complex process involving interactions of soil, crop and weather variables and results obtained with deterministic crop models comprise various types of uncertainty (Challinor et al., 2009b; Eitzinger et al., 2008; Palosuo et al., 2011; Rötter et al., 2011a; Rötter et al., 2012a). One way to capture such uncertainty in crop modelling is using the output of different simulation models. The need of a multi-model simulation approach has been suggested in response to crop model inter-comparisons performed in the framework of the European COST action "Impacts of climate variability and change on European agriculture" (COST 734) (Palosuo et al., 2011; Eitzinger et al., 2012; Rötter et al., 2012b). This need has been recognized and further examined for climate change studies in the Agricultural Model Inter-comparison and Improvement Project (AgMIP), which aims to improve the description of crop-climate interactions in models and to promote the application of multiple crop models in climate impact assessments (Rosenzweig et al., 2013b) with special emphasis on assessing uncertainty in crop simulation models (Asseng et al., 2013). The main objectives of this study were to assess the impacts of current climate variability on yield variability of widely used maize cultivars and to analyze existing yield gaps in the Central Rift Valley of Ethiopia, representative for other low input and semi-arid to sub-humid rainfed systems in Sub-Saharan Africa using two crop models for indicating model uncertainty.

3.2. Material and Methods

3.2.1. Description of case study area

The study was conducted in the Central Rift Valley (CRV). The CRV study region (center-point) is located 120 kilometers south of Addis Ababa and it is characterized by an alternating topography with a central valley floor at 1500-1700 meters above sea level (m.a.s.l) and bounded by a western and eastern escarpment with highest altitudes of over 4000 m.a.s.l. (Jansen et al., 2007). Based on annual rainfall distribution, CRV is characterized by a bi-modal rainfall pattern, which is a typical characteristic for the central, eastern and north-eastern parts of Ethiopia. Our crop simulations focused on the valley floor, which receives approximately180 to 360 mm rainfall during a short rainy season (March-May) and 420 to 680 mm during the main rainy season (June to September). Currently, rainfed cereal-based production systems and modest livestock rearing are the mainstays of livelihoods for households in the CRV. Maize (*Zea mays*) is the major crop cultivated and has a significant role in the livelihoods of smallholders in the CRV (Biazin and Stroosnijder, 2012).

3.2.2. Description of models

Crop models are powerful tools to assess the risk of producing a given crop in a particular soil-climate regime and to assist in management decisions that minimize the risk of crop production (Van Diepen et al., 1989; Tsuji et al., 1998; Van Ittersum et al., 2003; Hoogenboom et al., 2004; Challinor et al., 2009c). Crop models integrate knowledge from different disciplines and provide researchers with capabilities for conducting simulation experiments to supplement actual experiments (Jones et al., 2001). The models simulate dry matter production as a function of climate conditions, crop characteristics, soil properties and management practices. Two crop growth models, i.e. CERES-maize of Decision Support System for Agro-Technology (DSSAT, v4.5) and WOrld FOod STudies (WOFOST, v7.5) were used in this study. Table 3.1 presents the modelling approaches of these models in describing main crop growth and development processes.

DSSAT is a software package that contains a number of process-based, mechanistic and management oriented crop modules (Jones et al., 2003). CERES-maize is one of the various models embedded in DSSAT. The CERES-maize, hereafter referred to as DSSAT, simulates crop development and growth, and the partitioning of assimilates to various plant parts as a function of environmental factors such as soils, weather and crop characteristics. Phenological development and growth of a crop are specified in DSSAT by cultivar-specific genetic coefficients (Hoogenboom et al., 2004). DSSAT consists of soil water and nitrogen balance sub-modules. The soil water module simulates changes in soil water content across soil layers due to infiltration, soil evaporation, vertical drainage, unsaturated flow and root water uptake processes on daily time step (Jones et al., 2003). The nitrogen module simulates soil nitrogen balance processes such as mineralization, immobilization and nitrogen leaching. The performance of DSSAT has been tested for a range of soil and climatic conditions in various studies (see e.g. Ben Nouna et al., 2000; Eitzinger et al., 2004; López-Cedrón et al., 2005; Popova and Kercheva, 2005; Soler et al., 2007; Fosu-Mensah et al., 2012).

WOFOST is a dynamic crop model (Van Diepen et al., 1989) developed in Wageningen, The Netherlands. The model has been designed to simulate crop growth processes such as phenological development, assimilation, respiration and evapotranspiration as a function of crop characteristics and management, weather conditions, soil characteristics and soil water balance. It has been tested and applied in various environmental conditions (Rötter, 1993; Wang et al., 2011; Wolf et al., 2011; Boogaard et al., 2013). We used the version without nutrient limitation.

3.2.3. Model input data sets

The minimum input data set required to simulate crop growth is discussed in detail by Jones et al. (2003) for DSSAT and by Boogaard et al. (1998) for WOFOST. Generally, input data required for the models are crop management information, cultivar specific parameters (genetic coefficients), soil properties and daily weather variables of the study areas.

Crop data

Crop management data and cultivar information were collected from Melkassa and Awassa research centers of the Ethiopian Agricultural Research Institute and published sources (Gebre et al., 2002; Nigussie et al., 2002; Howard et al., 2003). General cultivar information and experimental data on phenology and yield components is presented in Table 3.2. The experimental data were from fertilizer trials with fertilizer rates ranging from zero (no fertilizer) to the recommended rates (100 kg) for the sites (Debelle et al., 2001; Biazin and Stroosnijder, 2012). For the model calibration, the treatments with the recommended fertilizer rates, i.e. 100 kg/ha urea and 100 kg/ha Di-ammonium Phosphate (64 kg N/ha and 46 kg P/ha) for BH540, and 65 kg/ha urea and 100 kg/ha DAP (48 kg N/ha and 46 kg P/ha) for Melkassa1 were used. The cultivars BH540 and Melkassa1 are widely used in the study areas.

Soil data

The dominant soils of the study area are Vitric Andosol and Haplic Luvisol (Table 3.3), hereafter referred to as Andosol and Luvisol, respectively. Specific soil parameters required for model input such as lower limit (LL), drained upper limit (DUL) and saturation, drainage

Table 3.1. Modelling approaches of CERES-Maize (DSSAT) and WOFOST for major processes of crop growth and development. Source: Modified after Palosuo et al. (2011).

Processes	CERES-Maize	WOFOST
Crop phenology	Function of temperature, photoperiod	Function of temperature and photoperiod
Leaf area development and light interception	Simple: Leaf area expansion is driven by temperature as a function of leaf number and assimilate availability	Detailed: Leaf area expansion is driven by assimilate availability, dry matter partitioning coefficients and specific leaf area
Light utilization	Descriptive (simple) radiation use efficiency approach. Constant radiation use efficiency is used to directly convert absorbed radiation into dry matter.	Explanatory (detailed) gross photosynthesis respiration approach. Intercepted radiation is divided into direct and diffusive parts and integrated over leaf area index distribution.
Dry matter accumulation	Driven by temperature as a function of phenology, limited by assimilate availability, excess assimilate partitioned to roots	Driven by assimilate supply and regulated by dry matter partitioning coefficients to all organs
Rooting distribution over depth	Exponential	Linear
Method to calculate evapotranspiration	Priestley–Taylor	Penman
Water dynamics	Capacity approach, multi-soil layer	Capacity approach, single soil layer
Model type	Crop specific, dynamic	Generic, dynamic
Simulation time step	Daily	Daily

coefficients and runoff curve number were estimated using the SBuild program available in the DSSAT as discussed in detail in Hoogenboom et al. (2004) and Jones et al. (2003) from measured soil profile data (Table 3.3). For simulation with WOFOST, soil parameters were based on the average soil profile characteristics considering the fact that WOFOST uses a single soil layer. Wang et al. (2011) used similar approach to determine the soil water balance parameters for WOFOST input data.

Table 3.2. General agronomic information and experimental data for phenology and grain yield of maize cultivars (Debelle et al., 2001; Nigussie et al., 2002; Worku et al., 2012).

General information of cultivars		
Agronomic information	**BH540**	**Melkassa1**
Altitude (m.a.s.l)	1000-2000	500-1600
Rainfall (mm)	1000-1200	600-1000
Days from planting to flowering (days)	66-75	48-49
Days from planting to maturity (days)	145	105
Plant height (cm)	240-260	150-170
Spacing between rows (cm)	75	75
Spacing between plants (cm)	30	20
Planting density (plants/m^2)	5.3	6.6
Recommended fertilizer rate (Urea/DAP kg/ha)	100/100	50/100
Potential yield (Mg/ha)	8-10	7

Experimental data

Site	Year	cultivar	Planting date	Planting density (plants/m^2)	Days from planting to anthesis	Days from planting to maturity	Grain yield (Mg/ha)
Awassa	2009 (Set I)	BH540	17-May	5.33	71	139	6.41
	2009 (Set II)		18-May	5.33	69	136	6.38
Ziway	2003	Melkassa1	29-Jun	6.66	51	106	5.04
	2004		26-June	6.66	52	104	5.99

Table 3.3. Main soil properties of the study areas used in model calibration and simulation. LL refers to the soil water content at wilting point and DUL is the soil water content at field capacity (Fritzsche et al., 2007; Biazin and Stroosnijder, 2012).

Soil type	Soil depth (cm)	Sand%	Silt %	Clay %	LL	DUL	Saturation
	0-13	66.5	31.3	2.2	0.11	0.26	0.52
Andosol	13-46	66.4	33.2	0.4	0.09	0.24	0.52
	46-130	87	12.2	0.8	0.05	0.12	0.43
	0-20	28	45.8	26.2	0.30	0.45	0.49
Luvisol	20-60	43	41.6	15.3	0.25	0.36	0.43
	60-105	37.9	46.1	16.1	0.28	0.41	0.45
	105-150	53.2	45.7	1.1	0.25	0.32	0.37

Weather data

Historical weather data (1984-2009) was obtained from the National Meteorological Agency of Ethiopia. The weather data (rainfall and temperature) had been previously quality checked and published by Kassie et al. (2013). Radiation data was estimated using the Angström (Supit, 1994) and the modified Hargreaves-Samani equations (Hargreaves and Samani, 1982; Allen et al., 1998; Annandale et al., 2002; Almorox, 2011). For years with records of sunshine hour, the Angström equation was used to estimate the radiation while for years with no sunshine hour records, the Hargreaves-Samani equation was used. We estimated the difference between the two methods.

3.2.4. Model calibration and evaluation

Site-specific calibration and evaluation of model performance is a precondition for using models for other locations than they were developed (Thornton et al., 1995; Tsuji et al., 1998; Jones et al., 2001; Van Ittersum et al., 2003). The main objective of model calibration was to adapt the model parameters to local conditions (e.g. soil types and weather conditions) to gain a good overall agreement between simulated and observed values. The models used in this study were therefore calibrated using the experimental data presented in Table 3.2. The datasets from 2003 and one set of 2009 (set I) were used for model calibration and the data set from 2004 and the second dataset of year 2009 (set II) were used for model evaluation. We focused model calibration on phenology first and then on growth and yield. Performance of the models was evaluated comparing the deviation between observed and simulated values. Statistical indicators, i.e. the root mean square error (RMSE), index of agreement (d)

(Willmott, 1981) and coefficient of determination (R^2) were used, as in other studies (e.g. Rötter et al., 2012b) for evaluating the performance of DSSAT. For the statistical evaluation of DSSAT performance, the nitrogen sub-routine of DSSAT model was turned-on and nitrogen-limited and high nitrogen treatments were simulated. Small values of RMSE and d-values, and R^2 close to 1 were considered as indicators for good performance of the DSSAT model. These statistical measures could not be used for WOFOST as its evaluation was restricted by too few data points and only one high nitrogen treatment.

3.2.5. Yield variability and yield gap analysis

After calibration and evaluation of the models, a multi-year simulation with historical weather data (1984-2009) was carried out to analyze yield variability and gaps. The simulation was done for three sites which represent rainfed maize production areas in the CRV. The onset of planting date within a planting window (April 15-July 7) was triggered when accumulated rainfall reached 40 mm in five consecutive days (Raes et al., 2004; Araya and Stroosnijder, 2010). Initial soil water contents were set to 50% of the water holding capacity, which provides nearly similar initial conditions at the start of the simulation for both models despite the differences in number of soil layers in the two models. Two levels of yields, namely water-limited and potential yield were simulated. Potential yield is the yield of a crop cultivar when grown with water and nutrients non-limiting and biotic stress effectively controlled (Van Ittersum and Rabbinge, 1997). Therefore, the potential yield is limited by climate conditions (temperature, solar radiation, CO_2 concentration) and plant genetic characteristics. The water-limited yield, which is also known as water-limited yield potential, is additionally influenced by rainfall and soil water characteristics. The inter-annual variability of simulated yields was evaluated using the coefficient of variation (CV).

Yield gap analysis involves quantifying the differences between simulated potential yield and farmers' yield levels and identifying those factors responsible for the yield differences (Lobell et al., 2009; Liang et al., 2011; Van Ittersum et al., 2013). The references for calculating yield gaps are yields under optimum management which are potential yield under irrigation conditions or water-limited yield under rainfed conditions (Van Ittersum and Rabbinge, 1997). Since maize is predominantly grown under rainfed conditions in our study area, we used the simulated water-limited yield as a reference to calculate current yield gaps. In case of African small holder agriculture, Tittonell and Giller (2013) suggested that the concept of yield gaps can be meaningful when at least two main components of yield gaps are distinguished: (i) the gap between water-limited and average farmers' yield and (ii) the gap between best yields attained in farmers' fields and average farmers yields. Accordingly, we calculated three types of yield gaps: (1) the gap between simulated water-limited yield and average farmers' yield, (2) the gap between water-limited yield and on-farm trial yield and, (3) the gap between on-farm trial yield and average farmers yield. We quantified gaps for each individual year and used the average to define the yield gap for each study site.

Average and on-farm trial yields

Average (actual) and on-farm trial yields were obtained from reports of agricultural research centers and the National Agricultural Extension Intervention Program (NAEIP) of Ethiopia (Gebre et al., 2002; Nigussie et al., 2002; Howard et al., 2003; Abebe et al., 2005; Rockström et al., 2009) and presented in Table 3.4. Average farmer yield refers to yield levels achieved with current conventional farming practices, often including low or no external inputs. A minimum of 5 recent years of average yield data are required to define a meaningful yield gap for a given study area (Hochman et al., 2013; Van Ittersum et al., 2013). The average yields in our yield gap calculation were based on data from 6 to 10 years depending on available databases for the study sites. On-farm trial yields are from on-farm technology demonstration and NAEIP field trials achieved with improved agricultural practices (e.g. fertilizer, improved seed) at farmers' plots and under farmers' management. On-farm demonstration and NAEIP field trials were designed to test and disseminate improved agricultural inputs and practices using so-called 'model farmers' (Howard et al., 2003; Spielman, 2008). Accordingly, the on-farm trial yields are assumed to be approximations for best farmers' yield (best yields attained in farmers' fields), i.e. yield levels that well-endowed farmers can achieve on their fields.

Table 3.4: Average farmers' and on-farm trial yields at three representative sites in the CRV, Ethiopia (Nigussie et al., 2002; Howard et al., 2003; Abebe et al., 2005; Worku et al., 2012).

Yield type	Awassa		Ziway		Melkassa	
	Years	Yield (Mg/ha)	Years	Yield (Mg/ha)	Years	Yield (Mg/ha)
Average farmers' yield	1992-2000, 2005-2007	2.3	1997-2000, 2005-2007	2.0	1988-2007	2.1
On-farm trial yield	1992-2003	5.2	2002-2007	3.8	2001-2007	3.1

3.3. Results

3.3.1. Model calibration and evaluation

Cultivar parameters of development and crop growth, which have been adjusted in the calibration procedure of DSSAT and WOFOST models, are presented in Tables 3.5 and 3.6, respectively. Model evaluation with the calibrated cultivar parameters provided good agreement between simulated and observed values of crop phenology and yield components (Table 3.7). Dates of anthesis were simulated with a deviation of 2 days (WOFOST) and 5 days (DSSAT) for BH540 and no deviation with WOFOST and 1 day with DSSAT for Melkassa1. Dates of physiological maturity were simulated with a deviation of 1 day (DSSAT) and 3 days (WOFOST) for BH540 and 2 days (WOFOST) for Melkassa1. The good agreement between simulated and observed yield is also indicated by low values of the RMSE (0.69 Mg/ha for BH549, 0.47 Mg/ha for Melkassa1), a close-to-one index of agreement (0.95 for BH540, 0.93 for Melkassa1) and a high coefficient of determination (0.89 for BH540, 0.96 for Melkassa1) calculated for DSSAT (not shown here). Comparison of model simulated water-limited yield and on-farm trial yield for the period 1992-2003 (Fig. 3.1) shows that in most cases, years with high simulated yields have also relatively high on-farm trial yields. However, the simulated yields are generally higher than on-farm trial yields. The main reason is that on-farm trials used for the comparison were not absolutely free from the effects of yield reducing factors (e.g. pests, disease, weeds), whereas in model assumptions such factors are perfectly controlled and management is optimal.

Table 3.5. Genetic coefficients of maize cultivars calibrated in DSSAT.

Code	Description	BH540	Melkassa1
P1	Thermal time from emergence to end of the juvenile phase, degree days	220.1	101.5
P2	Development delay for each hour increase in photoperiod above a maximum development rate, days	0.86	0.75
P5	Thermal time from silking to physiological maturity, degree days	840.1	685
G2	Maximum possible number of kernels per plant	266.2	375
G3	Kernel optimum filling rate during the linear grain filling stage, mg/day	10.65	11.65
PHINT	Phylochron interval: Thermal time between successive leaf tip appearances, degree days	38.9	40

Table 3.6. Cultivar parameters calibrated in WOFOST for the cultivars BH540 and Melkassa1.

Code	Description	BH540	Melkassa1
TSUM1	Temperature sums from emergence to anthesis (°C.d)	750	540
TSUM2	Temperature sums from anthesis to maturity (°C.d)	710	570
SPAN	Life span of leaves (days)	30	30
AMAXTB	Maximum leaf CO_2 assimilation rate (kg/ha/hr).	55	60
EFFTB	Light use efficiency	0.45	0.5
KDIFTB	Extinction coefficient for diffuse visible light	0.70	0.70
LAIEM	Leaf area index at emergence	0.026	0.026
RGRLAI	Maximum relative increase in LAI (ha/ha/day)	0.05	0.05
DEPNR	Drought sensitivity group	4.5	4.5

Table 3.7. Results of model evaluation for phenology and grain yield simulations of cultivars BH540 and Melkassa1. Observed values used for evaluation were experimental data of Awassa experimental station in 2009 (cultivar BH540) and Ziway in 2004 (cultivar Melkassa1).

Site/Cultivar	Phenology and yield characteristics	Observed	Simulated	
			DSSAT	WOFOST
Awassa/BH540	Days to anthesis (days)	69	62	71
	Days to maturity (days)	136	137	139
	Water-limited yield (Mg/ha)	6.3	7.4	7.0
	Potential yield (Mg/ha)	8-10	8.2	9.0
Ziway/Melkassa1	Days to anthesis (days)	52	51	52
	Days to maturity (days)	104	104	106
	Water-limited yield (Mg/ha)	5.9	6.5	5.8
	Potential yield (Mg/ha)	7.1	7.5	7.3

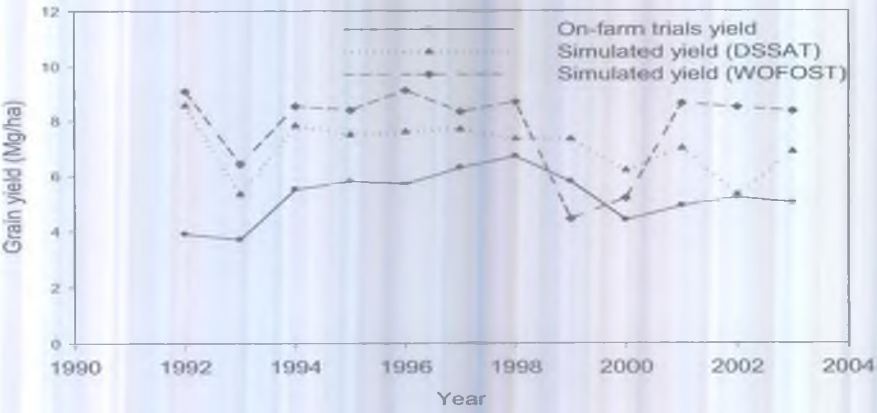

Fig. 3.1. Simulated water-limited vs. observed (on-farm trial) yields for a late maturing cultivar (BH540) at Awassa for the period 1992-2003.

3.3.2. Analysis of yield levels, variability and gaps

Potential yield

The mean potential yield ranged between 8.2 and 9.2 Mg/ha for the late maturing cultivar and between 6.8 and 7.1 Mg/ha for the short duration cultivar (Table 3.8); the lower yields were simulated with DSSAT. The minimum potential yield of the early maturing cultivar during the simulation period was 5.8 Mg/ha (not shown here), while the maximum potential yield varied between 8.3 (DSSAT) and 10.1 Mg/ha (WOFOST). For the late maturing cultivar, the minimum potential yield varies between 6.9 Mg/ha (DSSAT) and 7.9 Mg/ha (WOFOST) while the maximum potential yield was 10.5 Mg/ha. The coefficient of variation of the simulated potential yield ranged between 7% (WOFOST) to 10% (DSSAT) for the late maturing and 9% (DSSAT) to 14% (WOFOST) for the early maturing cultivar. The different methods used to estimate the solar radiation in this study did not show large differences in simulated potential yield. The mean simulated potential yield at Ziway (1996-2007) was 9.1 Mg/ha using radiation estimated with Angström equation and 9.5 Mg/ha using radiation estimated with Hargreaves equation which results in a difference of 4.2%.

Table 3.8. Mean potential yields (Mg/ha) of BH540 and Melkassa1 cultivars as simulated with DSSAT and WOFOST at three locations for the period 1984-2009.

Site	BH540		Melkassa1	
	DSSAT	WOFOST	DSSAT	WOFOST
Awassa	8.2	9.8	6.9	8.2
Melkassa	7.3	8.3	5.9	5.3
Ziway	9.0	9.4	7.7	7.8
Mean	8.2	9.2	6.8	7.1
CV (%)	10	7	9	14

Water-limited yield

The two soil types (Andosol and Luvisol) do not show much difference in mean water-limited yield since differences in water retention characteristics are small. Hence detailed results presented here are for one soil type (Andosol) only. For a late maturing cultivar, the average water-limited yield as simulated with DSSAT was 7.2 Mg/ha (Fig.3.2). The coefficient of variation for water-limited yield simulated with DSSAT ranges from 10 to 26% with an average value of 17%. The simulation with WOFOST indicates an average water-limited yield of 7.9 Mg/ha. The coefficient of variation of water-limited yield simulated with WOFOST ranged between 19 and 28% with an average value of 23%. For the early maturing cultivar, DSSAT simulates an average water-limited yield of 6.7 Mg/ha. The coefficient of variation ranged between 9 to 16% with an average value of 15%. The mean water-limited yield simulated with WOFOST was 6.1 Mg/ha. The coefficient of variation ranged between 22 to 35% with an average value of 28%. Generally, the mean water-limited yield simulated with DSSAT and WOFOST showed little difference, however, the inter-annual yield variability differed, i.e., CV 9-26% for DSSAT and CV 19-35% for WOFOST.

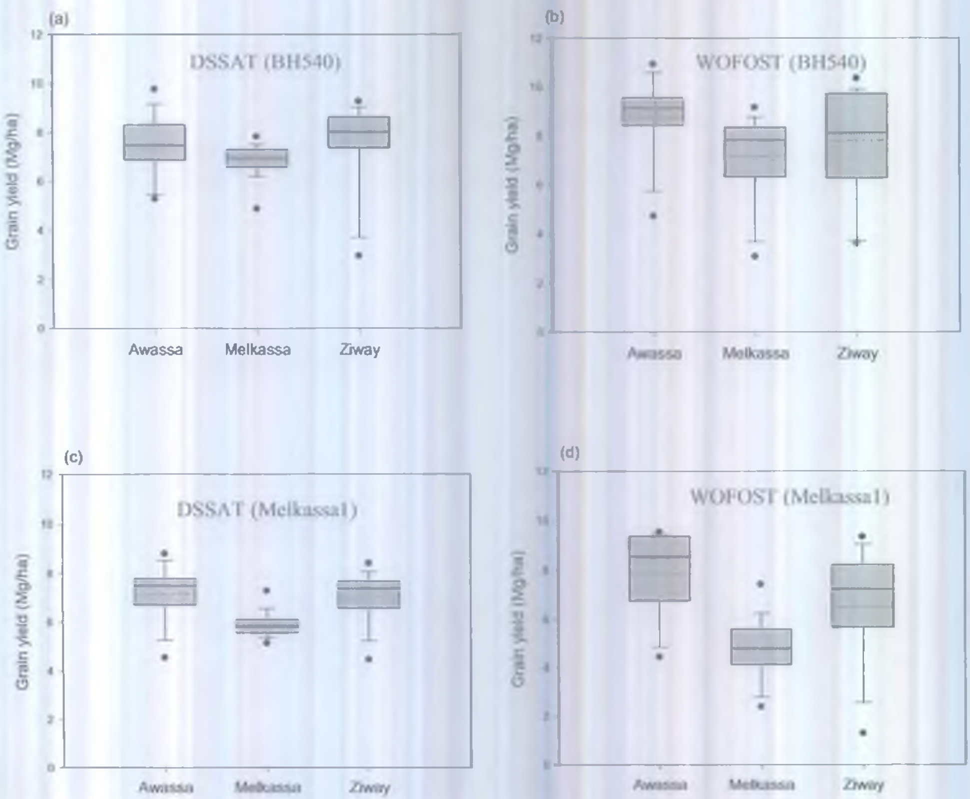

Fig. 3.2. Water-limited yield of a late maturing cultivar (BH540) and an early maturing cultivar (Melkassa1) as simulated with DSSAT and WOFOST models for the period 1984-2009 at three representative sites of the CRV on Andosol: (a) simulation with DSSAT for BH540, (b) simulation with WOFOST for BH540, (c) simulation with DSSAT for Melkassa1 and (d) simulation with WOFOST for Melkassa1. Boxes indicate the lower and upper quartiles. The solid line within the box is the median and the dotted line is the mean. Whiskers indicate the minimum and maximum values and dots outside the whiskers are outliers.

Yield gaps

The gap between simulated water-limited yield and average farmers' yield varied between 4.7 and 6.0 Mg/ha (Table 3.9). On-farm trial yield yields were 2.0 to 3.8 Mg/ha lower than the simulated water-limited yields. The gap between on-farm trial yield and average farmers yield varied between 1.1 to 3.1 Mg/ha. In relative terms, actual yields were 28-30% of the water-limited yield and 44-65% of on-farm trial yields while the on-farm trial yields were 50-73% of the water-limited yield. Time series analysis of observed yields at Melkassa for the period 1988-2007 showed an inter-annual variability of 35% (Fig. 3.3) while the simulated yield for the corresponding period had a coefficient of variation of 15% (DSSAT) or 32% (WOFOST).

Table 3.9. Yield gaps for rainfed maize at three sites in the CRV. The water-limited yield (Yw) is the average of 20 years (1990-2009) simulated with DSSAT and WOFOST models. The actual (Ya) and on-farm trial (Yb) yields are means for 6 to 12 recent years depending on data availability for each site (see Table 3.4 for the available dataset).

	Awassa	Melkassa	Ziway
Yield (Mg/ha)			
Average farmers' (Ya)	2.4	2.0	2.0
On-farm trial (Yb)	5.5	3.1	3.8
Simulated water-limited (Yw)			
DSSAT	7.5	6.7	7.3
WOFOST	8.4	6.8	7.6
Yield gap (Mg/ha)			
Yw-Ya (using DSSAT for Yw)	5.1	4.7	5.3
Yw-Ya (using WOFOST for Yw)	6.0	4.8	5.6
Yw-Yb (using DSSAT for Yw)	2.0	3.6	3.5
Yw-Yb (using WOFOST for Yw)	2.9	3.7	3.8
Yb-Ya	3.1	1.1	1.8

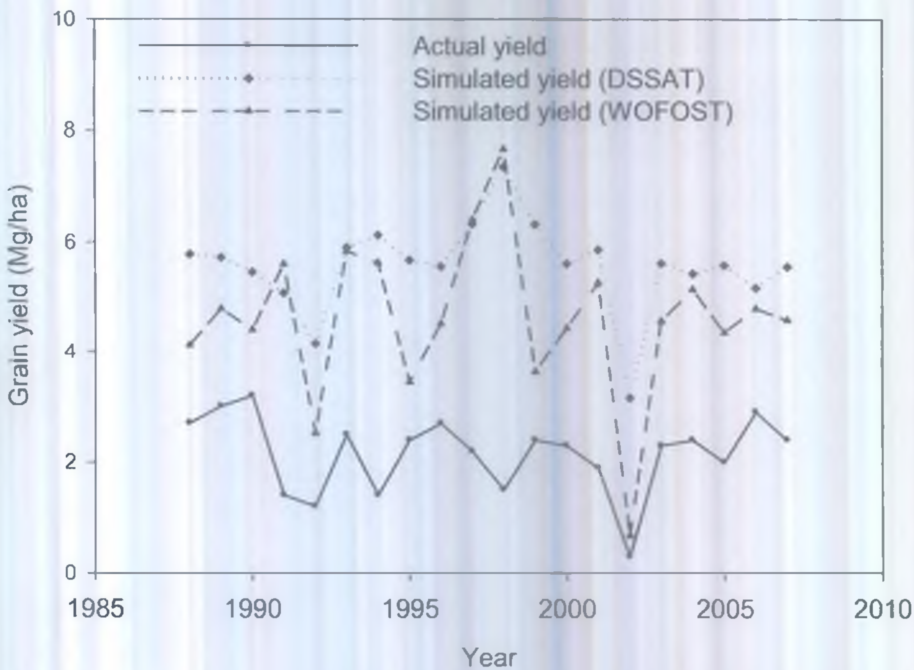

Fig. 3.3. Time series comparison of observed and simulated (water-limited) yield variability for an early maturing cultivar (Melkassa1) at Melkassa for the period 1988-2007.

3.3.3. Correlation between climatic factors and yield variability

The coefficient of variation of water-limited yield is higher than the coefficient of variation of potential yield showing the effect of rainfall variability on maize production. A correlation analysis between simulated water-limited yield and growing season minimum temperature, maximum temperature, solar radiation and rainfall had correlation coefficients (R) of -0.25, -0.54, -0.23 and 0.8, respectively, at Ziway (data not shown). Among the climate factors, growing season rainfall and maximum temperature showed significant correlation ($P<0.05$) with the water-limited yield. The growing season rainfall was clearly more variable (CV 21%) than the maximum temperature (CV 2%) and hence, is the major source of risk in rainfed maize production in the CRV. Generally, the yield increased with increasing seasonal rainfall totals (Fig. 3.4). The lowest water-limited yield over the simulation period (1984-2009) corresponded to years with lowest seasonal rainfall. Spatially, higher inter-annual variability of yields was associated with areas at lower altitudes (Ziway, 1640 m.a.s.l and

Melkassa,1550. m.a.s.l), which have lower annual rainfall and higher potential evapotranspiration than the area with intermediate altitude (Awassa, 1750 m.a.s.l). For instance, the yield variability for a late maturing cultivar was 16-18% at Awassa while it was 26-27% at Ziway.

Analysis for the water balance during the growing seasons indicates that the mean seasonal actual evapotranspiration (averaged across the three sites) simulated with DSSAT ranged between 480-610 mm while with WOFOST it ranged between 460-580 mm. An example of water balance components of both models is presented in Table 3.10 for Ziway. The correlation coefficient (R) between yield and evapotranspiration was 0.5 (DSSAT) to 0.7 (WOFOST) at Awassa (Fig. 3. 5) and is significant ($p<0.05$), while the correlation coefficient was 0.8 for both DSSAT and WOFOST at Ziway which is highly significant ($p<0.01$).

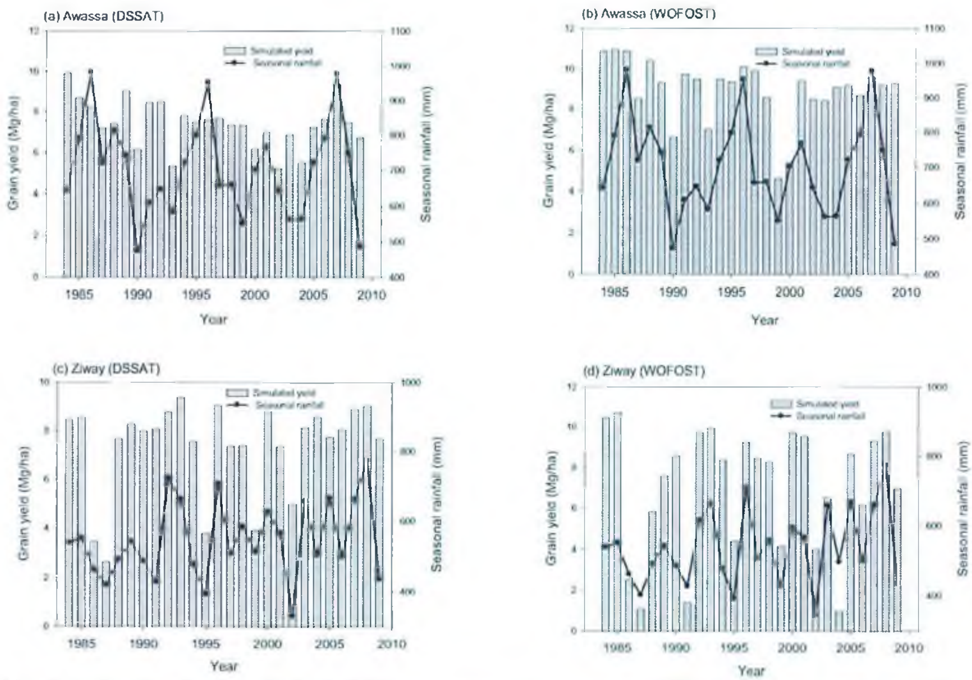

Fig. 3.4. Simulated water-limited yield versus growing season rainfall for a late maturing cultivar (BH540): (a) simulation with DSSAT at Awassa, (b) simulation with WOFOST at Awassa, (c) simulation with DSSAT at Ziway (d) simulation with WOFOST at Ziway.

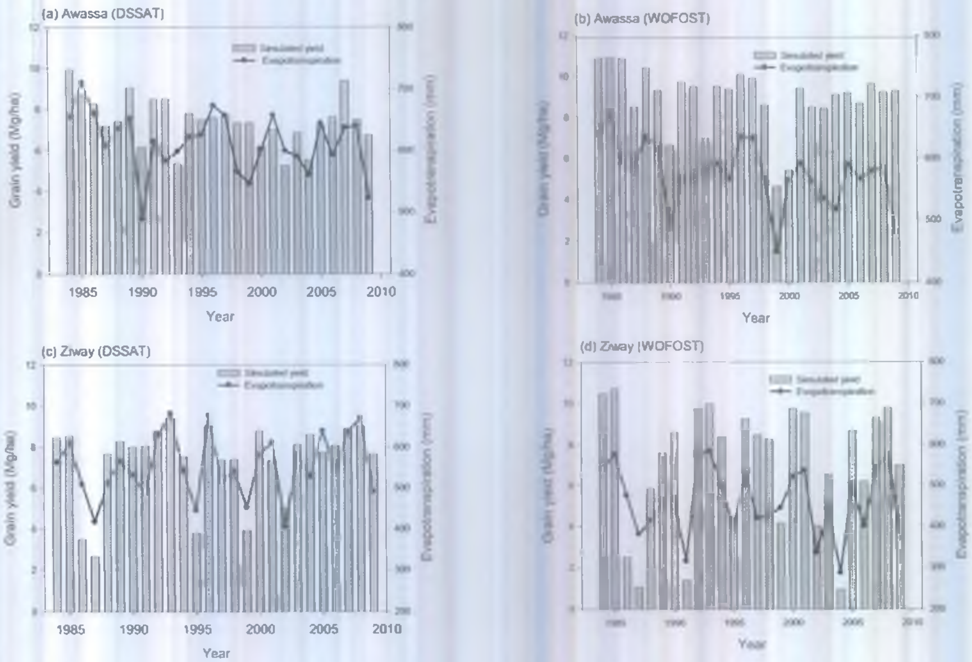

Fig. 3.5. Simulated water-limited yield versus growing season evapotranspiration for a late maturing cultivar (BH540): (a) simulation with DSSAT at Awassa, (b) simulation with WOFOST at Awassa, (c) simulation with DSSAT at Ziway and (d) simulation with WOFOST at Ziway.

Table 3.10. Water balance parameters as simulated with DSSAT and WOFOST for the growing season of maize (1984-2009) at Ziway.

Parameters	DSSAT	WOFOST
Transpiration (mm)	380	285
Soil evaporation (mm)	172	177
Runoff (mm)	25	32
Deep drainage (mm)	14	48
Rainfall (mm)	540	540
Soil water depletion (mm)*	51	2

*Soil water depletion refers to the difference in water content of the soil between the beginning and end of the growing season

3.4. Discussion

3.4.1. Model calibration, evaluation and application

The results of model calibration and evaluation showed that WOFOST and DSSAT models simulated grain yield and phenological development of maize reasonably well. However, long- term simulations indicate that the two models differ in capturing yield variability. The inter-annual variability of simulated yield is higher for WOFOST than DSSAT. Differences in simulated yields between WOFOST and DSSAT were 0.4-1.6 and 0.4-1.0 Mg/ha for potential yield and water-limited yield, respectively. These differences are substantial, even though they are relatively small compared to the large yield gaps in CRV. In line with our findings, other crop simulation studies reported differences between multi-model results (Eitzinger et al., 2004; Kersebaum et al., 2007; Palosuo et al., 2011; Rötter et al., 2012a).

In our study, one difference between the two models was that evapotranspiration was calculated using the Priestley-Taylor approach (Tsuji et al., 1998) in DSSAT, while WOFOST uses the Penman method (Van Diepen et al., 1989). The Priestley-Tailor estimates the reference-evapotranspiration from the solar radiation and temperature, whereas the Penman approach considers both radiation terms (solar radiation and temperature) and aerodynamic terms (wind speed and vapor deficit). Studies using these approaches indicate that WOFOST sometimes overestimates the effect of crop water stress reducing transpiration and crop growth (Supit et al., 2010), whereas DSSAT may overestimate evapotranspiration (De Jonge et al., 2012). Thus, the two models may consequently show differences in water use and transpiration simulations.

Another cause of divergences might be the different ways in which soil water uptake is simulated over the soil profile, whereby the differentiation in soil properties and layers is much simpler in WOFOST than in DSSAT. Details of the various approaches of water uptake in crop growth models can be found in Van den Berg and Driessen (2002), Van den Berg et al. (2002) and Eitzinger et al. (2004). DSSAT simulates the soil water balance for each soil layer with its specific soil water uptake relations, whereas WOFOST considers homogenous soil texture of the whole soil profile. In models that perform calculations considering homogeneous soil layers, water is assumed to be distributed over the entire rooting zone, whereas in reality, it is concentrated in the surface layer, where it is readily available. This approach seems less suited for applications in areas with variable rainfall distribution (Van den Berg et al., 2002). Furthermore, water uptake in WOFOST does not depend on rooting density but only on actual rooting depth and available soil water, whereas root density is important in DSSAT simulations. The two models also differ in the mechanisms of controlling the termination of root elongation, i.e., in WOFOST root growth terminates at anthesis whereas in DSSAT, it continues until maturity.

The different approaches in modelling the soil water balance dynamics cause the simulated differences in soil water depletion (changes in soil water content between the beginning and end of the growing season) and transpiration, and contribute consequently to differences in simulated crop yield variability. In addition to the differences in simulating water balance dynamics, DSSAT uses the relatively simple radiation use efficiency approach to model net photosynthesis (Tsuji et al., 1998; Palosuo et al., 2011), while WOFOST uses a more detailed approach for describing photosynthesis and respiration (Palosuo et al., 2011). The differences in simulating yields are related to different approaches used by the two models in describing the crop growth dynamics. Thus, a multi-model crop simulation approach is necessary to be able to quantify some of the uncertainties in such studies. Multiple model simulation enables to better represent uncertainty in model structure, parameters and input data as discussed, for instance, by Clemente et al. (2005), Tebaldi and Knutti (2007), Challinor et al. (2009c), Palosuo et al. (2011), Rötter et al. (2011a) and Asseng et al. (2013).

One of the limitations of this study was that the models have been calibrated and evaluated with a limited set of information. For instance, in-season measurements of crop growth parameters were not available. Furthermore, the nutrient management of the experimental data used for model calibration was based on local recommendation rates and it may have resulted in nutrient-limited conditions, while this was not assumed in the model configurations. We can thus not rule out the possibility that we have underestimated the yield potentials and thus underestimated yield gaps.

3.4.2. Yield levels and gaps

The simulated potential yield with both models is in good agreement with the highest yields of the cultivars reported from field experiments in the study areas. For instance, Worku et al. (2012) reported that potential yield of maize cultivar BH540 is about 9-10 Mg/ha and Biazin and Stroosnijder (2012) reported 8.5 Mg/ha. In our study, actual farmers' yields were 28-30% of simulated water-limited yield and 44-65% of on-farm trial yields. This result is consistent with similar studies in Sub-Saharan Africa. For instance, Tittonell et al. (2008) reported that the average farmers' yield of maize in Kenya was 25% of the water-limited yield potential. Rötter (1993) and Rötter and Dreiser (1994) found for several sites in semi-arid to sub-humid climatic zones of the Kenyan Rift Valley that maize yields at moderate levels of N and P fertilizer application (e.g. 50 kg N/ha and 22 kg P/ha) reached 40-60% of water-limited yields. Clearly such yield gaps are very significant and much larger than in high-input agricultural systems. Existing gaps between water-limited and farmers' yields indicate that recommended production technologies (e.g. NPK fertilizer) are hardly adopted at farmers' fields. This can also be clearly noticed from the existing gaps between on-farm trial and farmers' actual yields. The on-farm trails were conducted with farmers' management with supply of required inputs and extension advisory services, which suggest that improving access to agricultural inputs (fertilizer) and increasing resource use efficiency through agro-advisory services, could increase yield and consequently narrow yield gaps. Farmers in Ethiopia, as in many parts of Africa and some parts of Asia, generally, apply lower rates of fertilizer than the recommended amount. Soil nutrient balances are in many cases negative (Abegaz and van Keulen, 2009). The average fertilizer rate used by Ethiopian farmers is 21 kg N/ha (Spielman et al., 2011) which is much lower than the national recommendation rates of 60-100 kg N/ha (Debelle et al., 2001) and that in other parts of the world, e.g. 100 kg /ha in South Asia, and >200 kg/ha in Western Europe and North America (Potter et al., 2010). Detailed analysis of socio-economic factors that determine agricultural technology adoption in Ethiopia is beyond the scope of this study, but Spielman et al. (2011) indicated that high cost of inputs and insufficient credit services are among the most critical constraints to farmers to adopt the available seed-fertilizer technology packages, which is a widespread problem in Africa (Tittonell and Giller, 2013). The existing yield gaps indicate that maize productivity is currently far below what would be possible with good management in the CRV of Ethiopia. Exploiting the gaps between yields achieved currently on farmers' fields and those that can be achieved by using improved technologies, including climate risk management strategies, is a key pathway to feed the increasing population at local, regional and global scales (Cassman, 1999).

3.4.3. Climate-induced yield variability

Climate variability, particularly variable rainfall, is the main cause for inter-annual variability of rainfed maize production in the CRV. In this respect, the CRV is representative for very large portions of the semi-arid lands of Eastern Africa, especially the rift valley regions (e.g.

Rötter and Van Keulen, 1997; Cooper et al., 2008). Details of climate variability and change in the CRV have been discussed in Kassie et al. (2013). Our analysis indicates that the growing season rainfall amount explains about 60% of the variation in maize yields in Ziway. Other studies (e.g. Hellmuth et al., 2007; Dixit et al., 2011; Müller et al., 2011) confirm that climate-induced risks, and in particular rainfall-related risks, are the most important causes for uncertainty in crop production in most regions of Sub-Saharan Africa.

Rainfall variability affects crop yields not only by its direct impact on water availability but also indirectly through limiting the application of agricultural inputs (e.g. fertilizer). For that reason, already in the 1980s, scientists designed risk management strategies that represent adaptive management options based on rainfall criteria, i.e. empirical rules such as those related to the onset of the rainy season. For instance, the earlier the onset, the higher the probability of a favorable season as identified for "response farming" in East Africa (Stewart and Faught, 1984; Stewart, 1988). According to Keating et al. (1993), this practice, when applied to adapting nitrogen fertilization at Katumani (Kenya) did not much increase the average gross margin at farm level, but significantly decreased the risk of financial loss in poor rainfall years. Obviously, however, the practice of response farming has not yet been widely applied.

As many authors (e.g. Fufa and Hassan, 2006; Gebremedhin et al., 2009; Alem et al., 2010) have reported over the last decades, the agricultural extension program of Ethiopia has promoted fertilizer use, but its success in increasing agricultural productivity has been constrained mainly by uncertain rainfall patterns, as had been found in an early study on assessing risks and opportunities for smallholders of applying fertilizer to maize in similar environments in Kenya (Rötter and Dreiser, 1994; Rötter and Van Keulen, 1997). The low fertilizer inputs and rainfall variability result in yields being constantly low. Of course, low yield response to fertilizer can also be explained with poor agricultural extension and weak agro-meteorological services. Adaptation to the increasing climate variability is now imperative to sustain crop production in the CRV. Climate-proof strategies including better seasonal climate forecasts (Hansen et al., 2011), improved cultivars and efficient rain-water management are critical for improving rainfed agriculture.

3.5. Conclusion

The study showed that gaps between water-limited yield and actual yields are large and yield variability is high in the Central Rift Valley of Ethiopia. Growing season rainfall variability is the main cause of yield variability and production uncertainty. Comparisons of simulated potential and water-limited yields indicate that there is some scope to increase yields with improving water supply. Actual farmers' yields are only 27-30% of the water-limited. The large gaps between simulated water-limited and farmers' yield levels indicate a large potential to increase yields with improved agricultural inputs, especially nitrogen fertilizer, in conjunction with various climate risk management strategies (e.g. effective weather forecast service, response farming, efficient rain-water management). There is a need to invest in technology transfer and institutional arrangements for improving access to "best" agricultural practices as for instance practiced in the on-farm trials that yielded on average 44-65% of the water-limited yield.

This study also demonstrated the use of crop simulation modelling in characterizing yield variability and climate risks, which is not yet a common research tool in Ethiopia. It also showed how the use of more than one model provides some insight in uncertainty of model simulations.

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CHAPTER 4

Adapting to climate variability and change: Experiences from cereal-based farming in the Central Rift and Kobo Valleys, Ethiopia

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Abstract

Smallholder farmers in Ethiopia are facing several climate related hazards, in particular highly variable rainfall with severe droughts which can have devastating effects on their livelihoods. Projected changes in climate are expected to aggravate the existing challenges. This study examines farmer perceptions on current climate variability and long-term changes, current adaptive strategies and potential barriers for successful further adaptation in two case study regions - the Central Rift Valley and Kobo Valley. The study was based on a household questionnaire, interviews with key stakeholders and focus group discussions.

The result revealed that about 99% of the respondents at the Central Rift Valley (CRV) and 96% at the Kobo Valley perceived an increase in temperature and 94% at CRV and 91% at the Kobo Valley perceived a decrease in rainfall over the last 20-30 years. Inter-annual and intra-seasonal rainfall variability also has increased according to the farmers. The observed climate data (1977-2009) also showed an increasing trend in temperature and high inter-annual and intra-seasonal rainfall variability. In contrast to farmers' perceptions of a decrease in rainfall totals, observed rainfall data showed no statistically significant decline. The interaction among various bio-physical and socio-economic factors, changes in rainfall intensity and reduced water available to crops due to increased hot spells, may have influenced the perception of farmers with respect to rainfall trends.

In recent decades, farmers in both the CRV and Kobo have changed farming practices to adapt to perceived climate change and variability, for example, through crop and variety choice, adjustment of cropping calendar, and in-situ moisture conservation. These relatively low-cost changes in farm practices were within the limited adaptation capacity of farmers, which may be insufficient to deal with the impacts of future climate change. Anticipated climate change is expected to impose new risks outside the range of current experiences. To enable farmers to adapt to these impacts critical technological, institutional and market-access constraints need to be removed. Inconsistencies between farmers' perceptions and observed climate trends (e.g. decrease in annual rainfall) could lead to sub-optimal or counterproductive adaptations and therefore must be removed by better communication and capacity building, for example through Climate Field Schools. Enabling strategies, which are among others targeted at agricultural inputs, credit supply, market access, and strengthening of local knowledge and information services need to become integral part of government policies to assist farmers to adapt to the impacts of current and future climate change.

Key words: *farm households, adaptation strategies, perceptions, Central Rift Valley, Kobo Valley*

4.1. Introduction

Africa is vulnerable to climate change due to its dependence on rainfed agriculture (Boko et al., 2007; Bryan et al., 2009; Glantz et al., 2009; Below et al., 2010; Kahiluoto et al., 2012). Smallholder farmers are particularly vulnerable to changes that negatively affect their climate dependent livelihoods (Nhemachena and Hassan, 2007; Ngigi, 2009 ; Thornton et al., 2010). Various studies indicate that smallholder farming is affected by current climate variability and will be further threatened by on-going climate change. (Thomas, 2005; Boko et al., 2007; Thomas et al., 2007; Cooper et al., 2008; Conway and Schipper, 2011; Müller et al., 2011). With a business-as-usual development, crop production might be marginalized in various parts of Sub-Saharan Africa (Jones and Thornton, 2009). According to the IPCC reports (IPCC, 2007), rainfed crop yields will decline by 10-20% by 2050 and crop revenues could fall by 90% by 2100. However, food production needs to be significantly increased to feed an increasing population (Thornton et al., 2011).

Like most African countries, Ethiopia heavily depends on agriculture, which contributes about 50% to the national GDP, supplies 73% of the raw materials to agro-industries and generates 88% of the export earnings (Deressa and Hassan, 2009). Ethiopian agriculture is characterized by a low use of external inputs and it is highly vulnerable to climate variability and change (Bryan et al., 2009; Conway and Schipper, 2011; Demeke et al., 2011; Bewket, 2012; Funk et al., 2012). Extreme weather events have resulted in food shortages and famines in the past (Mersha and Boken, 2005; Cheung et al., 2008; Conway and Schipper, 2011; Gray and Mueller, 2012) and they continue to pose a serious threat to Ethiopia's development (FAO, 2007). Smallholder farmers who depend on agriculture for their livelihoods need to improve their management of current climate variability, which is a prerequisite for adapting to future climate change (Rötter and Van Keulen, 1997; Müller et al., 2011). An essential step in improving and recommending appropriate adaptation strategies is to assess the available practices currently adopted by farm households in their efforts to address climate induced risks. Depending on their long-term experiences and subjective assessments of risks, farm households continuously develop adaptive strategies to environmental and socio-economic changes as part of their production and consumption decisions (Thornton et al., 2010; Tittonell et al., 2010). However, anticipated climate change often goes beyond existing adaptation capabilities and will impose additional stress on agricultural systems. To enable farm households to adapt to these changes, new adequate adaptation options need to be identified while taking into account and building on current strategies.

A better understanding of farmers' perceptions of current climate variability and expected climate change as well as of local practices in response to the current climate variability is important for policy makers to shape conditions for future adaptation (Nhemachena and Hassan, 2007; Bryan et al., 2009; Eriksen and Lind, 2009). Farm households are better able to adopt new technologies and practices when these fit in the context of existing practices. Future intervention need to be based on assessment of farmers' adaptive resources towards integrating local practices with scientific innovations (Kandji et al., 2006; Thornton et al., 2011). Despite its important role in agriculture and food security, climate change and adaptation has not yet been mainstreamed in the national research system and development efforts, and local adaptive responses to climate variability and change are not well documented in Ethiopia (Bewket, 2012). The main objectives of the study were therefore to assess perceptions of farm households on current climate variability and change, to identify and characterize current adaptive strategies of farmers, and to investigate barriers to implementing promising new adaptation measures. Furthermore, it compares farmers' perceptions and observed climate trends and discusses implications in addressing climate risk management. The study in general, draws insights from two contrasting case regions, both important for food security in Ethiopia and identifies lessons which could be relevant for mainstreaming of climate change adaptation at local, regional and global efforts.

4.2. Material and Methods

4.2.1. Descriptions of the study areas

The study was conducted in Adamitulu Jido Kombolcha and Dugda districts, hereafter called Central Rift Valley (CRV) in central Ethiopia, and Kobo Valley in northern Ethiopia (Table 4.1). The two districts in the CRV are situated 150 km south of Addis Ababa. The two bordering districts cover together approximately 273,500 ha and are situated at an altitude of 1500-2300 meters above sea level (m.a.s.l). Kobo Valley lies some 600 km north of the capital Addis Ababa, at the western-most range of the great escarpment of the Ethiopian Rift Valley. It is surrounded with mountains on the east and west, some over 3000 m high, whereas the valley itself, where this case study was conducted, is at 1300-1500 m.a.s.l. The total catchment area of Kobo valley is about 250,000 hectares.

The two case study regions represent small scale, mainly cereal-based mixed farming systems with relatively contrasting potentials and farming experiences. Kobo is food insecure with a long agricultural tradition (about 4000 years) but a low agricultural potential (Georgis et al., 2004). Increased population in recent decades has resulted in deforestation and degradation, and the cultivation of marginal hill side areas. The predominant rainfed agriculture with low external inputs is frequently unable to allow for local food security. Kobo is part of the area that was most affected during the 1983-84 famines and it faces food shortages almost once every three years (Bewket, 2008). It has poor access to markets with the closest urban center (Dessie) about 170 km away. The CRV districts, on the other hand, were dominated by pastoralists which during the past 20-30 years mostly became mixed farmers (Garedew, 2010; Kahiluoto et al., 2012). In relative terms, the CRV is a high potential area for agricultural production with soils of shorter cultivation history and less degradation, access to the fresh water Lake Ziway and better access to markets (Awassa and Adama within 50 km and Addis Ababa within 150 km). During the last decade, these favorable conditions have attracted various horticulture and floriculture enterprises, increasing the competition for scarce land and water resources and the environmental risks (Jansen et al., 2007).

Based on annual rainfall distribution, both study areas are characterized by a bi-modal rainfall pattern with a short rainy season, locally known as *belg* (March-May) and main rainy season, locally known as *kiremt* (June-September). Major crops (teff, maize, wheat, sorghum) are produced during the *kiremt* season. In recent decades, delayed onset and erratic distribution of *belg* rain frequently provided unfavorable conditions for crop production. Whenever the *belg* season gets adequate rain, short maturing cultivars of maize and teff in the CRV and sorghum in Kobo are produced.

4.2.2. Data collection and analysis

The study was based on interviews with key stakeholders, household surveys and focus group discussions. The household surveys were conducted in three villages in the CRV and two villages in the Kobo Valley from September to December 2010. The villages were selected based on discussions with experts and local development agents considering their vulnerability to climate risks such as recurrent drought, erratic rainfall, limited infrastructure and representativeness of cereal-based farming systems.

Table 4.1. Bio-physical and socio-economic characteristics of the study areas.

Characteristics	CRV	Kobo
Biophysical characteristics		
Altitude	1500-2300	1300-4000
Annual mean temperature (°C)	20.0-22.5	21.5-23.0
Annual mean rainfall (mm)	650-1000	600-850
Dominant soil types (FAO)	Andosols	Eutric vertisols
Topography	Plain land with small mountains	Undulated to plain
Socio-economic characteristics		
Total population	286,300	203,321
Population density (km^{-2})	136.8	127.6
Household size	5.4	5.7
Farm size (ha)	0.75-2.5	0.5-1
Production activities		
Farming system	Cereal-based mixed farming	Cereal-based mixed farming
Major food crops	Maize, teff, wheat	Sorghum, teff
Major cash crops	Haricot bean, teff, onions, tomato	teff
Livestock	Cattle, sheep	Cattle, goat, camel

A list of farm households was obtained from the agricultural district office and a total of 120 farmers in the CRV and 80 in Kobo were selected randomly from this list. The surveyed farm households varied in age, education level and land holding (Table 4.2). Both open and closed questions were interviewed with a semi-structured questionnaire (available from the corresponding author). Respondents were asked (i) to provide baseline information (household age, education level, land size, major crops and livestock); (ii) to list and prioritize major constraints to crop production; (iii) whether they had experienced any change in climate conditions of their local areas over the past 20-30 years. If respondents had experienced any change, they were asked subsequent questions to state the observed changes, causes and effects; (iv) to identify the various adaptive responses to the observed changes and effects; (v) to list future adaptation options needed and (vi) to identify any barriers for successful adaptation. Responses from the questionnaires were compiled and analyzed using the SPSS version 16 statistical analysis package (SPSS Inc., 2007). Five focus group discussions with a total of 53 farmers and 17 extension experts and development agents were also conducted to cross check the information obtained from the household survey and pinpoint perceptions, major risks and responses with particular emphasis on future needs and barriers for successful adaptation. The discussions were conducted first with the farmers and then with the extension experts and development agents. In addition to quantitative descriptive statistics, qualitative information in the form of narrative experiences and observations are provided in text boxes (Section 4.3).

Farmers' perceptions of climate change and variability were compared with climate records provided by the National Meteorological Agency of Ethiopia. Daily rainfall and temperature data was analysed to quantify variability and trends for the period 1977-2009 for two selected meteorological stations in the study areas, i.e., Ziway and Kobo. Ziway station is located at $7^0 56'$ latitude and 38^0 29' longitudes at an elevation of 1640 m.a.s.l in the CRV, whereas the station in the Kobo Valley is located at $12^0 09'$ latitude and $39^0 54'$longitude at an altitude of 1470 m.a.s.l. Rainfall variability was expressed for both stations by the coefficient of variation (CV) in a given period. Inter-annual variability was evaluated using standardized anomalies for rainfall with respect to the long-term average values. Linear regressions were established for temperature and rainfall trends.

Table 4.2. Characteristics of the surveyed households at the Central Rift Valley (CRV) and Kobo, Ethiopia. The total number of surveyed households for the analysis in this and the other tables was 120 at CRV and 80 at Kobo.

Characteristics	CRV %	Kobo %
Age		
20-30	23	13
31-60	73	79
>60	4	8
Educational level		
No education	18	54
Primary education	71	44
Secondary education	6	1
Post-secondary education	5	1
Household size		
0-3 members	26	13
4-6 members	38	56
> 6 .members	36	31
Landholding		
< 1 hectare	13	57
1-2 hectare	52	38
> 2 hectares	35	5

4.3. Results

4.3.1. Perceptions on climate variability and change

About 99% of the respondents in the CRV and 96% in Kobo perceived an increase in temperature and 94% in the CRV and 91% in Kobo perceived a decrease in main season (*Kiremt*) rainfall amount over the last 20 years (Fig. 4.1). In their opinion, rainfall distribution has changed as well: delayed starting dates and reduced number of rainy days in the main (June-September) rainfall season and increased heat waves were mentioned as the key characteristics of these changes. Both inter-annual and intra-seasonal rainfall variability have increased according to the respondents. All respondents in the CRV and 94% in Kobo stated that the rainfall has become more erratic and the frequency of drought has increased. According to farmers' views, 20 years ago drought occurred once in every 7 to 10 years but they think that droughts occur now every 3 to 4 years. Most of the respondents faced declining crop productivity, which they related to the decreasing and more erratic rainfall conditions. All respondents indicated that both in the CRV and Kobo, the short season (*Belg)* rains are no longer reliable for crop production due to decline in rainfall over the past two decades. Narratives from two respondents representing general perceptions of climate change are given in Box 4.1. Most of the respondents related changes in climate with deforestation. Particularly households in the CRV remembered that their region was covered with dense acacia forest, of which many have been cleared for crop cultivation resulting in "*Ye Ayer Mezabat*", meaning climate change. Few respondents (6%) associated the changes in climate with a natural phenomenon, which is only known by their God (data not shown here).

4.3.2. Comparing climate analysis with farmers' perceptions

Rainfall variability

In both study areas, rainfall showed high inter-annual and intra-seasonal variability (Fig. 4.2). The short season rainfall (March-May) at Ziway station in the CRV varied between 65 and 488 mm (CV=43%) and the main season rainfall (June-September) varied between 420 and 680 mm (CV= 24%). For the short rainy season, 45% of the years during the period 1977-2009 showed negative rainfall anomalies relative to the long term average. The main rainy season showed negative rainfall anomalies for 48% of the years. Annual and seasonal rainfall at Ziway generally exhibited a slight decline over the period 1977-2009 but there is no statistically significant trend. For Kobo station, the short season rainfall ranges between 16 and 319 mm (CV= 53%) and the main season rainfall varies between 117 and 693 mm (CV= 31%). About 48% of the years over the period 1977-2009 showed negative rainfall anomalies for the short rainy season and 58% exhibited negative rainfall anomalies for the main rainy season relative to the long term average. However, also for Kobo the rainfall trends are not statistically significant.

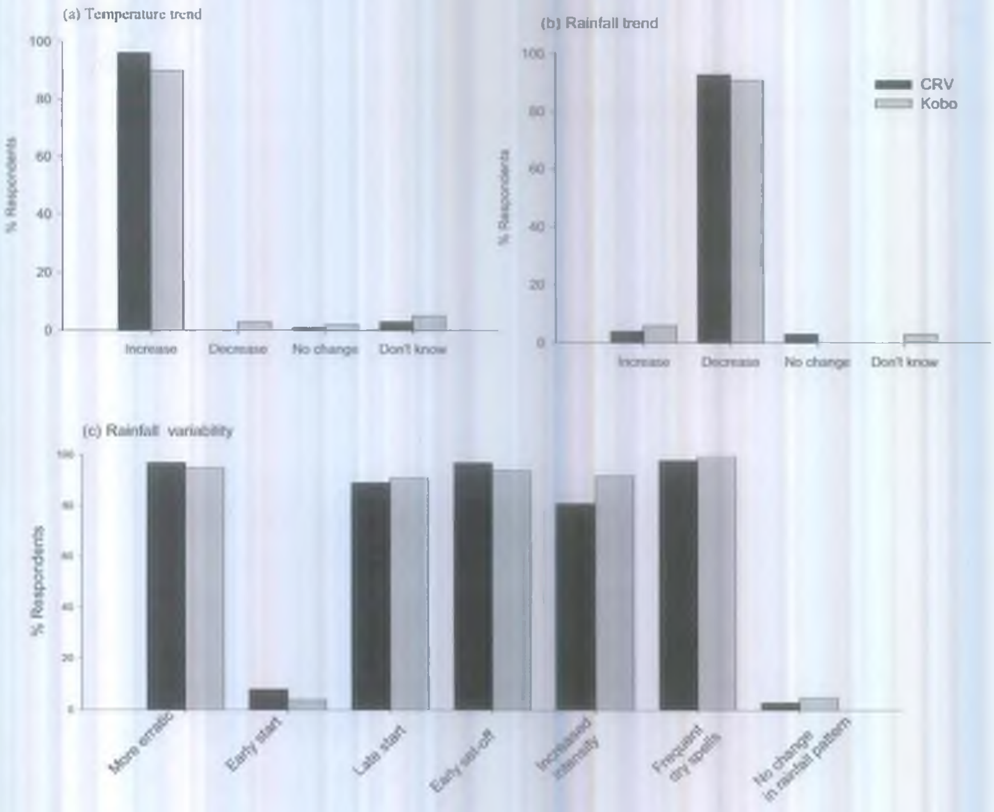


Fig. 4.1. Farm households' perceptions on climate variability and change: (a) temperature (b) rainfall trends and (c) long-term rainfall variability (based on interviews with 120 farmers in CRV and 80 in Kobo Valley, Ethiopia).

Temperature changes

Statistical analysis of temperature records of Ziway (CRV) and Kobo stations for the period 1977-2009 showed significant ($P < 0.05$) increasing trends (Fig. 4.3). For Ziway station, the daily minimum and maximum temperatures of the short rainy season increased with 0.6 and 1.2 °C per decade, respectively. Daily minimum and maximum temperatures for the main rainy season at Ziway increased with 0.7 and 0.9 °C per decade, respectively. The number of days with daily maximum temperature exceeding 32 °C (heat waves) increased significantly ($P < 0.05$) over the period 1977-2009 (not shown here). For Kobo station, the short rainy season daily minimum and maximum temperatures has increased with 0.4 and 0.9 °C per decade, respectively.

Box 4.1. Narratives of farmers' perceptions on climate variability and change to exemplify respondents' way of understanding a changing climate and associated risks (household survey, 2010)

A 62 year old farmer from Kobo presented his perception of climate variability and change as "Just 20 years ago, I used to cultivate "Degalit" (long duration sorghum variety) year to year and the crop harvest was much higher (about 80 "Kishkish" which is equivalent to 4 tons per hectare). In recent years, however, I am not able to plant "Degalit" because the rain starts too late. In previous years, the rain used to start around the mid of May to early June and continued till the end of October but recently it starts late (usually mid of July) and ends early (early September or sometimes mid of August). Season breaks and dry spells are frequent. Furthermore, in the past, the amount of rainfall per rainy day was not too much or too little but recently, it looks as if "it gets angry at something", i.e. higher rainfall intensity over shorter periods. In the past, the planting dates were on time and almost consistent year to year but recently we follow the approach of "Ende-Tale Zira" which means sow whenever it rains. The day time temperature is soaring. Crops face severe moisture stress starting from the early development stages and yield is usually low. Livestock is extremely affected by frequent droughts. I lost five cattle in the 2002/2003 drought, which was as severe as in 1984 and two cattle in the 2009 drought"

A 57 year old farmer at CRV mentioned his perception of climate change: "Thirty years ago, I used to live in Asab (Hottest arid place in Eretria, formerly part of Ethiopian administrative region) and that place is too hot to live. But in recent years, our local area (CRV) is also becoming hotter and hotter. I am afraid it is going to be as hot as at Asab. In the past, the rainy season was on time, and once the rainy season started it extended to October. But in recent years, the rainy season starts late and is short. Previously, the CRV was an agro-pastoral area and we had large herds but recently the livestock population has been reduced as a consequence of frequent droughts. For example, I had forty animals but now I have only five. Crop yields have been reduced. We did not know food aid but now many households appeal for food aid.

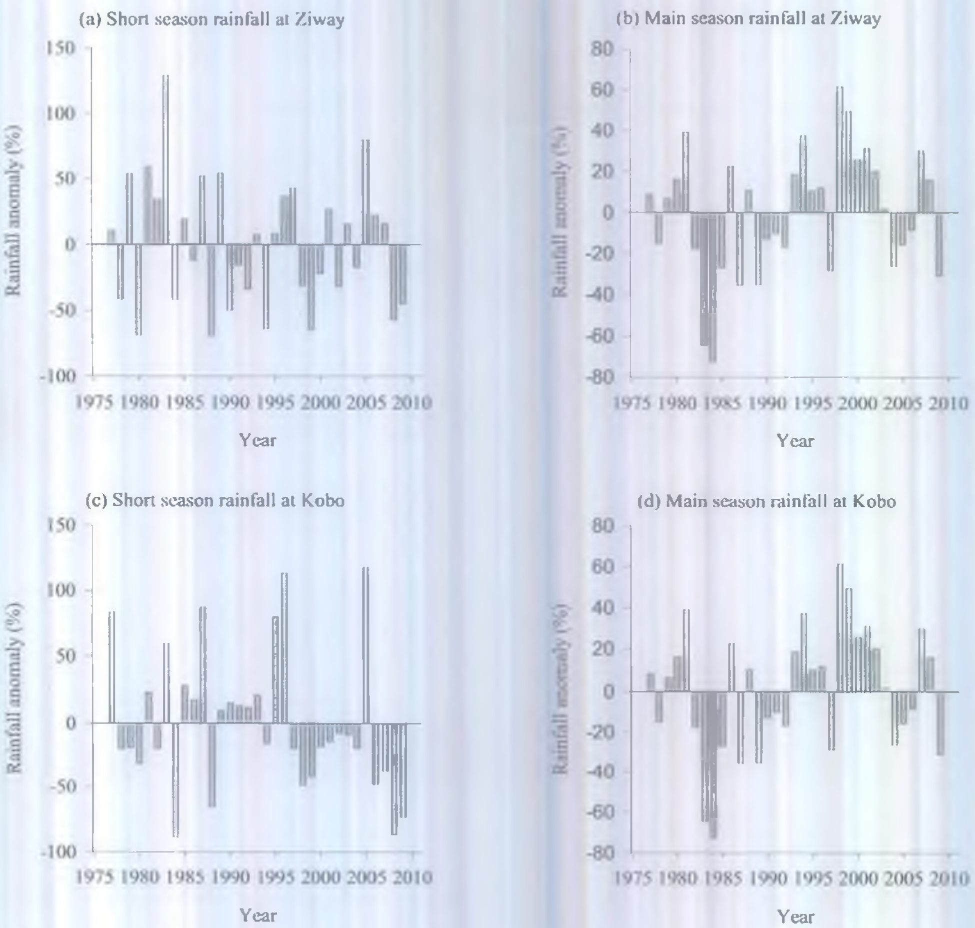


Fig. 4.2. Seasonal rainfall deviations from the long term mean (anomalies) over the period 1977-2009 at Ziway and Kobo weather stations, Ethiopia

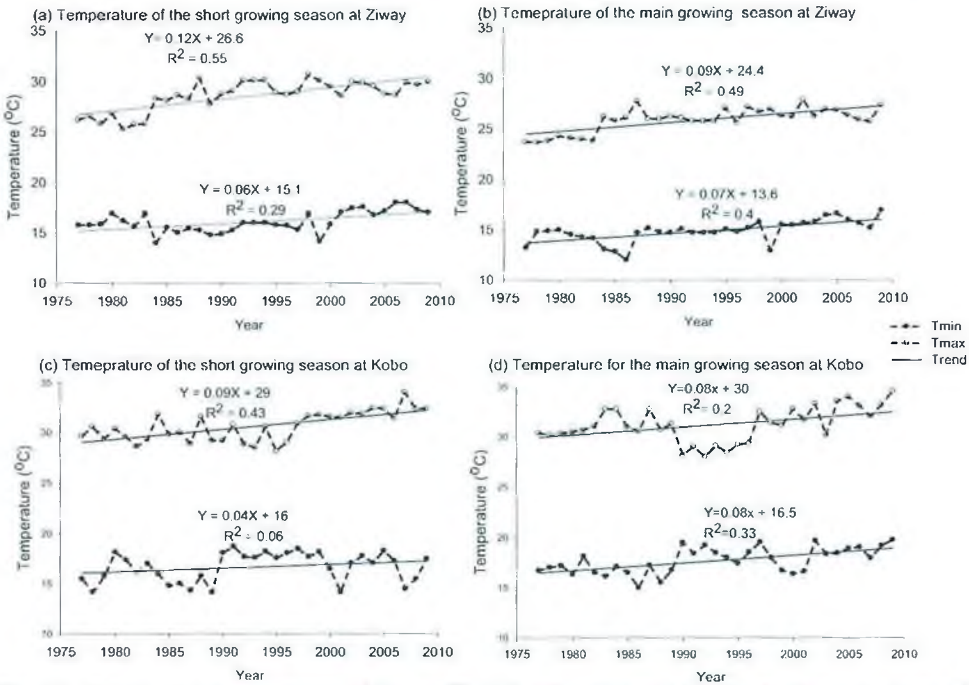


Fig. 4.3. Trends of growing season minimum (Tmin) and maximum (Tmax) temperatures observed over the period 1977-2009 at Ziway and Kobo weather stations, Ethiopia.

4.3.3. Perceived effects of climate variability and change

Table 4.3 presents bio-physical and socio-economic effects associated with climate variability and change. Farmers mentioned various aspects of climate induced effects such as decline in agricultural productivity and consequently increased food insecurity. A more quantitative analysis on perceived effects showed that reduction in crop yield and in some years loss of an entire crop was the most prevalent effect mentioned by all the respondents (Table 4.4). Almost all respondents in the CRV and Kobo stated that the traditional long duration, high yielding maize, teff and sorghum varieties cannot be grown any longer because of the changes in climate conditions. Most respondents (89% in the CRV and 91% in Kobo) indicated that pest and disease prevalence has increased in recent years associated with the changes in climatic conditions (Table 4.4). Respondents from Kobo mentioned that pests such as stalk borer on sorghum and shoot fly on *teff* are associated with low rainfall and high temperature, causing serious yield reductions.

Table 4.3. Effects of climate variability and change on agricultural production and resources as perceived by farm households (focus group discussions, 2010).

Attributes of climate	Perceived impacts	Cases mentioned
Increased temperature	Increased heat stress for crops and livestock, increasing evapotranspiration, increased pest and disease incidences	Increased occurrence of crop pests such as stalk borer on sorghum and shoot fly on teff, increased crop failure
Decreased rainfall	Decline of fresh surface water resources Inadequate moisture for crops Shortage of water for domestic and livestock use	Drying up of lakes and rivers (e.g. Lake Abijata in the CRV), River flows have reduced, some perennial rivers/streams have become ephemeral rivers/streams (e.g. Golina river in Kobo), local springs dried out
Total break of the short rainy season and discontinuity of main rainy season.	Rainfed agriculture impossible Total/partial crop failure	Failure of sorghum and maize crops in 2003 and 2009 cropping seasons
Increased rainfall intensity	Increased soil erosion and sediment load in rivers and runoff flash flood Accelerated surface runoff Damage to crops	Flood and sediment from hill sides of Kobo caused damage on downstream crop land (once every 2-3 years during the main rainy season) Overflow of Awash and Meki rivers in the CRV due to heavy rainfall event in 2005 damaged 814 hectare of farmland and displaced 7,000 households
Delayed onset and early set of the rainy season	Change in cropping calendar , reduced length of growing period, loss of crop diversity	High yielding, long duration crop varieties cannot be grown successfully (e.g. Degalit, long duration sorghum variety is not used any more)
Dry spells during growing season	Reduced crop yield, low response to agricultural inputs (fertilizer)	
Erratic rainfall distribution	Difficult to use recommended agricultural practices Water stress at critical crop growth stages	
Rain out of season	Damage to crops Delay in harvesting time	Unexpected rain in November/December caused damage to crops at maturity and delay in harvesting
Increasing drought events	Damage on resource base (crops, water, livestock) Increasing food insecurity	Number of households appealing for food aid increases.

Farmers indicated that in unfavorable low rainfall seasons, agricultural inputs do not lead to yield gains due to the effect of moisture stress. For low rainfall seasons, they estimated maize productivity to be ca. 1.2 Mg/ha in Kobo and 0.6 Mg/ha in the CRV, but for favorable rainfall seasons they assessed yields to be about 2.7 Mg/ha in Kobo and 2.2 Mg/ha in the CRV (Fig. 4.4). It is remarkable that despite the fact that Kobo is less suitable for crop production in terms of annual rainfall, farmers perceived higher yields than in the CRV, both under favorable and unfavorable rainfall conditions. We have no time series yield data to substantiate the difference.

Table 4.4. Quantitative perceived effects of climate variability and change on agricultural production and management by farmers in the CRV and Kobo (based on household survey, 2010).

Observed effects	CRV	Kobo
	% response (N=120)	% response (N=80)
Reduced crop yield	100	100
Partial or total crop failure	96	94
Shortened length of the growing season	98	97
Shift in cropping calendar (delayed planting date)	98	99
Change in crop varieties	91	95
Increased pest and disease prevalence	89	91
Soil erosion	51	85
Land use/land cover change	28	61
Shortage of feed for livestock	98	100
Reduced livestock	96	90

Farmers indicated that climate risks affect livestock feed availability as well. In the CRV, elderly respondents stated that their herds were considerably larger 20 years ago but reduced significantly in recent years (box 1). They called this change a "forced reduction of livestock" and mainly attributed it to "*Ye Ayer Mezabat*" (climate change). Declined water resources and increased soil erosion were also mentioned as environmental problems being aggravated by increasing temperature and changing rainfall patterns. About 96% of the respondents in the CRV and 71% in Kobo witnessed a decline of springs and lake levels (Table 4.4). The overall effect of climate variability and change was felt within households in terms of increasing food insecurity. All respondents and key stakeholders assured that the number of households appealing for food aid has been increasing.

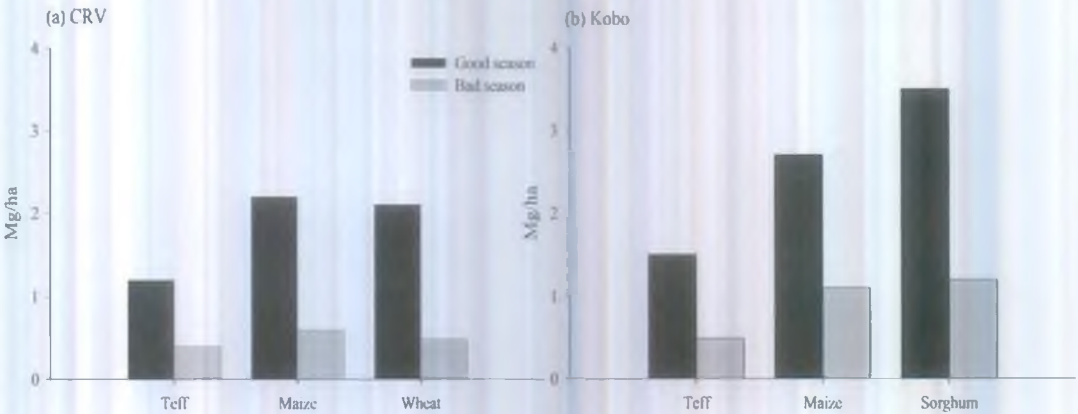


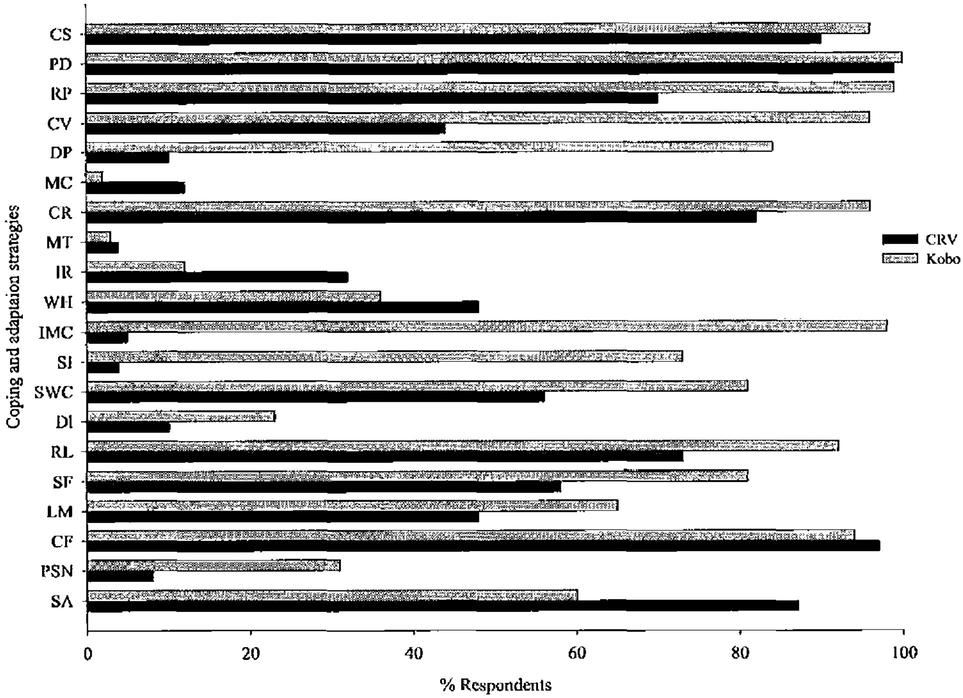
Fig. 4.4 Perceptions of households in terms of the difference in observed yields between "good and bad" seasons/years for major cereals. Good years are defined by farmers as years with adequate seasonal rainfall suitable to cultivate a range of crops. Bad years are years with inadequate rainfall and erratic distribution.

4.3.4. Adaptation strategies

Farm households adopted a variety of practices in response to perceived climate variability and change (Fig. 4.5).

Crop management strategies

Ca. 90% of the interviewed farmers in the CRV and 96% in Kobo indicated crop selection as their main adaptation strategy. Crop selection involves changing either the crop variety or the crop type, depending on the observed and expected growing season characteristic. When rain starts late, farmers tend to grow early maturing varieties but if the timing of rain is early or normal, local late maturing varieties are preferred as they have a yield advantage (e.g., three times higher sorghum yield according to farmers in Kobo). Interviewed farmers stated that before the 1980s, farm management and its timing was mostly constant and did not change much with seasons. More recently, however, farmers adjust the cropping calendar to the onset of rain. In local language, they called it "*Ende Tale Zira*", which means 'plant your seed when it rains'. Planting is delayed at late onset of the short rainy season (March-May), but in



CS	Crop selection (selecting crop varieties matching the season)	IMC	Shilshalo (In situ moisture conservation)
PD	Planting date adjustments	SI	Flood diversion ("Spate irrigation")
RP	Replanting with early maturing variety of the same crop when earlier crop fails	SWC	Soil and water conservation
CV	Changing crop type when replanting	DI	Diversification of livelihood (e.g. labour, remittance)
DP	Dry planting	RL	Reduce livestock number
MC	Mixed Cropping	SF	Supplement livestock feed (e.g. feeding tree branches)
CR	Crop rotation	LM	Seasonal migration of livestock to pastoral areas
MT	Minimum tillage	CF	Conserve fodder /crop residue for dry years
IR	Small scale irrigation	PSN	Productive Safety Net Programs
WH	Water harvesting	SA	Sale of assets (asset depletion) for purchasing food

Fig. 4.5. Adaptation strategies in response to effects of climate variability and change (based on farm household survey). See text for details of each of the strategies.

Kobo, 84% of respondents use dry planting for sorghum before the main rainfall season (June-September) to ensure that any drop of rain is used. Early planting generally gives higher yield but if the first rainfall events are too small, poor crop establishment can lead to reduced yields or even crop failure. In response to crop failure after early planting, 70% of farmers in the CRV and 99% in Kobo replant an early maturing variety of the same crop (Fig. 4.5). If the rainfall is not yet adequate after replanting, the crop type is often changed to teff (*Eragrostis tef*), which is considered as an 'emergency' crop. A farmer from Kobo explained the effect of rainfall on a cropping pattern as "If you observe 75% or more of the farm fields planted with teff, the onset of the rainy season was delayed and it was even too late for sorghum planting. If you see almost equal proportions of sorghum and teff, it means the rain was on time".

Crop diversification in space and time is the most widely used income smoothing mechanism, i.e. a farmer sows different types of crops at various moments and fields to minimize crop losses and to spread farm risk. Farmers also adjust some agronomic practices such as planting density, fertilizer rates and frequency of tillage to maximize utilization of the scarce water resource in low rainfall seasons (Table 4.5).

Livestock husbandry is an integral component of mixed-farming systems in the study areas. The main strategies to minimize the risk of livestock production include the use of alternative feed sources (e.g. feeding tree branches), conservation of fodder, collection and use of crop residues, and reduction of the herd. In the CRV 48% and in Kobo 65% of respondents indicate that seasonal migration of livestock to pastoral areas is another strategy to cope with feed shortage in low rainfall seasons (Fig. 4.5).

On-farm water management strategies

Ca. 73% of the respondents in Kobo practice spate irrigation, i.e., diversion of flood water from a seasonal river, directing it to cultivated fields through building earth embankments prior to the start of rainfall. In the CRV, 32% of the respondents have access to small scale irrigation using water from rivers, shallow groundwater and Lake Ziway. About 48% of the respondents in the CRV and 36% in Kobo also indicated water harvesting as an adaptation option (Fig.4.5). Most farmers employ in-situ soil moisture conservation techniques that increase rainfall infiltration and storage in the soil for crop use. For instance, 98% of the farmers in Kobo used "*Shilshalo*", a form of in-situ moisture conservation, mainly on sorghum farmlands: when the crop is about 30 cm high farmers make furrows across the field at various intervals to reduce run-off and increase soil infiltration. Another similar technique employed in both study regions is to create wide furrows shortly before rainfall is expected

Table 4.5. Comparison of some farm management options for normal and below normal /dry seasons as perceived and practiced by farm households in the CRV and Kobo, Ethiopia (household survey, 2010).

Normal season	Dry season	Perception for preferring the farm management option
Lower seed /plant density	Higher seed /plant density	During dry season, germination rate might be lower and hence seed rate high to ensure adequate seedling establishment
Recommended rate of fertilizer	Less or no fertilizer	Fertilizer could result in extreme moisture stress (Dehydration of seedlings results in "burning of seedlings") Response to fertilizer is very low during years with inadequate rainfall
Frequent cultivation for suppressing weed and for good seed bed preparation	Minimum cultivation	Hard to plough the land during dry season
Early or on time planting	Late planting	Adjusting the planting date enables to use the available rainfall
Long duration varieties	Short duration varieties	Long duration varieties give high yields when the season is normal but short duration varieties are the only alternatives when rain is late

and to invert the furrows immediately after the rainfall to conserve soil water. Farmers in Kobo practiced building ridges that are 20-30 cm high and commonly spaced 75 cm apart and ties at 2 m intervals (*tied ridges*). Building soil and stone bunds are also common practices in both regions to control run-off and increase soil moisture retention.

Income diversification and safety nets

Some households diversify income through non-agricultural activities, especially through temporary migration (Fig. 4.5). Mainly male members migrate to nearby urban and other rural areas during the off-season (dry season) for employment opportunities, mostly in the construction sector as well as in the recently emerging large-scale horticulture and floriculture sector, particularly in the CRV. Some household members, mainly young and single women without children, migrate to nearby countries (e.g. Sudan, Dubai and Saudi Arabia) to earn remittances. Renting out labor during peak periods (e.g. weeding and planting) especially to farms with irrigated land, also provides options to diversify household income. A special form of renting out of labor is the system locally called "*Yekul*" in which the landlord shares grain with the one who lends him labor or assets like oxen for ploughing. Renting out of labor is mainly an option for large households (with surplus labor) or households with few other assets (e.g. land, oxen).

Social networks are important for inter-household income transfers and loans. Households most affected by droughts, for example, are supported by relatives or neighbors, especially during periods of crop failure. The last resort for households to cope with periods of low agricultural production is selling some of their farm assets such as animals, particularly small ruminants (e.g. sheep and goat). However, respondents indicate that livestock will be in excess supply at local markets and prices will be relatively low in dry seasons. Some households are temporarily supported through government interventions such as productive safety-net programs (PSNP). Chronically food insecure households eligible for PSNP support participate in public works such as road maintenance, tree planting, and community pond construction to receive money or food. About 8% of the respondents in the CRV and 31% in Kobo are beneficiaries of the PSNP (Fig. 4.5).

4.3.5. Barriers to implementing promising adaptation measures

Lack of affordable improved technologies, high costs for agricultural inputs, unstable market prices, lack of effective early warning systems, small and fragmented land size and risk averse behavior of households were identified as major barriers to effective adaptation to climate variability and change (Fig. 4.6).

Technology, financial and market constraints

Farmers indicated that some of the available technology packages are not affordable, such as improved crop varieties which only perform well in combination with expensive fertilizers (Fig. 4.7). Since farmers have no or limited access to rural credit systems (see next paragraph), fertilizer-improved seed packages promoted by the government are not adopted at larger scale (Box 4.2). Despite that market prices for agricultural products are highly volatile, farmers hardly benefit from price peaks, i.e. farmers usually sell their products immediately following the harvest season (January-March) to satisfy cash needs, at a moment that prices are lowest because of market saturation.

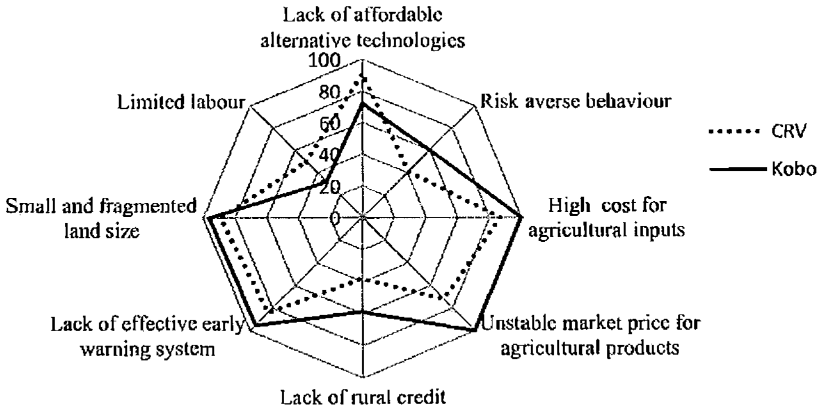


Fig. 4.6. Barriers for successful adaptation of rainfed agriculture to climate change and variability as identified by farm households (% of respondents).

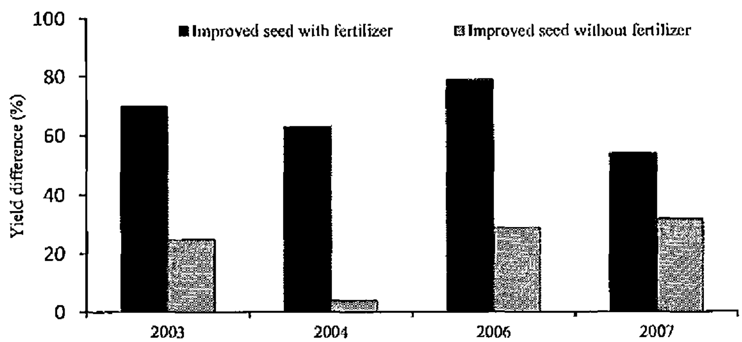


Fig. 4.7. Cereal yield differences obtained from improved varieties with and without fertlizer compared to yied from traditional practices (adopted from CSA, 2008).

Box 4.2. Farmers' views why a promoted improved seed and fertilizer package is not adopted at a wider scale (based on focus group discussion).

The existing improved crop varieties perform poorly under farm conditions (low yield advantage) if not used in combination with other inputs (fertilizer, agro-chemicals, water). When we use the improved seed-fertilizer package, it costs much and the yield benefit we can get cannot compensate the low output/input price ratio. Higher costs of these inputs limit farmers' capacity to use the promoted, recommended full technology package

Lack of effective early warning system

About 84% in the CRV and 60 % in Kobo receive weather forecast information mainly at village meetings and rarely from radio. Only few respondents mentioned that such information is relevant for farm management as most information arrives too late or is too general and inappropriate for tactical decision-making at farm level.

Land tenure and household characteristics

Farmers with small land holdings are more reluctant to adopt technologies such as improved varieties and fertilizer (Fig. 4.8a). Furthermore, the existing land tenure system does not allow farmers to use land as collateral to secure credits from local banks. According to the country's constitution, except for the government, no one can sell or use land as other means of exchange (e.g. collateral for credit). Therefore, farmer's access to formal credit is limited and it is one of the barriers to access yield enhancing inputs and new technologies. For some households, limited labor availability also constrains adequate adaptation to climate variability and change. With increasing production risks, households, particularly those nearby towns and private firms engage in off farm activities to generate immediate income at the expense of labor for their farm management.

Because of a risk-aversive behavior, many farm households stick to traditional practices instead of adopting improved technologies. A respondent explained his experience of the 2003 cropping season when he purchased fertilizer on credit to apply at his teff crop. Because of a poor rainfall that season the yield was low and the sale of his production was just enough to repay the credit but left his family without food. Since then, this farmer is reluctant in applying new farm practices that require credit. Levels of education and farming experience also have an influence on farmers' decision of using new technologies. Educated or experienced farmers use more fertilizers, improved varieties and soil and water conservation methods, compared to illiterate and/ or young inexperienced farmers (Fig. 4.8b, c).

4.3.6. Needs for future adaptation

Focus group discussions and consultations with research and extension experts pinpoint adaptation needs for agriculture. Improved crop and animal breeds, responsive farming strategies, irrigation and water harvesting technologies, sustainable land management, agro-forestry and risk insurance schemes were identified as promising options for adapting rainfed agriculture to anticipated climate change (Table 4.6 & Box 4.3).

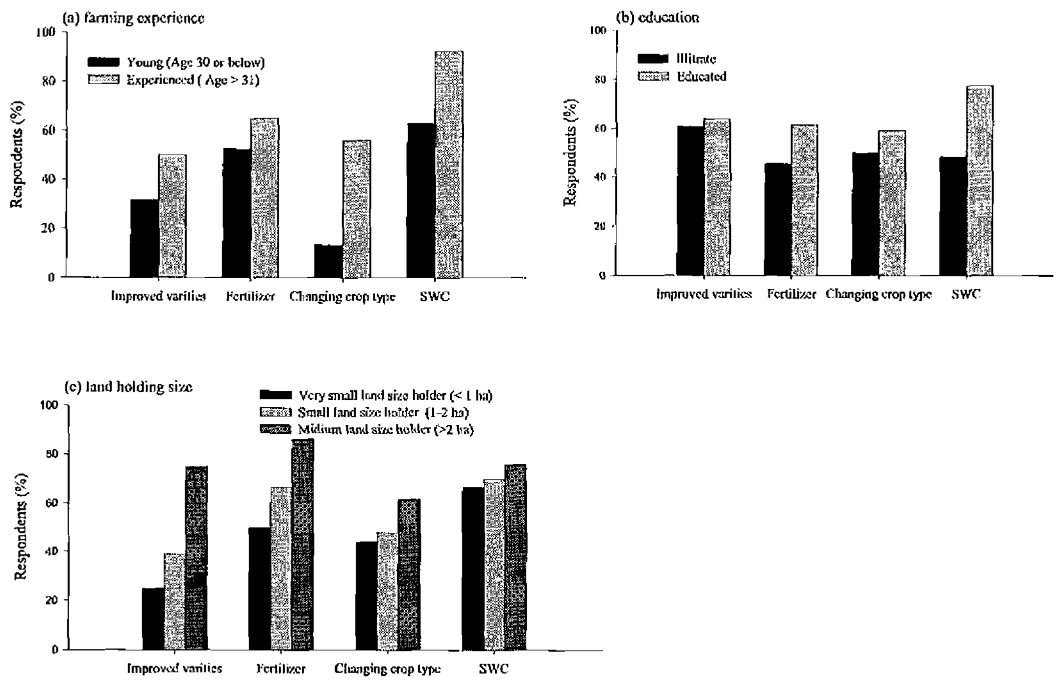


Fig. 4.8. Effects of selected farm and household characteristics on farmers' decision to use adaptive technologies (based on household survey).

Table 4.6. Promising adaptation strategies, expected contributions to climate risk management and prerequisites to implement the required adaption options (based on key informants and focus group discussions).

Adaptation options for anticipated climate change	Contribution to climate risk management	Prerequisites
Improved crop varieties (drought tolerant, pest resistant, fast maturing, high yielding)	Crop varieties that are resistant to stresses associated with climate change (pests, diseases, water and heat stress) could help to reduce vulnerability and ensure that crop productivity increases under changed climate conditions.	Access to inter-related technologies such as seeds, fertilizer, agrochemicals, mechanization Access to rural credit services and market
Crop diversification	Crop diversification spreads production risks	Adequate and timely supply of required inputs
Improved animal breeds	Increased livestock productivity	
Responsive farming (adjusting cropping management such as date of planting, fertilizer application, seed rate, tillage frequency, cropping sequences to weather outlook)	Minimizes production risks	Reliable weather forecast and effective early warning systems
Small scale irrigation and water harvesting	Production less rainfall dependent	Institutional support in infrastructure and capacity building
Sustainable land management	Increased nutrient retention, rainfall infiltration , reduced erosion and land degradation	Land use planning at catchment scale
Agro-forestry practices	Improved rainwater management and reduced erosion, enable income diversification	Changing the current free grazing system. Secured land tenure system
Climate risk insurance	Reduced vulnerability of farmers by providing financial compensation for production losses	Synergies between government and private insurance companies in bearing risks

The needs for future adaptation options were almost similar in both study areas with only slight differences. For instance, farmers in Kobo consider improved crop varieties (drought tolerant, pest resistant, fast maturing, and high yielding) important while farmers in the CRV consider improved animal breeds equally important options to adapt to climate change. Extension workers in both study regions also have similar positive opinions towards access to improved crop cultivars and effective weather forecast services, but extension workers in the CRV prioritized effective agricultural services and small scale irrigation while those in Kobo prioritized improved soil moisture retention technologies (e.g. tied ridging) as promising adaptation options.

Box 4.3. View of an expert (Agronomist) for successful adaptation to climate change (based on focus group discussion)

For successful adaptation, adequate and timely supply of agricultural inputs (improved seeds, fertilizer, and improved farm equipment), provision of improved weather forecast and adaptive technologies need to be critically addressed. Adequate training on available technologies needs to be conducted. Farmers must not only be informed about potential adaptation options but also need to be trained on technologies such as integrated watershed management, water harvesting, moisture conservation and improved agronomic practices. Linkage among research, farmers and extension could be strengthened. Various options of technologies such as early maturing crop varieties, improved animal breeds, improved agronomic and agro-forestry practices has to be available for wider choice.

4.4. Discussion

4.4.1. Farmers perceptions on climate variability and change

Observed climate data of both the CRV and Kobo showed an increasing trend in temperature and high inter-annual and intra-seasonal rainfall variability, which are in agreement with farmers' perceptions. In contrast to farmers' perceptions of a decrease in rainfall totals, observed rainfall data showed no statistically significant decline over the period 1977-2009. Other studies in Ethiopia also showed increasing temperature trends but no clear trend for rainfall (e.g. Conway et al., 2004; Seleshi and Zanke, 2004; Seleshi and Camberlin, 2006; Cheung et al., 2008). Farmers' perceptions are not always supported by actual climate records (Slegers, 2008a; Bryan et al., 2009; Osbahr et al., 2011; Rao et al., 2011). The discrepancy between the actual rainfall trend and farmers' perception may be because farmers generalize their views based on memories of recent drought years (Meze-Hausken, 2004; Amsalu et al., 2007; Slegers, 2008b; Bryan et al., 2009) or due to the fact that the same rainfall was distributed over fewer rainfall events and, therefore, possibly reduced effective rainfall (i.e. infiltrating into the soil). The number of days with maximum temperature exceeding 32°C (hot days) increased significantly. The increased temperature may also result in higher soil evaporation that reduces water available to cropping. Furthermore, there is a tendency that the rainy season is delayed, which can push the crop growing period towards days with more heat stress resulting in less soil moisture available to the crop. The interaction of climate with other environmental changes such as a decline in soil fertility and land cover change, which may have affected crop water availability, could have further influenced the perception of farmers of declining rainfall. Haileslassie et al. (2005) reported that soil fertility depletion is one of the main biophysical causes of declining per capita food production, particularly in the semi-arid mixed farming systems of Ethiopia and Rao et al. (2011) reported the same in Kenya. The population of Ethiopia has increased more than threefold from 24 to 84 million during the period 1960-2007 (Kidanu et al., 2009) and food production did not increase proportionally (CSA, 2008). which might be another compounding factor influencing farmers' perception to associate food deficit with declined rainfall. Annual rainfall is more favorable in CRV than in Kobo. The fact that farmers in Kobo perceived their yields to be higher than this in CRV is remarkable and points at the need to be cautious with farmers' perceptions.

Generally, analysis of perceptions of climate change needs detailed investigation of the local environmental, socio-economic and cultural conditions of people affected (Meze-Hausken, 2004; Slegers, 2008b), which was beyond the scope of this study. Clearly, caution is needed when adaptation strategies are based on perceptions of local actors only, as our case studies shows. Lower rainfall is perceived as a major challenge, which can be dealt with by irrigation (CRV) or water harvesting (Kobo) according the focus group discussions (Table 4.5). However, without a clear understanding of the local conditions affecting the perception of actors more appropriate adaptation strategies such as the introduction of improved varieties and more fertilizer use can easily be overlooked and it may result in poorly targeted interventions resulting in maladaptation (Coe and Stern, 2011). The science community needs to play a role in sharing current knowledge and uncertainties with the farming community to help them understanding climate variability and change (Asseng et al., 2013).

4.4.2. Adaptation strategies

In response to the perceived climate variability and change, farm households in our study regions are implementing various coping and adaptation strategies. The most important strategies include crop selection, adjusting cropping calendar, in-situ moisture conservation and income diversification. Such practices when implemented properly are effective strategies in response to climate risks (Nhemachena and Hassan, 2007; Thomas et al., 2007; Thornton et al., 2007; Tompkins and Eakin, 2011; Trærup and Mertz, 2011). During the past 20 years, farmers have shifted from late maturing to early maturing varieties (e.g. long duration local varieties of sorghum such as "*Degalit*" have been replaced by early maturing varieties such as "*Gobiye*"). Improved soil and water conservation technologies are other adaptation options that can have significant impacts on reducing production risk in Ethiopia (Kato et al., 2011). Moisture conservation techniques such as tied-ridges, *shilshalo* and spate irrigation are implemented in the case study areas to cope with the effects of erratic rainfall distribution. Georgis et al. (2004) reported an increase in yield of sorghum and maize of more than 50% at Kobo and Melkassa (CRV) using tied ridges compared to flat planting. Araya and Stroosnijder (2010) also indicated 30% yield advantage for barley using tied-ridging. According to development agents in the study area *shilshalo* is already widely used to cope with moisture stress, but untimely ridging often results in substantial plant damage. Extension experts suggested that damage to the crop would be enhanced when *shilsaho* is implemented at the early growth stage (4-6 leaf stage for sorghum and 6-8 leaf stage for maize), however, this needs experimental validation. Spate irrigation is a form of water management widely used particularly in Kobo Valley where mountain catchments border lowlands. Spate irrigation is practiced in semi-arid areas of other countries such as Eretria, Yemen, Sudan, Tunisia and Pakistan (Steenbergen et al., 2011). Despite its significant role in adapting to climate variability, this practice is so far the least studied (Mehari et al., 2011).

Income diversification, among others through temporal and permanent migration, is another important adaptation strategy in the study regions. Recently, the frequency of migration has increased in Ethiopia due to perceived increased negative impacts of climate variability and change on livelihoods (Gray and Mueller, 2012). Gray and Mueller (2012) indicated that 10% of the male labor force migrates during severe drought. This implies that developing alternative income generation options for rural areas is crucial. Government interventions such as the PSNP, which has been developed originally for protecting chronically food insecure households, may also be suitable safety nets for temporary food insecure households during times of climate related hardships.

The two study regions differ in crop farming experiences with Kobo having crop farming since many years whereas the CRV farmers were pastoralists and cropping started in recent decades. Such differences are clearly reflected in adaptation as farmers in Kobo practice relatively more adaption activities such as *shilshalo*, flood diversion and tied-ridging. Farmers in the CRV, on the other hand, are relatively better endowed with farm resources and use small scale irrigation and agricultural inputs (fertilizer, and biocides). This reflects how current adaptation strategies are shaped by locally available knowledge and resources. It further suggests that valuable experiences and indigenous knowledge need to be explored in detail and scaled out from one region to other regions with similar agro-ecological conditions.

4.4.3. Barriers to successful adaptation

The main barriers to successful adaptation are associated to the costs of new technologies and market linkages (Fig.4.6). Some adaptation options may not be economically feasible for small scale farmers (Adger et al., 2007). The current improved seed technology package promoted by the government extension program (Deressa et al., 2009), for instance, requires the use of agricultural inputs (fertilizer and agro-chemicals) for increasing yields. However, only few households can afford the complete input package and most rather minimize input costs. This implies that farmers need low-cost options matching their adaptive capacity, or better access to credit to be able to bear the input costs at the start of the growing season. Farmers emphasized that lack of credit and limited financial capacity constraints the use of adaptation measures. The land tenure system is another important factor that affects technology choice and adaptation as it does not allow farmers to use land as collateral. Furthermore, with declining land area per household associated with a growing population, small and fragmented plots may constrain the use of some potential adaptation options. Finally, our data suggests that farmers' experience, their level of education and their risk-averse behavior, all influence adaptive actions.

Lack of reliable information on weather conditions of the forthcoming season compounds the barriers. Weather forecast and early warning has been disseminated for decades in Ethiopia but these have not yet been integrated effectively into agricultural decision-making processes. According to Hansen et al. (2007) climate risk management could involve effective use of weather and seasonal forecast information to help farmers' decision-making and reduce uncertainty. Kandji et al. (2006) indicated that in a study at Machakos, Kenya, 83% of the interviewed farmers would base their decisions on forecasts if these are accurate in at least 3 out of 5 seasons. Our study showed that farmers in both the CRV and Kobo have strong interest in receiving accurate forecast information and climate risk management advice, including information about timing (e.g. onset of rainy season, risk of dry spells).

4.4.4. Lessons and implications for improving adaptation capacity

In recent decades, farmers have changed farming practices to adapt to climate change and variability, for example, through crop choice, adjustment of cropping calendar, and in-situ moisture conservation. These relatively low-cost changes in farm practices were within the limited adaptation capacity of farmers, which may be insufficient to deal with the impacts of future climate change. Future climate change is expected to impose novel risks beyond the scope of current experiences (Boko et al., 2007; Cooper et al., 2008; Müller et al., 2011; Thornton et al., 2011). For instance, the number of hot days (heat stress events) is significantly increasing and as a result there will be a need to develop new crop varieties with greater heat tolerance. To enable farmers to adapt to these impacts critical technological, institutional and market-access constraints need to be removed. These constraints are typical for most countries in SSA and they are commonly addressed in national development agendas (Davidson et al., 2003; Huq et al., 2004; NMA, 2007). It is therefore crucial that climate change adaptation is mainstreamed with such development agendas.

The study also indicates that communication between climate scientists and farmers need to be improved. Improving information to farmers on the characteristics and magnitude of climate change contributes to the adaptive capacity of farmers in developing countries. Increasing farmers' adaptive capacity could be through participatory approaches such as Climate Field Schools (CFS) (Stigter, 2008), which are learning-by-doing and information exchange platforms based on experiences obtained with "Farmer Field School" approach (Van den Berg and Jiggins, 2007). The CFS approach (Stigter, 2008) provides an opportunity to (i) increase farmers knowledge on climate variability and change (ii) improve mutual learning between farmers and other actors (e.g. research, extension, policy) with respect to the impacts of weather extremes, climate trends and risks (iii) ensure that farmers get relevant and timely seasonal weather forecast information and (iv) improve the capacity of farmers to adapt to climate change impacts. Furthermore, CFS would support setting a research agenda better aimed at the needs of farmers who need to adapt to climate change. Such participatory platforms for various stakeholders (farmers, extension workers, researchers and policy makers) could be introduced and enhanced to facilitate the process of mainstreaming climate change adaptations and to enable farmers for future adaptation to climate change.

4.5. Conclusions

Farmers perceived climate variability and change and they are concerned about the impacts on agricultural production and livelihoods. In response to the perceived climate variability and change, farmers are already employing a range of adaptation strategies. However, the current actions are relatively low-cost changes in farm practices within the limited adaptation capacity of farmers, which may be insufficient to deal with the impacts of expected climate change. On-going climate change is expected to impose more and new risks for which farmers will need to prepare for and adapt to.

A remarkable finding from the research is that some farmers' perceptions (e.g. a decrease in annual rainfall) are not confirmed by observed climate trends. This may lead to sub-optimal or even counterproductive adaptations and therefore such misperceptions require attention through better communication and capacity building. Participatory learning platforms such as Climate School Fields can improve understanding of climate variability and change and its impacts and support the development of effective climate risk management strategies.

Local knowledge and existing adaptation strategies are essential inputs to explore and further plan improved adaptive technologies for the case study regions and other areas with similar agro-ecological and socio-economic conditions in Sub-Saharan Africa. This study highlighted that farmers are aware of the necessity to make long term adjustments to sustainable agricultural production under a changing climate. However, affordable technological options, strengthening the communication between actors, and new policy arrangements to remove market and institutional barriers and to support smallholder farmers are needed to assist in shaping adaptation to current and future climate risks.

Acknowledgments

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CHAPTER 5

Exploring adaptation options for maize production in the Central Rift Valley of Ethiopia using different climate change scenarios and crop models

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Abstract

Exploring adaptation strategies for different climate change scenarios to support agricultural production and food security is a major concern to vulnerable regions, including Ethiopia. The main objectives of this study were to assess the potential impacts of climate change on maize yield and explore specific adaptation options under contrasting climate change scenarios for the Central Rift Valley of Ethiopia. We estimated the impacts of climate change and evaluated adaptation options using three General Circulation Models (GCMs: CanESM2, CSIRO-MK3 and HadGEM2) in combination with two recently released Representative Concentration Pathways (RCP4.5 and RCP8.5) and two crop models (DSSAT, v4.5 and WOFOST, v7.1).

Results indicate that maize yield decreases on average by 20% in 2050s relative to the baseline (1980-2009) due to climate change. The negative impact of climate change on maize yield is very likely, while the extent of the negative impact is more uncertain with estimates ranging from -2 to -29% depending on crop model, GCM and RCP. A higher share in the uncertainties of our impact projections is attributed to GCMs than to the RCPs and crop models. Comparison of yield simulations under climate change scenarios with and without CO_2 effect indicated that the increased atmospheric CO_2 concentration had little effect on maize yield (5%). The main driving factors for lower maize yield were increased temperature (1.6-3.5 °C during the growing period) and decreased rainfall, particularly during the critical period (June to July), resulting in a shortened growing period (14-33 days across the climate change scenarios). Increasing nutrient fertilization and use of irrigation were identified as important adaptation options, which would offset negative impacts. However, the response of yield to increased nitrogen fertilization and irrigation supply will be less for climate change scenarios than under the baseline climate implying that the negative impact of climate change will not be totally compensated. Changes in planting dates (about three weeks later than the baseline optimum planting time) also reduced the negative impacts of climate change, while changing the maturity type of maize cultivars was not effective in most scenarios. The multi-model based analysis allowed estimation of some of the climate change impact and adaptation uncertainties, which can provide valuable insights and guidance for adaptation planning processes.

Key words: Climate change impact, uncertainty, planting dates, fertilization, DSSAT, WOFOST

5.1. Introduction

As indicated in successive assessment reports of the Intergovernmental Panel on Climate Change (IPCC) (e.g. Meehl et al., 2007) and various other studies (e.g. Parry et al., 2004; Branković et al., 2010; Thornton et al., 2011), there is strong evidence that anthropogenic climate change is a serious threat to food security, particularly for developing nations depending mainly on small-scale agriculture (Wheeler and von Braun, 2013). Agricultural systems are inherently vulnerable to climate variability (Boko et al., 2007; Challinor et al., 2007b; Müller et al., 2011) and climate change is expected to increase this vulnerability (Haile, 2005; Challinor et al., 2007b; Cooper et al., 2008; Thornton et al., 2010). Various global and regional studies warned that the progressive climate change is expected to negatively affect crop productivity in most parts of the world, particularly in Sub-Saharan Africa (Müller et al., 2011; Cairns et al., 2013; Rosenzweig et al., 2013a; Rötter et al., 2013a). For instance, a recent study by Waha et al. (2013) indicates that crop yields could decline by 18-45% in Southern and Western Africa with an overall mean decline of 24% in most of the Sub-Saharan Africa by the end of this century, as projected with three General Circulation Models (GCMs: MPI-ECHAM5, UKMO-HadCM3 and NCAR-CCSM3) using the SRES A2 emission scenario. Exploring adaptation strategies for climate change scenarios to support agricultural production and food security is therefore a major concern to vulnerable regions including sub-humid to semi-arid areas of Ethiopia as found in the Central Rift Valley.

Adaptation to climate change can take place through reducing risks and /or enhancing resilience of agricultural systems in response to the projected future climate (Adger et al., 2007; Parry, 2007). It involves actions targeted to adjust agricultural management in response to expected climatic change and its impacts. Various studies indicated that adaptation to climate change has the potential to significantly reduce negative impacts on crop production (Downing, 1991; Smit and Skinner, 2002; Adger et al., 2005; Howden et al., 2007; Mertz et al., 2009). Adaptation research involves the evaluation of management options under current and changed climatic conditions, which is important for decision makers to identify appropriate adaptation strategies and to support those through science-based and informed policies. Developing countries including Ethiopia have responded to the increased global attention for climate change adaptation (Rötter et al., 2011b; Coumou and Rahmstorf, 2012; Dow et al., 2013) through the development of National Adaptation Programs of Action

(NAPA), which identify priority areas for adaptation research and development. Ethiopian NAPA promotes the building of a climate resilient economy through the support of adaptation at national, regional and community levels (EPA, 2011). However, studies on climate change have often been limited to impact assessments. For example, Arndt et al. (2011) and Deressa (2007) estimated the economic impacts of climate change using an econometric approach without considering adaptation options. Projections of climate change impacts are inherently uncertain due to a wide range of knowledge gaps, starting from the assumptions involved in future greenhouse gas (GHG) emission scenarios, to partial understanding or oversimplification of processes incorporated in climate models, down-scaling methods and imperfect crop simulation models (Rötter et al., 2012a; Asseng et al., 2013; Osborne et al., 2013; Wheeler and von Braun, 2013). According to Walker et al. (2003), uncertainty can generally be defined as being "any departure from the unachievable ideal of complete determinism". While uncertainty in GHG emission pathways and climate models have been examined in most of the climate change impact studies, its importance and need to study with respect to biophysical impact models such as crop simulation models has only recently been recognized (Challinor et al., 2005; Rötter et al., 2011a; Asseng et al., 2013; Rosenzweig et al., 2013a; Rosenzweig et al., 2013b). Various crop models describe crop-climate interactions differently which can result in diverging model outcomes (see e.g. Aggarwal and Mall, 2002; Eitzinger et al., 2004; Asseng et al., 2013). Uncertainty in projected impacts due to crop models can be substantial (Asseng et al., 2013). Addressing research questions such as what share of impact uncertainty can be attributed to climate models and crop models (Yao et al., 2011; Ramirez-Villegas et al., 2013) and how to reduce these uncertainties (Rötter et al., 2012a; Asseng et al., 2013) are emerging issues.

This study uses climate model projections from three GCMs in combination with two Representative Concentration Pathways (RCPs) and two crop models to define the range of potential outcomes as a measure of the uncertainties in climate change impact projections for maize. The main objectives of our study were (i) to assess the potential impacts of climate change on maize yield using different state-of-the-art climate change projections (ii) to explore alternative adaptation options under contrasting climate change scenarios for a representative site in the Central Rift Valley of Ethiopia using two of the most widely applied crop models in Eastern Africa, i.e. the Decision Support Systems for Agro-technology Transfer (DSSAT) and WOrld FOod STudies (WOFOST) and (iii) to capture some of the uncertainty and the sources of uncertainty of climate change impact and adaptation assessment.

5.2. Materials and Methods

5.2.1. The study area and site conditions

The study was conducted in the Central Rift Valley of Ethiopia (CRV), located about 120 km south of Addis Ababa and characterized by an alternating topography with a central valley floor at 1500–1700 m.a.s.l., bounded by western and eastern escarpments. The CRV was previously a pastoral area covered by dense woodlands and there was no permanently cultivated land before the 1950s (Garedew et al., 2009; Biazin and Sterk, 2013) but in recent decades, it has been converted to cereal-based mixed farming system with maize as the major staple crop. The CRV rainfall exhibits high intra-seasonal variability with a coefficient of variation of 15-40%, and temperature increased significantly (0.12-0.54 °C per decade) over the past 30 years (Kassie et al., 2013b). The increase in inter-seasonal variability and intra-seasonal dry spells associated with the increasing temperature imply severe challenges to rainfed crop production. Soil groups of the CRV are (according to the FAO classification) Andosol, Luvisol, Fluvisol, Cambisol and Solonetzes (Zewdie, 2004; Abdelkadir and Yimer, 2011). We chose an Andosol soil for this study which is the most dominant soil in the CRV. Andosols are formed from largely volcanic ashes and pumice deposits and they are generally well-drained with a predominantly sandy loam texture (Table 3.3).

5.2.2. Climate change scenarios

Awassa, a synoptic weather station with relatively many years of observations, situated at 7°05′ latitude, 38°29′ longitude and 1750 m.a.s.l was selected as a representative location in the CRV for this study. Daily weather data for the present climate, hereafter referred to as baseline, was obtained from the national Meteorological Agency of Ethiopia for the period 1980-2009. Climate change impact studies are based on climate change scenarios which consist of combinations of climate and concentration pathways. Climate scenarios are coherent, internally consistent and plausible descriptions of possible future states of climate while concentration pathways describe future increase in atmospheric greenhouse gas concentration due to emissions. Climate change scenarios were derived from General Circulation Models (GCMs), which are the most widely used tools to develop future scenarios for climate change impact and adaptation assessment (Meehl et al., 2007) in combination with Representative Concentration Pathways (RCPs). We used outputs from three GCMs: CanESM2, CSIRO-MK3-6-0 and HadGEM2-ES (Table 5.1) and two RCPs, for creating six climate change scenarios. The time horizon for the climate change scenario analysis was for the mid-century (2040-2069), hereafter referred to as "2050s". The sensitivity of the climate system to an increase in greenhouse gas concentration was considered with low and high emission scenarios. For the past decades, most climate change studies used the Special Report on Emission Scenarios (SRES) of the Coupled Model Inter-comparison Project Phase 3 (CMIP3). Recently, CMIP5 coordinated by the World Climate Research Program in support of the IPCC Fifth Assessment Report generated new RCPs in an attempt to improving climate model projections narrowing the uncertainties in projected future climates (Moss et al., 2010; Knutti and Sedláček, 2012; Ramirez-Villegas et al., 2013). We used two of the new RCPs, namely, RCP4.5 and RCP8.5 in this study. The RCPs and their corresponding atmospheric CO_2 concentration are presented in Table 5.2. RCP4.5, which refers to a radiative forcing pathway of 4.5 W/m^2, in the year 2100, represents a low emission scenario, while RCP8.5, which refers to a rising radiative forcing pathway leading to 8.5 W/m^2 in the year 2100 represents a high emission scenario (Van Vuuren et al., 2011).

Table 5.1. Description of General Circulation Models (GCMs) of the Coupled Model Inter-comparison Project phase5 (CMIP5) used in this study.

GCM	Resolution (lat. * long.)	Institute	References
CanESM2	2.8*2.8°	Canadian Centre for Climate Modelling and Analysis, Canada	(Chylek et al., 2011)
HadGEM2-ES	1.88*1.25°	Hadley Centre for Climate Prediction and Research / Met Office, UK	(Collins et al., 2011)
CSIRO-MK3-6-0	1.88*1.88°	Australian Commonwealth Scientific and Industrial Research Organization, Australia/	(Gordon et al., 2002)

The baseline climate data was changed based on the GCMs/RCPs outputs to obtain the changed climate scenarios using the "Delta method" (Wilby et al., 2004) that adjusts daily historical observations to match mean monthly climate changes (Ruane et al., 2013). There are various methods for down-scaling climate projections for impact modelling, none are necessarily superior to others but each with advantages and disadvantages (Räisänen and Räty, 2012; Rötter et al., 2012a). With the delta method, changes in rainfall are created by multiplying the rainfall scenario change factors with the baseline daily values, while changes in minimum and maximum daily temperature are obtained by adding the temperature change factors to the baseline values. Many studies (e.g. Alexandrov and Hoogenboom, 2000; Cuculeanu et al., 2002; Webb and Stokes, 2012; Rosenzweig et al., 2013b; Ruane et al., 2013; Sultan et al., 2013) applied this approach in creating climate change scenarios for impact and adaptation assessment. A projected change in annual and seasonal rainfall and mean temperature for the different GCMs and RCPs by 2050s is presented in Figure 5.1 for the selected climate change scenarios.

Table 5.2. Emission scenarios used in this study, their time coverage and CO_2 concentration.

Scenario	Period (Coverage)	Mid-year	CO_2 concentration (ppm)
Baseline	1989-2009	1995	360
RCP4.5	2040-2069	2055	499
RCP8.5	2040-2069	2055	571

5.2.3. Crop management scenarios for adaptation

The adaptation strategies considered for model evaluation in this study were selected based on farmers' adaptive responses to current climate variability and future needs for adaptation in the CRV (Kassie et al., 2013a). Currently, farmers in the CRV implement adaptive strategies such as changing crops and cultivars, replanting (when rain fails after the first sowing), and soil moisture conservation to cope with the risks of climate. Discussion with the local farmers and extension experts enabled the identification of future aspirations and needs for adaptation. Response farming (e.g. adopting the cropping calendar to the prevailing weather), increasing levels of agricultural inputs (e.g. fertilizer, pesticides), drought-tolerant crop varieties, and expanding irrigated agriculture are among the main strategies for future adaptation (Kassie et al., 2013a). Consequently, this study evaluated the effects of planting dates, different levels of nitrogen fertilizer, irrigation and crop cultivar using the crop modelling approach for a range of climate change scenarios.

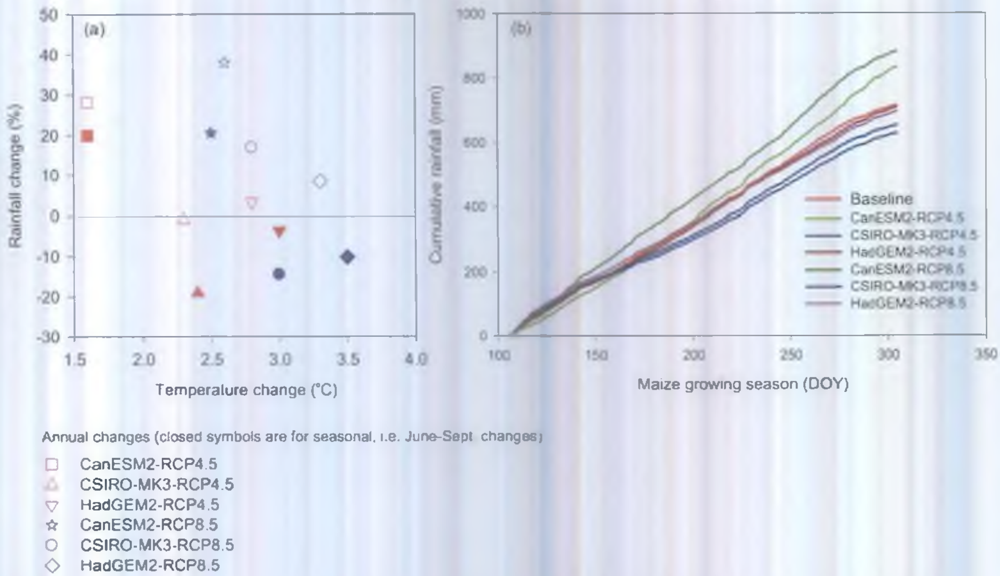

Fig. 5.1. Changes in annual and seasonal (June-September) rainfall and temperature as projected for two Representative Concentration Pathways (RCPs 4.5 and 8.5) by different climate models in 2050s (2040-2069) relative to the base period (1980-2009) (a) and associated cumulative rainfall during the growing season of maize (b) in the Central Rift Valley, Ethiopia.

(i) Planting dates:

Different approaches are applied to set planting dates in crop simulation studies. Most studies used pre-defined sowing dates based on observations (e.g. Alexandrov and Hoogenboom, 2000; Jones and Thornton, 2003; Liu et al., 2008; Laux et al., 2010), while others used optimization algorithms, which select sowing dates based on crop water and temperature requirements (e.g. Bondeau et al., 2007). Another approach is to optimize sowing dates by selecting the date which leads to the highest simulated crop yield (e.g. Southworth et al., 2002; Žalud and Dubrovský, 2002; Soler et al., 2008; Waha et al., 2012). We determined sowing dates for the baseline and climate change scenarios based on the first occurrence of rainfall between April 15 and July 7 while at least 40 mm of rainfall accumulated within 4 rainy days (Raes et al., 2004; Kipkorir et al., 2007; Mugalavai et al., 2008). We assumed that the timing of sowing is dependent on rainfall onset, which is typical in (semi)-arid environments and is a common practice in the CRV (Kassie et al., 2013b). However, planting a rainfed crop based on the occurrence of the first possible sowing may not be the appropriate strategy for adaptation under increasing temperature (Laux et al., 2010; Sacks et al., 2010; Bannayan et al., 2013). Comparing yield simulations with planting at specified dates applied for all scenarios is necessary to evaluate and identify optimum planting dates for adaptation (Luo et al., 2009; Thornton et al., 2010). Optimum planting dates were therefore, evaluated with runs of the baseline and the climate change scenarios using weekly intervals around the sowing date as determined by the sowing rule within the planting window.

(ii) Nutrient management:

We simulated the impacts of three levels of nitrogen fertilizer i.e. low (20 kg N/ha), moderate to high (80 kg N/ha) and very high fertilization (no nitrogen limitation), while P and K are assumed to be adequately supplied in all cases. The low nitrogen (20 kg/ha) is approximately the average application rate currently used for maize in Ethiopia (Spielman, 2008; Cairns et al., 2013) and the moderate and very high nitrogen fertilizer levels are considered, with a somewhat optimistic perspective, for climate change adaptations in the 2050s. The source of nitrogen was assumed to be urea, which is currently the most frequently applied nitrogen fertilizer in Ethiopia. Nitrogen application for low and moderate doses was split between 50% at planting and 50% at 30 days after planting, which is common practice in the study area.

(iii) Irrigation:

Staple crops are commonly produced under rainfed conditions in the study area. However, irrigated vegetable production is rapidly increasing near suitable ground water and surface water resources in the area (Van Halsema et al., 2011), and points at possibilities for irrigated staple production as well. In addition, water harvesting through capture of runoff in reservoirs that can be used to irrigate crops when rainfall is insufficient to secure crop harvest is strongly promoted by the Ethiopian Government and various foreign donors (Moges et al., 2011). Expansion of small scale irrigation is among the top priorities of stakeholders in the area (Kassie et al., 2013a) and has been identified as a promising adaptation strategy in NAPA (NMA, 2007). Considering the prospects for irrigation, we assess its effects as an adaptation option under a range of climate change scenarios. The simulations for the different climate change scenarios were conducted under rainfed and full irrigation (no-water stress) and no nutrient limitation conditions to gain insight into the possibilities of optimum management (full irrigation and full fertilization) options to reduce the impacts of climate change. We also evaluated effects of supplementary irrigation with moderate (80 kg/ha) fertilizer application assuming that this combination of management options may be more realistic at smallholder farm conditions in the near future. Supplementary irrigation simulations received a total of 70 mm of additional water during important growth stages of maize.

(iv) Changing cultivars:

One of the most common practices of farmers to cope with current climate variability is to replace late maturing cultivars by early maturing cultivars when the main rainy season starts late (Kurukulasuriya and Mendelsohn, 2006; Waha et al., 2012; Kassie et al., 2013a). We evaluated the impact of cultivar choice under future climate change scenarios. See tables 3.5 and 3.6 for cultivar parameters used in the model simulations.

5.2.4. Crop simulation models

Crop simulation models provide opportunities for users to simulate crop yields in response to climate scenarios thereby enabling to assess impacts of various management strategies on growth and yield of the crops. In this study, we used the CERES-maize model embedded in Decision Support Systems for Agro-technology Transfer (DSSAT, v4.5), hereafter referred to as DSSAT and WOrld FOod STudies (WOFOST, v7.1) models to assess impacts of climate change scenarios on maize yield and to evaluate the adaptation options described in Section 2.3. These models were chosen because they are well accepted and widely used for analyzing the impacts of climate change and allow the incorporation of elevated levels of atmospheric CO_2 and evaluating various adaptation options (Tubiello and Ewert, 2002; Eitzinger et al., 2004; White et al., 2011; Rötter et al., 2012b). In addition, they have been tested and intensively used in the environments of Sub-Saharan Africa including Ethiopia (e.g. Rötter, 1993; Wafula, 1995; Rötter et al., 1997; Hengsdijk and Van Keulen, 2002; Jones and Thornton, 2003; Wokabi, 2003; Thornton et al., 2009; Cairns et al., 2013).

DSSAT was originally developed by an international network of scientists, cooperating in the international Benchmark sites Network for Agro-technology Transfer Project (Jones et al., 2003; Hoogenboom et al., 2010) to facilitate the application of crop models in a systems approach to agronomic research. WOFOST was developed at Wageningen University based on the SUCROS model (Van Diepen et al., 1989; Van Ittersum et al., 2003). Both DSSAT and WOFOST are designed to simulate crop growth as a function of crop features and management, weather conditions and soil characteristics. However, the two models differ in details of describing some of the crop-growth processes. For instance, DSSAT uses a relatively simple radiation use efficiency approach to model net photosynthesis (Tsuji et al., 1998; Palosuo et al., 2011), while WOFOST uses a more detailed approach for describing photosynthesis and respiration (Palosuo et al., 2011). DSSAT simulates the soil water balance for each soil layer with its specific soil water uptake relations, whereas WOFOST considers a homogenous soil texture of the whole soil profile. Details of some differences in modelling approaches of the two models are presented in Table 5.3. The two models were previously calibrated and tested for different maize cultivars in the CRV of Ethiopia in a study of climate variability and yield gap analysis (Kassie et al, 2013, in review). The widely cultivated late maturing maize cultivar (BH540) was used for the climate change impact analysis (see Tables 3.5 and 3.6 for model input parameters).

To account for the effects of elevated CO_2 on crop growth and yield, simulations were carried out by keeping the CO_2 concentration at the current level for the baseline period and by changing the CO_2 concentrations for each climate change scenario to their corresponding level (e.g. Alexandrov and Hoogenboom, 2000; Hoogenboom et al., 2010; Ruane et al., 2013). The evapotranspiration routine in the DSSAT crop models include the ratio of transpiration under elevated CO_2 concentrations to that under ambient concentrations (Alexandrov and Hoogenboom, 2000). For the simulations with WOFOST, the values of correction factor /relative transpiration rate (CFET) was modified for each CO_2 concentration level following Wolf et al. (2010).

The key procedures of the simulation experiment were (i) running the crop models with the current (baseline) and climate change scenarios (i) comparing these crop model results to quantify yield changes and (iii) analyzing the effects of the various management strategies and selecting promising options which reduce negative impacts of climate change. Evaluations for planting dates, cultivar choice and optimum irrigation options were simulated with both DSSAT and WOFOST assuming nutrient non-limiting conditions. The evaluation of the different nitrogen fertilization levels, supplementary irrigation and combination of nitrogen and irrigation options were done with DSSAT only. Furthermore, climate change impact simulations assume that pests and diseases are controlled and that no problematic soil conditions (such as salinity and acidity) or catastrophic weather events occur.

Table 5.3. Differences in modelling details of CERES-Maize (DSSAT) and WOFOST for major processes of crop growth and development (Modified afterPalosuo et al., 2011).

Processes	CERES-Maize	WOFOST
Leaf area development and light interception	Simple: Leaf area expansion is driven by temperature as a function of leaf number and assimilate availability	Detailed: Leaf area expansion is driven by assimilate availability, dry matter partitioning coefficients and specific leaf area
Light utilization	Descriptive (simple) radiation use efficiency approach. Constant radiation use efficiency is used to directly convert absorbed radiation into dry matter.	Explanatory (detailed) gross photosynthesis respiration approach. Intercepted radiation is divided into direct and diffusive parts and integrated over leaf area index distribution.
Dry matter accumulation	Driven by temperature as a function of phenology, limited by assimilates availability, excess assimilate partitioned to roots.	Driven by assimilate supply and regulated by dry matter partitioning coefficients to all organs.
Rooting elongation and distribution over depth	Exponential, root growth continues until maturity	Linear, root growth terminates at anthesis
Water balance dynamics	Simulates the soil water balance for each soil layer with its specific soil water uptake relations; water uptake depends on rooting density.	Considers homogenous soil texture of the whole soil profile; water uptake does not depend on rooting density.
Model type	Crop specific	Dynamic
Simulation	Simulates nutrient limited, water-limited and potential yields.	The used version (v7.1) simulates only water-limited and potential yields.

5.3. Results

5.3.1. Projected changes in temperature and rainfall

The baseline average annual minimum temperature is 12.6 °C and maximum temperature is 27.1 °C with mean annual temperature of 19.9 °C. According to the climate change scenarios used in this study, the average annual minimum temperature is expected to increase by 2.2 to 3.5 °C and the maximum temperature by 1.1 to 3.2°C. As a result, the mean annual temperature will increase by 1.6 to 3.3 °C in 2050s (Fig. 5.1). The lowest change in annual mean temperature is projected by CanESM2 model (1.6 and 2.6 °C for RCP4.5 and RCP8.5, respectively) and the highest annual mean temperature change is projected by HadGEM2 model (2.8 and 3.3 °C for RCP4.5 and RCP8.5, respectively). During the main rainy season (June-September), the average minimum temperature is likely to increase by 1.9 to 3.3 °C and the maximum temperature by 1.2 to 3.6°C, resulting in mean seasonal temperature changes by 1.6 to 3.5 °C in 2050s.

Projected changes for the annual rainfall varies widely between -1% and 38%. A decrease in annual rainfall was projected only by one climate change scenario (CSIRO-MK3, RCP4.5) while others projected an increase in annual rainfall and the highest increase was projected by the CanESM2 model (28 and 38% for RCP4.5 and RCP8.5, respectively). During the main rainy season (June-September), four of the six climate change scenarios (HadGEM2 and CSIRO-MK3 climate models in combination with the RCP4.5 and RCP8.5) projected rainfall to decrease by 4 to 20% whereas two of the scenarios (CanESM2 climate model in combination with RCP4.5 and RCP8.5) projected an increase of rainfall by 20-21%.

5.3.2. Impacts of climate change on maize yield

Simulated mean yield for maize ranges between 7.6 and 8.3 Mg/ha in the baseline scenario and between 5.4 and 8.1 Mg/ha in the climate change scenarios (Fig. 5.2a). Among the climate change scenarios, CanESM2 with the RCP4.5 gave the highest mean yield (7.1-8.1 Mg/ha, ranges are for crop models) while CSIRO-MK3 with RCP8.5 predicted the lowest mean yield (5.4 Mg/ha) (Table 5.4). All climate change scenarios and both crop models used in this study projected reduction in mean maize yield relative to the baseline climate (Fig. 5.2b). Reductions in maize yield by 2050s under the various climate change scenarios were simulated to be similar with DSSAT (-3 to -29%) and WOFOST (-2 to -29%). The projected decrease was highest for HadGEM2 model (-27 to -29%) while the CanESM2 model projected the lowest decrease in maize yield (-2 to -13%). There was at least 61-65% probability of a mean yield decline across the RCP4.5 scenarios and 81-87% across the RCP8.5 scenarios (Fig. 5.2b). The overall mean decline in maize yield of the scenarios and crop models was 20% in 2050s relative to the baseline. The range of projected yield outcomes (uncertainty) is higher among the GCMs (-8 to -28%, averaged over crop models and RCPs) than between crop models (-19 to -20%, averaged over GCMs and RCPs) or RCPs (-17 to -22%, averaged over GCMs and crop models). Comparison of yield simulations with and without CO_2 effect indicates that the increased atmospheric CO_2 provides little direct stimulation (5.3%) for maize yield.

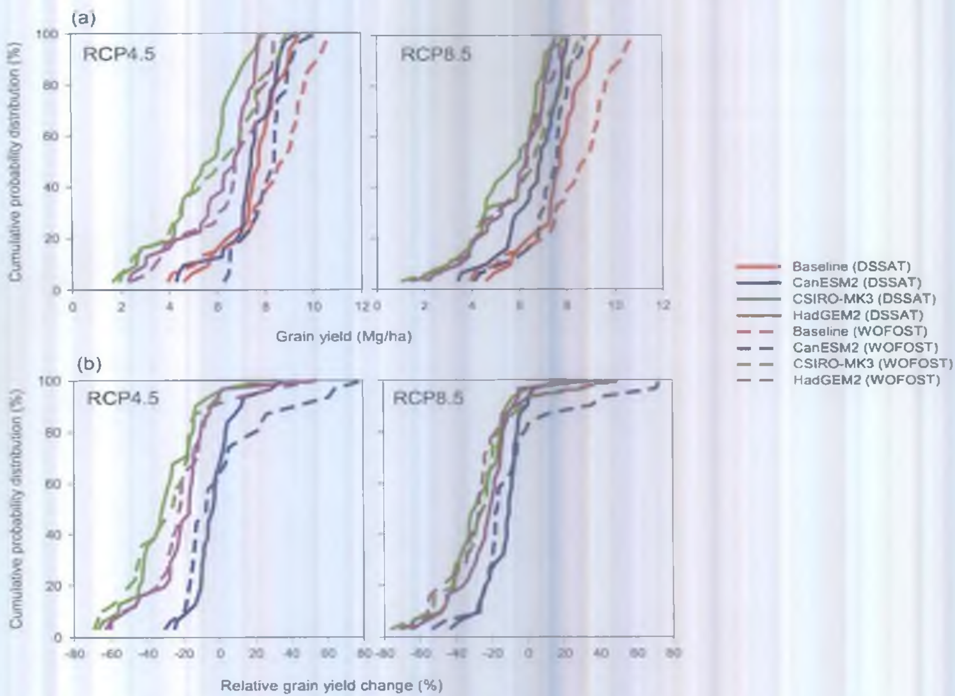

Fig. 5.2. Cumulative probability distribution of simulated maize grain yield for the baseline period (1980-2009) and future climate change scenarios (2040-2069) (a) and cumulative probability distribution of maize yield changes for future climate change scenarios (2040-2069) relative to the baseline period (1980-2009) (b) as simulated with DSSAT and WOFOST crop models. The CO_2 concentrations considered in the simulations were 360, 499 and 571 ppm for the baseline, RCP4.5 and RCP8.5 scenarios, respectively.

The decrease in simulated maize yield in the climate change scenarios is mainly associated with a shorter growing duration as increased temperature accelerates crop maturity. The simulated growing period for maize was shorter than the baseline scenario between 14 days (CanESM2) and 33 days (HadGEM2) (Table 5.5). The number of days with which the crop growth period decreased was similar for DSSAT (16-31 days) and WOFOST (14-33 days), while it was somewhat higher for RCP8.5 (25-33 days) than for RCP4.5 (16-26). Overall, climate change will shorten the growing period of maize by 9-22% compared to the baseline associated with a 1.6-3.5 °C higher average temperature during the growing period.

Table 5.4. Ranges of yield predictions and yield change of maize among crop models, Representative Concentration pathways (RCPs) and Climate models (GCMs) by 2050s in the CRV, Ethiopia.

Crop model	RCPs	GCMs	Mean yield (Mg/ha)	S.D	Max	Min	Median	25%	75%	Mean yield change (%)
DSSAT		Baseline	7.6	1.2	9.5	4.6	7.7	7.3	8.3	
	RCP4.5	CanESM2	7.4	1.3	9.4	4.3	7.4	7.1	8.3	-2.6
		CSIRO-MK3	5.4	1.7	8.1	1.9	5.9	4.3	6.5	-29.2
		HadGEM2	6.1	1.7	7.8	2.3	6.8	5.4	7.3	-19.5
	RCP8.5	CanESM2	6.6	1.3	8.1	3.4	6.9	5.7	7.6	-12.6
		CSIRO-MK3	5.5	1.6	7.7	1.9	6.1	4.5	6.7	-27.1
		HadGEM2	5.9	1.5	7.6	2.1	6.3	4.8	7	-22.7
WOFOST		Baseline	8.3	1.8	10.8	3.9	8.9	7.5	9.6	
	RCP4.5	CanESM2	8.1	1.0	10.2	6.3	8.4	7.5	8.8	-2.4
		CSIRO-MK3	5.9	2.2	8.9	1.6	6.4	4.2	7.6	-29.0
		HadGEM2	6.5	1.8	8.6	2.3	6.8	5.9	7.7	-21.7
	RCP8.5	CanESM2	7.3	1.1	8.8	4.1	7.6	6.8	8	-12.5
		CSIRO-MK3	6.1	2	8.5	1	6.7	4.4	7.7	-26.9
		HadGEM2	5.9	1.7	8.1	1.4	6.4	4.5	7.1	-29.4

Table 5.5. Changes in maize growth duration (in days) under the various climate change scenarios in the Central Rift Valley, Ethiopia.

Crop model	CanESM4.5	CSIRO-MK4.5	HadGEM4.5	CanESM8.5	CSIRO-MK4.5	HadGEM8.5
DSSAT	-16	-23	-26	-25	-27	-31
WOFOST	-14	-23	-28	-26	-28	-33

5.3.3. Adaptation options

Change in planting dates

Optimum planting dates which provided maximum yields occurred between end of May (day of year 141) to mid-June (day of year 169) for the baseline climate while maximum yields were simulated with planting dates between mid-June (day of year 162) and end of June (day of year 183) in climate change scenarios with slight differences between the two crop model simulations (i.e. WOFOST shows stronger response to planting dates than DSSAT) (Fig. 5.3). This indicated that optimum planting dates will be delayed by approximately three weeks in future climate relative to the baseline climate. It should be noted that the early possible planting dates, which are dictated by the start of the rainfall season, did not shift much in the climate change scenarios because rainfall increased during April and May by

20.8 and 4.9 % (averaged over climate change scenarios), respectively (data not shown). However, rainfall in June and July was reduced by 5.9 and 5.4% (averaged over climate change scenarios), respectively, which in combination with the increased temperature reduced yields for the earliest planting dates. On the other hand, rainfall during August, September and October increased by 2.2, 3.8 and 16.8% in the future scenarios, respectively, which favored maize growth with the late planting dates.

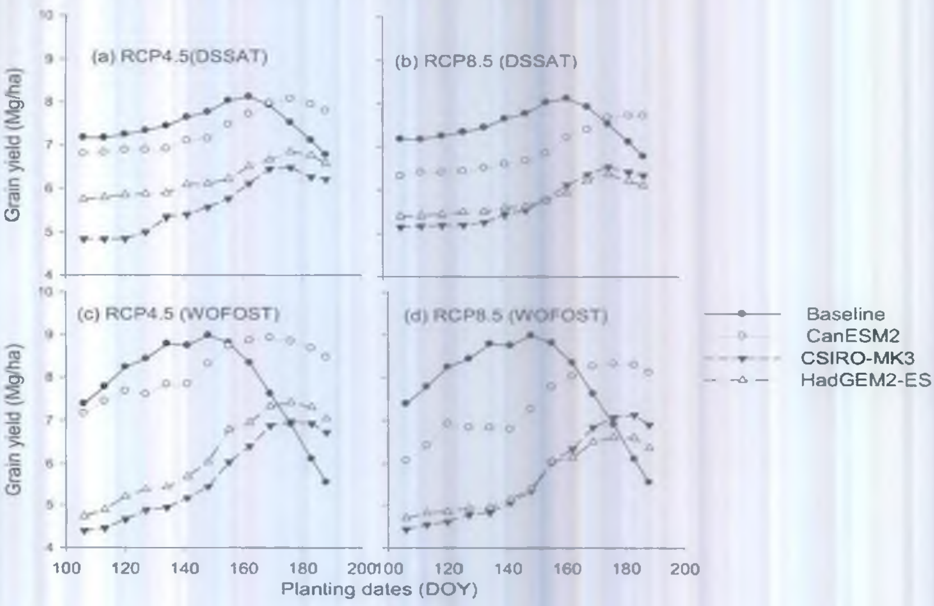

Fig. 5.3. Effects of planting dates on maize grain yield under the baseline and future climate change scenarios in the Central Rift Valley, Ethiopia. Each value is the average of 30 years simulation (1989-2009 for baseline climate and 2040-2069 for future climate change scenarios).

The increase in temperature was also highest in June and July (2.6 and 2.7 °C, respectively) and lowest in August and September (2.5 °C). It appeared that late planting has an advantage in reducing heat stress and dry spell effects at the critical growth stage of grain filling. In other words, it appeared that with increased temperatures and consequently increased evaporative demand, the early planting dates led to early depletion of soil moisture, resulting in a poor crop establishment and reduced yield, whereas later planting dates allowed the crop to grow under relatively better moisture and thermal conditions.

Nitrogen application

In all climate change scenarios, higher nitrogen levels increased maize yields, but full nitrogen supply (no nitrogen limitation) provided little additional yield advantage (12-17% across the climate change scenarios) compared to 80 kg N/ha (Fig. 5.4). The predicted yield with 20 kg N/ha varied between 2.6 and 3.4 Mg/ha and with 80 kg/ha between 4.9 and 6.3 Mg/ha across the climate change scenarios. For RCP4.5, simulated yield with 20 kg N/ha varied between 2.6 and 3.4 Mg/ha and with 80 kg N/ha between 4.8 and 6.3 Mg/ha (increase in yield by 85-89%) while for RCP8.5, simulated yield with 20 kg N/ha varied between 2.6 and 3.2 Mg/ha and with 80 kg N/ha between 5.1 and 5.7 Mg/ha (increase in yield by 78-86%).

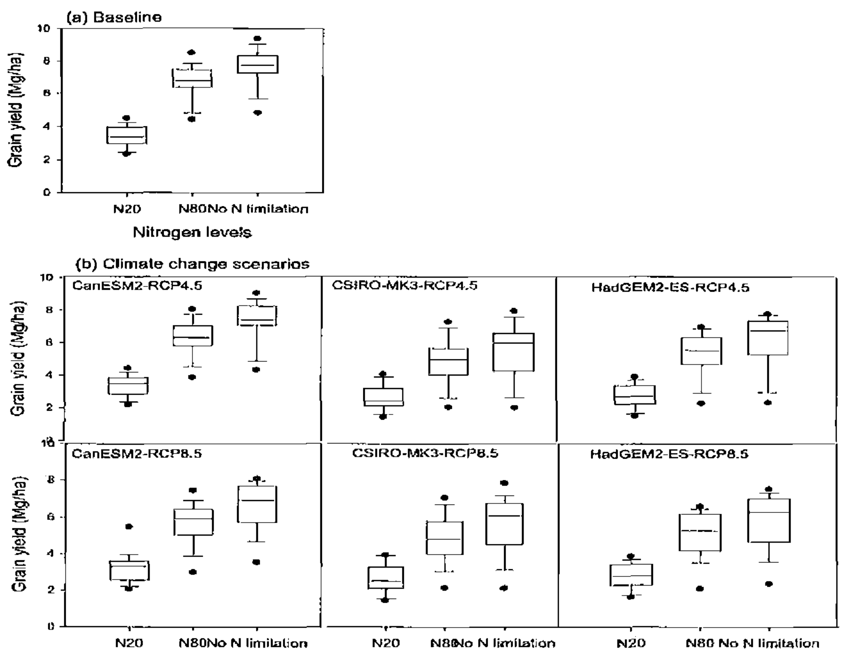

Fig. 5.4. Effects of nitrogen fertilization rates on maize grain yield simulated with DSSAT crop model under the baseline and future climate change scenarios. N20, N80 and No-N stress stands for the nitrogen levels of 20 kg/ha, 80 kg/ha and no nitrogen stress scenarios, respectively. The low nitrogen level (N=20 kg/ha) is approximately the average rate currently used by Ethiopian farmers and hence can be referred as "current management".

Overall, increasing the nitrogen rate by 60 kg/ha did yields increase by 78-89% in the climate change scenarios. However, simulated yields with 20 kg N/ha in the climate change scenarios were lower than the simulated yields with 20 kg N/ha under the baseline and the same still holds for the yields simulated with 80 kg N/ha simulations (Fig. 5.4), which suggests that crop yields will be less responsive to nitrogen under climate change conditions.

Irrigation application

Application of full irrigation resulted in a modest increase in yield under the baseline and climate change scenarios (Fig. 5.5). Yields increased by 11-16% (ranges are for crop models) under the baseline scenario. It did not significantly increase under the wet scenarios (CanESM2), while it increased by 15-22% under HadGEM2 and by 22-39% under CSIRO-MK3. Simulated water-limited maize yield ranged from 5.4 to 8.1 Mg/ha, while maize yields with irrigation (potential yield) ranged from 7.0 to 8.4 Mg/ha across the crop models and climate change scenarios. The increase in yield due to irrigation in DSSAT simulations ranged between 12 and 39% and in WOFOST between 4 to 22%. For the RCPs, the yield increase due to irrigation varied by 4 to 39% (RCP4.5) and 5 to 33% (RCP8.5). The inter-annual variability of yield under climate change scenarios was also reduced with full irrigation compared to rainfed conditions (CV was 12.5-37.4% for rainfed and 7.0-8.5% for irrigation). Note, however, that yields simulated with irrigation under climate change scenarios are lower than yields simulated with irrigation for the baseline climate (Fig.5.5), implying that irrigation is somewhat less effective under climate change conditions than under the baseline. The above results highlight the role of full irrigation with high nutrient management. However, full irrigation with high fertilization could be a costly investment for smallholder farmers. In such a case, supply of small amounts of water during moisture sensitive growth stages of maize (flowering and grain filling) can be economic. Under rainfed conditions and the supply of 80 kg N/ha, climate change reduced yields by 6-29%. However, with supplementary irrigation of 70 mm, the climate change impact was reduced to 5-15%. The simulated yield of maize under rainfed conditions ranged from 4.9 to 6.3 Mg/ha while with supplementary irrigation from 5.7 to 6.6 Mg/ha. Hence, supplementary irrigation increased yields by 5-21% relative to the rainfed production (Table 5.6).

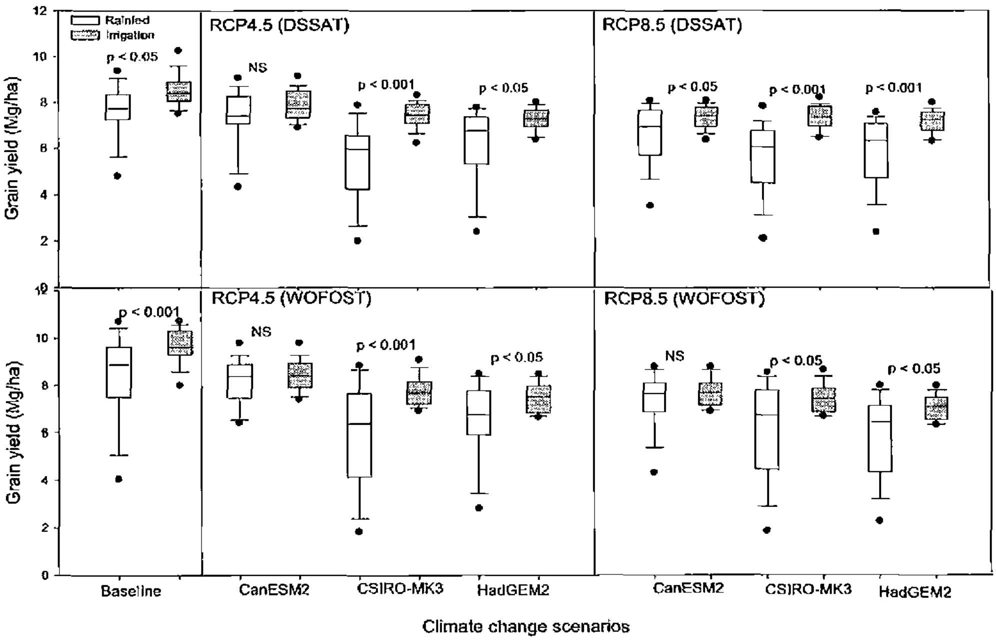

Fig. 5.5. Effect of irrigation on maize grain yields compared to the current management (rainfed) under the baseline and future climate change scenarios with no nutrient limitation conditions in the CRV, Ethiopia. NS indicates a statistically non-significant difference.

Table 5.6. Simulated effects of supplementary irrigation on maize yield (Mg/ha) compared to rainfed production under baseline climate and climate change scenarios in the CRV, Ethiopia, using DSSAT. Nitrogen application was 80 kg/ha and the supplementary irrigation simulations received 70 mm of water.

		RCP4.5			RCP8.5		
	Baseline	CanESM2	CSIRO-MK3	HadGEM2	CanESM2	CSIRO-MK3	HadGEM2
Rainfed	6.7	6.3	4.8	5.3	5.7	4.9	5.1
Supplementary Irrigation	7.2	6.6	5.7	6.0	6.1	5.9	5.9
Yield change (%)	7.4	4.8	18.8	13.2	7.0	20.4	15.7

Changes in cultivar

Under the baseline, the late maturing variety yielded significantly more than an early maturing variety (7.6-8.3 Mg/ha versus 6.8-7.2 Mg/ha, based on the two crop models) (Fig. 5. 6). Under climate change scenarios, only with the CanESM2 (wet scenario), the late maturing variety yielded significantly higher (16-20%) than the early variety. There was a maximum of about 29% yield reduction with the late maturing cultivar and about 23% with the early maturing cultivar across the various climate change scenarios. Despite no statistically significant yield differences in most of the climate change scenarios, yield was somewhat lower for the early maturing cultivar than the late maturing under all climate change scenarios. This indicates that changing the maturity class of the cultivars would not be a suitable adaptation option for the projected climate change.

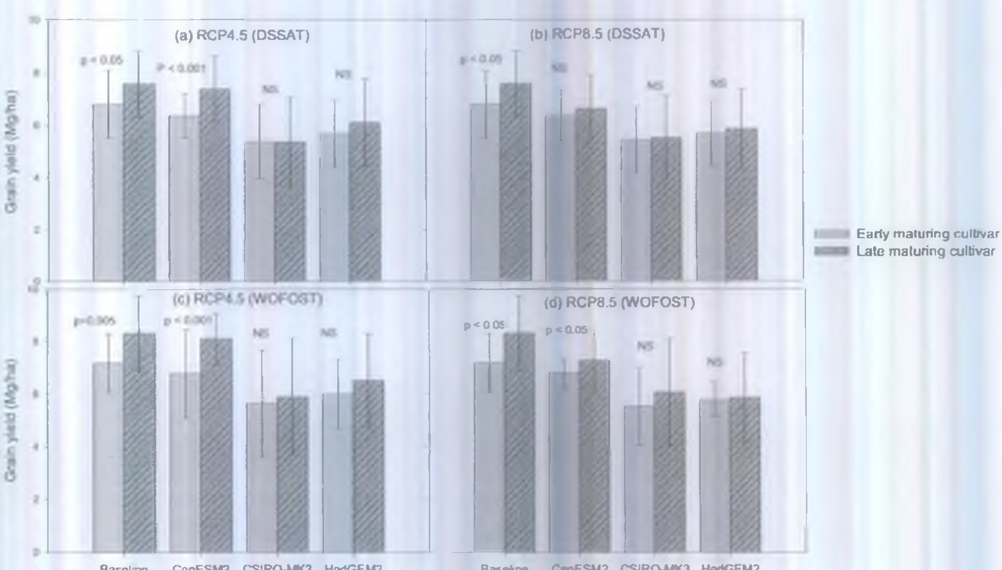

Fig. 5.6. Simulated grain yields for early and late maturing cultivars under the baseline (1980-2009) and future climate change scenarios by 2050s in the Central Rift Valley, Ethiopia. NS indicates a statistically non-significant difference.

5.4. Discussion

5.4.1. Methodology of the climate change impact projection: merits and shortcomings

This study showed the potential applicability of a multi-model systems approach to assist climate change adaptation decision making in Ethiopia. Since a single crop model fails to represent uncertainties known to exist in crop responses to climate change (Challinor et al., 2005; Rötter et al., 2011a; Asseng et al., 2013; Rosenzweig et al., 2013a), we used two crop models which, in combination with selected climate scenarios, enables us to use ranges of outcomes as estimates of impact uncertainties. It is now widely assumed that reporting ranges of possible outcomes quantified from multiple model simulations can provide better information and guidance for agricultural planners and policy makers. We are aware that using larger ensembles of crop and climate models could provide more details of impact uncertainties. For instance, Asseng et al. (2013) suggested that at least five crop models are required for robust assessment of impacts of increases of up to 3 °C temperature on wheat yield. Note, however, that it is essential to only use crop models suitable for the domain (purpose and conditions) of application.

Here we applied a delta change approach in creating future climate change scenarios (see Section 5.2.2), which has a drawback in that it assumes the behavior of current climate variability being the same in the future. While such an assumption may not necessarily be true, e.g. according to IPCC (2012), it is expected that climatic extremes become more frequent and severe under a changing climate, the delta change approach is still widely applied (see e.g. White et al., 2011; Rosenzweig et al., 2013b). In general, each approach for downscaling climate change projections for impact models has its drawbacks (Räisänen and Räty, 2012). The delta change approach is adequate when the impact of changes in mean climate on crops is of interest, while the use of other approaches (e.g. weather generators) will be required if changes in extremes are the focus. In addition, GCMs, still have deficiencies that make projections, especially those on changes in variability is quite uncertain, even in well-studied European regions as shown by Boberg and Christensen (2012). GCMs also had the highest contribution of uncertainties on simulated impacts in our study. Note, that the crop models applied in this study - as most other models of the current generation - do not adequately capture impacts of extreme events on crop yields (Rötter et al., 2011a; Schaap et al., 2011). Further research is required to quantify the share of this source of uncertainty (Lobell et al., 2013) and reduce it (Asseng et al., 2013; Rosenzweig et al., 2013b).

Also, widely applied crop models, such as DSSAT and WOFOST, lack the capability of quantifying impacts of occurrence of pests and diseases on crop growth and development. Such shortcomings need to be taken into account in interpreting crop model simulation results, especially in low-yielding environments with limited crop protection such as in the CRV.

5.4.2. Climate change impacts and uncertainties

Maize production is very likely to be negatively affected by climate change in the CRV and similar agro-ecological zones of Ethiopia. Because impact studies often differ by climate scenarios, time horizon and, more generally assessment methodologies, it is difficult to directly compare results with those from other studies (e.g. White et al., 2011). However, the order of magnitude of the yield change we found is broadly consistent with previous studies in tropical and sub-tropical regions. For instance, Schlenker and Lobell (2010) indicated maize yield reductions of about 22% in Sub-Saharan Africa by 2050s and many others reported nearly similar ranges of yield reduction (e.g. Tingem et al., 2008; Jones and Thornton, 2009). The main driving factor for changes in maize yield is increasing temperature resulting in a growing period shortened by 14-33 days across the climate change scenarios. Also other studies indicated that increased temperature is the main driver of yield changes under climate change scenarios (e.g. Lobell et al., 2013), although a shortened growing period may interact with rainfall patterns (Ruane et al., 2013). The negative impacts of increased temperature can be compensated by the effects of elevated CO_2 which reduces the impact of water stress on crop yields (Tubiello et al., 2000; Žalud and Dubrovský, 2002; Kimball, 2010). However, our analysis indicated that the effect of CO_2 , fertilization is rather small as expected for maize, a crop with a C4 photosynthetic pathway (Cairns et al., 2013). Nevertheless, the magnitude of the impact of elevated atmospheric CO_2 on crop physiology and growth remains debated topic of on-going research (Kimball, 2010; Berg et al., 2013; Lehmann et al., 2013).

Uncertainties in climate change impact studies are generally associated with climate scenarios (i.e. GCM projections) and greenhouse gas emission scenarios (Osborne et al., 2013; Whitfield, 2013). In addition, there is uncertainty from crop models (Aggarwal, 1995; Challinor et al., 2005; Rötter et al., 2011a; Asseng et al., 2013). However, uncertainties in crop models are often less thoroughly evaluated than climate uncertainty in impact assessments (Lobell et al., 2006). The various sources of uncertainties propagate through the simulation procedure resulting in biased estimates. For instance, maize yields in the CRV will be reduced due to climate change by 2 to 13% according to the CanESM2 climate model, while by 27 to 29% according to CSIRO-MK3, which reflects that there is large uncertainty among the GCMs. Uncertainties due to RCPs and crop models are narrower in this study, which is similar to the finding by Lobell et al. (2006), who reported that climate models had larger impact on projections than crop models. However, the number of crop models considered also matters (Asseng et al., 2013). Nevertheless, it often has been shown that uncertainties from GCMs dominate regional impact assessments for mid-century (Hawkins and Sutton, 2011), although on larger scales this may not be the case (Rosenzweig et al., 2013a)

5.4.3. Adaptation options

Adjusting planting dates is among the most widely studied strategies of adapting to climate change (White et al., 2011). Currently, CRV farmers practice flexible planting dates based on the onset time of the rainfall season, however, crop failure due to false starts of the rainfall season is a common risk (Kassie et al., 2013a). Our analysis indicated that optimum planting dates for future climate occurred later than the optimum planting dates under the baseline climate. For the early planting dates (mid-April to May) under future climate, critical growth stages of maize (i.e. during June and July) faced a decline in rainfall and increased temperature. Hence, the late planting dates had an advantage to avoid heat and drought stress at the early growth stage. In line with our results, Alexandrov and Hoogenboom (2000) in Bulgaria, Cuculeanu et al. (2002) in Romania and Tachie-Obeng et al. (2010) in Ghana reported an increase in maize yields with delayed planting dates for climate change scenarios.

The response of yield to nitrogen applications is higher for baseline climate than future climate change scenarios. Similar to our result, Luo et al. (2009) reported that changing the nitrogen levels from 25 to 75 kg/ha increased wheat yield under climate change in Australia, however, the projected yield increase was less than for the baseline. Similarly, Turner and Rao (2013) indicated that increasing nitrogen fertilizer rate from 20 to 80 kg/ha under a 3°C temperature rise increased yields of sorghum by 15-70% in Kenya, but yields remained lower than for the baseline climate. Yield of maize was significantly increased with irrigation under climate change except the wet (CanESM2) scenarios. With given conditions of water constraints, supply of supplementary irrigation during moisture sensitive growth stages of maize (flowering and grain filling) would help reducing the negative impacts of climate change. This implies that the practical and economic (e.g. Finger et al., 2011) potential of water harvesting and small scale irrigation (Moges et al., 2011) needs to be explored in the CRV.

The magnitude of climate change impacts will differ between crops and cultivars (Challinor et al., 2007a) and hence the choice of cultivars which fit best with the changing climate conditions will be an important adaptation strategy. Our analysis indicates that yields of late and early maturing cultivars were significantly different with the baseline climate, but showed no difference under climate change scenarios except the wet climate model (CanESM2). This implies that climate change will disfavor the late maturing cultivar more than the early maturing cultivar. However, early maturing cultivars are not outperforming under climate change implying that such cultivars are also not a suitable adaptation option to projected climate change. Developing more heat tolerant and high yielding, new cultivars is critical to sustain crop production under future climate change (e.g. Kurukulasuriya and Mendelsohn, 2006; Araus et al., 2008; Burke et al., 2009; Luo et al., 2009).

5.5. Conclusion and outlook

Climate change and its impact, as projected by the three GCMs in combination with two representative concentration pathways and two crop models, leads to reductions in maize production in the CRV and similar agro-ecological zones of Ethiopia and elsewhere. The study showed that potential productivity of maize will decrease on average by 20% (averaged over climate change scenarios and crop models) relative to the baseline due to climate change by 2050s. While the negative impact of climate change on maize yield is very likely, the extent of the negative yield impact is more uncertain ranging from -2 to -29%. The share in uncertainties of impact projections is higher for GCMs than it is for the RCPs and crop models. The projected decrease in maize yield is mainly caused by increased temperature and reduced growing season rainfall, which resulted in a shortened growing period of maize by 9-22%. Maize yield is reduced even for wet scenarios (that predict an increase in rainfall) implying that the impact of increased temperature is more pronounced than rainfall under climate change.

Results for adaptation analysis indicate that increasing nutrient fertilization, use of irrigation and changes in planting dates (slightly shifting to late planting by three weeks relative to the baseline planting dates) can compensate the negative impacts of climate change on maize production. However, it should be noted that the response of yield to increased nitrogen fertilization and irrigation supply will be less for climate change scenarios than the baseline climate implying that negative impacts of climate change will not be totally compensated. The increase in yield with nitrogen and irrigation application under climate change scenarios is also conditional on application of flanking measures, such as adjusted crop protection, to enable realization of potential yield increases. Currently available late and early maturing cultivars are likely less optimal under climate change, which implies that the breeding research in Ethiopia in collaboration with international research centers (see Cairns et al., 2013) needs to be tailored towards developing high yielding and heat tolerant cultivars, and preferably also disease and pest-resistant, in order to effectively adapting crop production to future climate. Some of the adaptation options such as irrigation and nitrogen fertilization may involve considerable costs and thus require further studies based on economic feasibilities (see e.g. Finger et al., 2011). This study has considered a narrow spectrum of adaptation options that can be examined with crop models alone, and future research needs to be more integrative including socio-economic effects of introducing various adaptation options at farm level. The multi-model based analysis allowed for estimation of some of the climate change impact and adaptation uncertainties, which can provide valuable insights and guidance for adaptation planning processes.

Acknowledgments

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CHAPTER 6

General discussion and conclusions

6.1. Objectives and design of the study

The main objective of this study was to improve understanding of impacts of climate variability and climate change on cereal-based production in selected vulnerable regions of Ethiopia and to explore adaptation strategies to reduce these climate-induced risks. The study investigated how crop production is affected by current climate variability and how it might be affected by anticipated climate change including analysis of current adaptive practices and options to adapt to projected climate change. Its specific objectives were to:

1. Characterize trends, variability and changes of agro-climatic conditions and associated risks for rainfed crop production in the Central Rift Valley (Chapter 2);
2. Quantify climate-induced yield variability; and yield gaps of maize in the Central Rift Valley (Chapter 3);
3. Analyze farmers' perceptions on climate variability and change and identify climate risk management strategies as well as needs and barriers for future adaptation in the Central Rift Valley and Kobo Valley (Chapter 4);
4. Explore impacts and adaptation strategies for maize production under different climate change scenarios in the Central Rift Valley (Chapter 5).

In the context of the aforementioned objectives, the study addresses the twin pillars of adaptation (Cooper et al., 2013), i.e. helping farmers (i) to cope better with the current climate-induced risks and (ii) to adapt to future climate change. To improve understanding of the interactions between climate and agricultural production, the study first characterizes ago-climatic conditions of current and future climate. Relevant agro-climatic variables have been analyzed under the current climate (baseline) and future climate change scenarios and implications for rainfed crop production have been discussed (Chapter 2). Then, the study quantified how climate variability is affecting maize productivity (Chapter 3) and it explored how maize productivity may be affected by anticipated climate change (Chapter 5). Adapting agriculture to climate change requires that farmers are aware of the changes in climate. The study, therefore, assesses farmers' perceptions to climate variability and change and compares these perceptions with measured climate data (Chapter 4). The results of these qualitative and quantitative analyses in conjunction with results from stakeholder discussions on their aspirations and regional constraints allow for an exploration of promising adaptation strategies. Current climate risk management strategies (Chapter 4) and potential adaptation options for climate change scenarios (Chapter 5) have been identified and constraints and barriers have been discussed.

To achieve the objectives, the study applied empirical statistical analyses, field survey methods, and a systems-analytical approach, using field experimental data in combination with climate-crop simulation modelling. A general scheme of the methodology applied throughout Chapters 2 to 5 is presented in Fig. 6.1. In this chapter, a synthesis of the main results of the previous chapters is presented and discussed. Scientific insights and implications for climate risk management and issues for further research are described.

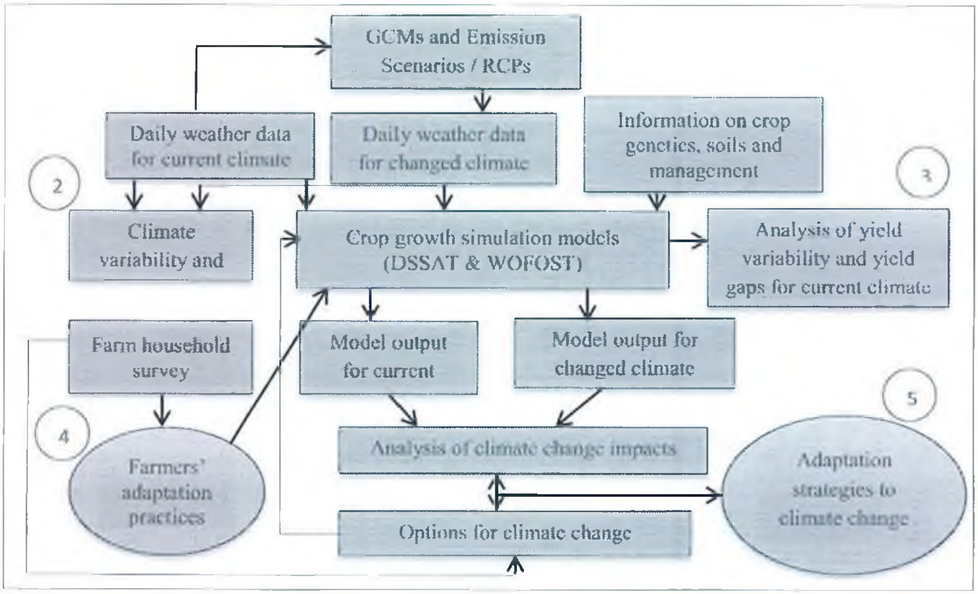

Fig. 6.1 Schematic overview of the general methodology used in climate variability and change analysis. Numbers in circles indicate the chapters of this thesis in which parts of the methodology have been applied. GCM refers to General Circulation Models and RCPs to Representative Concentration Pathways.

6.2. Climate variability and change and impacts on crop production

Understanding climate variability and changes and their impacts is essential for devising adaptation strategies. In Chapter 2, we analyzed historical trends and future changes of climate in the CRV of Ethiopia. The annual rainfall in the CRV showed no significant trends over the period 1977-2007 (Table 2.3) and reports from other studies at regional and national scales are mixed: Some studies have identified decreasing trends in parts of Ethiopia (e.g.

Cheung et al., 2008) but others did not find strong evidence for consistent changes in the annual rainfall (e.g. Seleshi and Camberlin, 2006). The seasonal rainfall (June-September) exhibited high inter-annual variability (CV=15-40%) during the period 1977-2007 (Chapter 2). The variability in rainfall is noticed by local farmers (Chapter 4). According to farmers' perceptions, the seasonal rainfall is characterized by late start, early cession and erratic distribution associated with increased dry spell events (Fig. 4.1). There was large inter-annual variability in the length of the growing season, ranging from 79 to 239 days. Also the number of rainy days decreased and was associated with an increase (statistically not significant) in the intensity per rainfall event for the main rain season. Most of the historical drought episodes that occurred in the semi-arid regions of Ethiopia such as the Central Rift Valley (CRV) are related to the variation in the seasonal rainfall (Viste et al., 2013). Analysis for future climate change scenarios based on four GCMs (HadCM3, CSIRO2, CGCM2 and PCM) and two emission scenarios (SRES, A2 and B1), which were accessible at the time of analysis, suggested that the annual rainfall may change by -40 to +10% in 2080s relative to the 1971-1990 base period (Chapter 2; Table 6.1). More recent climate change projections based on CMIP5 data sets of three contrasting GCMs (CanESM2, CSIRO-MK3, and HadGEM2-ES) and two Representative Concentration Pathways (RCP4.5 and RCP8.5) indicate that the annual rainfall may change by -1 to +38% in 2050s relative to the 1980-2009 baseline period (Chapter 5; Table 6.1). The annual increase in rainfall results from a substantial increase during months (November-January) that are agriculturally less relevant under current conditions. Most of the GCMs projected a decrease of rainfall during the main growing season (June-September). Yet, there is on-going debate with respect to high uncertainties of climate projections for the East African region suggesting that most GCMs may not be able to capture the distinct effects of a rapid warming in the Indian Ocean on circulation and precipitation patterns (Funk et al. 2008). In recent decades this phenomenon has led to suppressed convection over tropical eastern Africa, reducing rainfall during March-June - a trend that is expected to continue for some time but not or poorly captured by most GCMs (Williams and Funk, 2011).

With regard to temperature, there is a clear indication for warming trends under the current and future climate. The mean temperature in the CRV exhibited an increasing trend of 0.12-0.54 °C per decade with an average increase of 2.2 °C over the period 1977-2007. Farmers also perceived the increasing trends in temperature over the past 20 to 30 years (Fig. 4.1).

Analysis for future climate change scenarios showed that the mean temperature will continue to increase by 1.6-3.3°C in 2050s and by 1.8-4.1 °C in 2080s (Table 6.1). Temperature trends of these scenarios are consistent with other regional and global analyses. For instance, Conway and Schipper (2011) indicate that the annual temperature of Ethiopia will increase by 2.2 °C in 2050s. The global surface temperature has increased by 0.4 to 0.8 °C in the twentieth century and is projected to further increase by 1.4 to 5.8 °C by the end of this century (IPCC, 2007).

Table 6.1. Historical trends and projected changes in annual and seasonal rainfall and temperature in the CRV. Historical trends are calculated for the period 1971-2007 and projected changes are relative to a base period of 1971-1990 for 2080s (Chapter 2) and 1980-2009 for 2050s (Chapter 5). Seasonal rainfall and temperature refers to the months June to September. Units of trends are in °C per decade for temperature and mm/decade for rainfall while projected changes are in °C and percentage, respectively, for temperature and rainfall.

	Historical records		Projected changes	
	Mean	trends	2080s	2050s
Annual rainfall	830	0.20	-40 to +10	-1 to +38
Seasonal rainfall	520	-0.14	-50 to +4	-19 to +21
Annual temperature	18.9	0.22	1.8 to 4.1	1.6 to 3.3
Seasonal temperature	20.2	0.34	1.3 to 4.0	1.1 to 3.0

Climate variability and change are among the main challenges for agricultural production in Ethiopia, particularly, in the semi-arid lowlands such as the CRV. The warming trends and rainfall variability are already posing risks to rainfed crop production in the CRV (Chapter 2 and 4). The actual impacts of climate variability on agricultural systems, of course, depend on location and adaptive capacity (Vermeulen et al., 2013). In the CRV, crop production is predominantly rainfed, with irrigation agriculture accounting for less than 1% of total area and climate, particularly, rainfall is highly variable (Chapter 2) while smallholder farmers have less adaptive capacity (Chapter 4). The inter-annual variability of rainfall associated with intermittent dry spells during the crop growing period and increasing temperature, thus, adversely affects crop production and rural livelihood (Table 4.4). Climate variability also discourages farmers' investment in improved agricultural technologies. Farmers indicated that in years with low or erratic rainfall distribution, agricultural inputs such as chemical fertilizers do not provide yield gain. Because of such risk-averse behavior, many farm households adhere to traditional practices instead of adopting improved technologies (Chapter 4).

Quantitative analysis of the effects of current climate variability on rainfed crop yields using crop simulation models (Chapter 3) revealed that simulated water-limited yield exhibited high inter-annual variability (CV= 36%). The annual variability of crop yield is strongly correlated with climate variability, particularly rainfall within and between seasons (Fig. 3.4 and 3.5), which is a typical problem of production uncertainty in most rainfed farming systems of Sub-Saharan Africa (Cooper et al., 2009; Cooper and Coe, 2011; Müller et al., 2011). About 60% of the variability of simulated water-limited yield was explained by rainfall variability during the growing season. There is also a large gap between simulated water-limited yields and farmers' actual yields; the latter being only 27-30% of the simulated water-limited yields (Table 3.9). Existing yield gaps are reflections of sub-optimal agronomic practices and inadequate climate risk management strategies (Chapter 4). From the existing yield gaps, we can deduce that the recommended production technologies (e.g. fertilizer and agro-chemicals) are not fully adopted at farmers' fields.

With highlights on impacts of current climate variability, the next question would be what is the likely impact of future climate change on crop production? This question is addressed in Chapter 5 analyzing the impacts of various climate change scenarios on maize production in the CRV. The results revealed that maize yield will decrease on average by about 20% (ranges between -2 to -29% across climate change scenarios and crop models) relative to the baseline (1980-2009) due to climate change in the 2050s (Fig. 5.2). The main driving factors for lower maize yield under future climate change scenarios are increasing temperature (1.6 to 3.5 °C during the growing season) confounded with a decrease in seasonal rainfall resulting in a shortened growing period by about 14-33 days (Table 5.5). The impact of increase in temperature is more pronounced than rainfall under climate change scenarios, which can be deduced from the result that maize yield also decreased for scenarios that predicted an increase in growing season rainfall (CanESM2; Fig. 5.1 and Table 5.4). The results in Chapter 5 generally imply that with a business-as-usual development, the progressive climate change is expected to negatively affect crop productivity in the CRV. Various global and regional studies also warned that climate change may adversely impact agricultural productivity in most parts of the world, particularly in Sub-Saharan Africa (e.g.

Morton, 2007; Jones and Thornton, 2009; Cairns et al., 2013; Müller, 2013) putting agricultural adaptation and risk management strategies in the spotlight.

6.3. Adaptation to climate variability and change

6.3.1 Options for adaptation

Adapting agriculture to climate variability and change refers to adjustments in management strategies to actual or expected climatic conditions or to their impacts, in order to reduce risks or exploit any opportunities (Adger et al., 2007). Adaptation actions fall into two broad overlapping categories (Vermeulen et al., 2013): (i) practices evolved over time through farmers' long-term experiences in response to perceived impacts and (ii) planned adaptations to on-going and future climate change, for example, integrated packages of improved agricultural technologies such as breeding, agronomic practices and policy options. Chapter 4 presents current adaptive strategies of farmers from two case study regions, i.e. the Central Rift Valley and Kobo Valley, both representing main cereal-based farming systems with relatively contrasting development potentials and farming history. Main adaptation strategies include crop and cultivar selection, planting date adjustments, replanting (when a crop fails) and various *in situ* moisture conservation techniques such as tied-ridges, shilshalo and spate irrigation (Fig. 4.5). Farmers adjust some of the agronomic practices such as seed density, tillage frequency and fertilizer rates to fit with the prevailing weather condition which indicates that guiding agronomic practices with effective weather outlooks (response farming) is highly required to reduce the impacts of climate variability. Farming experiences, land size and education of farm households influence the diversity of adaptive responses at farm levels (Fig 4.8) which indicate that current adaptation is shaped mainly by locally available resources and knowledge. Some households also attempt to diversify their income from non-agricultural activities such as through renting out labor and temporal migration. Social networks contribute in inter-household income transfer and loans during climate shocks. Safety nets (food or cash-based transfer) are popular among the humanitarian support and government programs, to protect chronically food insecure households.

The current adaptation strategies are important in responding to current climate variability, however, future climate is expected to impose novel risks beyond the scope of current experiences (Boko et al., 2007; Cooper et al., 2008) and the current relatively low-cost changes in farm practices may not be sufficient to deal with the impacts of future climate change (Boko et al., 2007). In the light of this concern, stakeholders' aspirations for future adaptation were assessed (Chapter 4) and more quantitative analyses were conducted for adapting maize production in the CRV under various climate change scenarios (Chapter 5). Stakeholders (farmers and extension workers) identified access to improved crop varieties (drought and heat tolerant, pest resistant) agricultural inputs (fertilizer, improved seed), small scale irrigation and water harvesting, effective weather forecasting service and climate risk insurance as promising adaptation options to future climate change (Table 4.6). Crop model-based evaluation of adaptation options under future climate change scenarios (Chapter 5) revealed that increasing input levels (fertilizer), supply of irrigation water and shifting to late planting (about three weeks later than the baseline) would reduce the likely negative impacts of climate change. For instance, increasing nitrogen fertilization from 20 to 80 kg/ha increased rainfed yield by 78-86% under different climate change scenarios. Application of irrigation also provided an increase in yield by 15-39% relative to rainfed production across the climate change scenarios. The inter-annual variability of yield under climate change scenarios was also reduced with irrigation compared to rainfed conditions (CV was 13-37% for rainfed and 7-9% for irrigation). Nutrient fertilization and irrigation would be part of solutions for farmers needs' as to future adaptation as discussed in Chapter 4. Note, however, that crop yield will be less responsive to both nitrogen fertilization and irrigation under climate change relative to a baseline climate (Fig. 5.4 and 5.5) implying that the negative impacts of climate change will not be totally removed or compensated. Guiding planting date decisions with effective weather outlooks is another essential component of climate change adaptation. Currently, most farmers practice planting at the earliest possible planting time (when the first rain comes), however, the critical growth stages of their crops are very much affected by intermittent dry spells and moisture stress leading to crop failure (Chapter 4). As farmers have to deal with more variable weather conditions under climate change, developing weather-based cropping calendars towards determining optimum planting time is crucial. Changing current maize cultivars from late to early maturity types was not a suitable adaptation option under future climate change scenarios. Increasing temperature in the future would necessitate the use of new cultivars with more heat tolerant traits and hence breeders need to consider robustness to climate change in their programs. Various studies showed that developing new cultivars that can better cope with the changing climate is critically needed to adapt cropping systems to future climate change (Kurukulasuriya and Mendelsohn, 2006; Burke et al., 2009).

6.3.2. Technological and institutional limitations

In Chapter 4, we presented a number of barriers that need to be removed in order to increase the adaptive capacity of farmers and enhance adaptation to climate induced risks. One of the constraints is the lack of effective weather forecast and early warning service. A weather forecast and early warning service has been disseminated for decades in Ethiopia but it has not yet been integrated effectively into agricultural decision making processes. A typical forecast in Ethiopia expresses rainfall aggregated over a large spatial scale and is described in qualitative terms, such as above normal, normal and below normal rainfall; it cannot support farmers' decision-making. Weather forecast services can only be useful for climate risk management when it contains information about the timing (e.g. onset of rainy season or dry spells), and can be interpreted at a local scale and delivered to farmers through trusted channels (Hansen et al., 2007). Thus strengthening weather forecast and early warning services is vital for supporting farmers and shaping adaptation.

Increasing prices for agricultural inputs and lack of agricultural credit systems already limit farmers' capacity to use available technologies such as fertilizer and improved seed (Chapter 4, see also IPCC, 2001). The current improved seed technology package promoted in Ethiopia by the government extension program (Deressa et al., 2010), for instance, requires the use of agricultural inputs (fertilizer and agro-chemicals) for increasing yields, which is not affordable for most households (Chapter 4). Furthermore, insecure land tenure system and small land holdings constrain farmers' willingness to adaptation. Securing land rights and tenure is an important issue to encourage farmers to invest in agricultural innovations and adaptive technologies. The issue of land size implies the need to intensify cropping systems. Agricultural intensification leading to increasing productivity, would help to enhance mitigation through more efficient use of agricultural inputs (Burney et al., 2010). An intensification program, however, should not be based on a "one-size-fits-all" strategy that fails to recognize variation in terms of agricultural potentials in different agro-ecologies and farming systems. Effective rural credit systems need to be established and prices of agricultural inputs have to be affordable to smallholders in order to intensify agriculture and increase productivity. Furthermore, linkages among research systems, extension services and farmers need to be strengthened. At present, there is no coordinated program of research on climate change in Ethiopia, rather it is *ad hoc*, where research efforts and findings tend to appear through poorly linked projects, which is a typical problem in most Sub-Saharan Africa

(Conway, 2011). Improving coordination among the various actors and building capacity are essential pre-requisites to enhance agricultural adaptation in Africa, including Ethiopia (Desanker and Justice, 2001; Washington et al., 2006; Cooper et al., 2013).

6.4. Uncertainties in modelling climate-crop growth interactions

6.4.1. Classification of uncertainty

According to Walker et al. (2003), uncertainty can generally be defined as being "any departure from the unachievable ideal of complete determinism" and can be characterized and classified according to three dimensions: source, level and nature (Refsgaard et al., 2013). Based on sources, Walker et al. (2003) classified uncertainty in model simulations into five main categories:

(i) *Model context and framing uncertainty*: these are uncertainties related to the boundaries of the systems to be modeled. A model context is basically determined at the initial stage of a study when the problem is identified and characterized. Thus model context uncertainties arise from framing socio-economical, environmental, technological and political conditions that form the context of the problem.

(ii) *Model structure uncertainty*: is a conceptual uncertainty due to incomplete understanding and simplified descriptions of modeled processes as compared to the reality, for example, when the conceptual framework or model used for analysis does not include all the relevant processes or relationships.

(iii) *Input uncertainty*: Model inputs uncertainties arise from incomplete determination of particular values of input data (such as climate, edaphic and crop data), or these data are inaccurate or not fully representative for the object of study.

(iv) *Parameter uncertainty*: if the system is well known, initial and input conditions can be manipulated and output can be observed with no error, however, calibration and evaluation might be either ignored, based on trial and error or based on some optimization principles which would result in uncertainty.

(v) *Model technical uncertainty*: arising from computer code implementation of the model or, for instance, due to numerical approximations (i.e., resolution in space and time).

The level of uncertainty characterizes how well the uncertainty can be described and it can be classified as statistical, scenario and recognized ignorance types (Yao et al., 2011). *Statistical uncertainties* are those which can be expressed statistically as a range with associated probability. For example, statistical expressions for measurement inaccuracies and model parameter estimates are a statistical uncertainty. *Scenario uncertainties* are those which cannot be depicted adequately in terms of probabilities but which can be specified in terms of ranges of possible outcomes. *Recognized ignorance* concerns uncertainties of which we realize their existence but we cannot establish any useful estimates due to unknown processes. The nature of uncertainty can be, generally, either epistemic or stochastic /or both (Walker et al., 2003). *Epistemic uncertainty* is that caused by incomplete knowledge and can be reducible by more studies, e.g., by improving the data analysis, making additional monitoring (time series of data), or by deepening our understanding of how the modeled system works. *Stochastic uncertainty* is that due to inherent variability (e.g. climate variability) and is non-reducible i.e. no matter how perfect data collection and mechanistic understanding of the system are, there will always be some uncertainty inherent to the natural system and perfect knowledge on such natural phenomenon cannot give us a deterministic prediction, but would enable us to characterize the natural variability. Recent studies have applied the scheme of Walker et al. in modified form for characterizing and quantifying uncertainties in crop models for climate impact modelling (e.g. Palosuo et al., 2011; Rötter et al., 2012b; Asseng et al., 2013).

6.4.2. Bio-physical data scarcity

Crop-climate modelling is an effective, advanced method to understand crop-climate interactions (Chapter 3) and evaluate various agronomic adaptation strategies (Chapter 5). However, the success of such approaches depends on quality of input data used. Bio-physical models need extensive field validation to assess the range of their validity (Jame and Cutforth, 1996; Jones et al., 2003). Experimental data on crop and soil management are key inputs for calibration and validation of agricultural simulation models. However, these are very scarce or not very well organized in Ethiopia, a problem typical for many countries in Sub-Saharan Africa (Chapter 3, see also Conway, 2011; Ramirez-Villegas and Challinor, 2012). At present, experimental data is collected by various researchers in Ethiopia, however, storage and backup of such data sets is highly fragmented, resulting in a poor institutional memory. As Whitfield (2013) underlined, standardized methods of data collection, processing, sharing and reuse is an essential component of agricultural research. There is a need to compile and reorganize existing data so as to establish institutional memory for bio-physical data (climate, soil, crop management), so that data remain accessible, sharable and reusable in the long run (Diekmann, 2012).

Limited access to climate data is another constraint for climate research. At present, there are difficulties in obtaining climate data due to constraining data use policy. I obtained the observed climate data used in this study from the National Meteorological Agency of Ethiopia through long administrative negotiations and lobbies. Climate data need to be considered as a public good provided that it is used for research and development efforts. According to Cooper et al. (2013), one of the foundations upon which effective climate change research could be built in Africa is by improving access to information such as historical climate data and databases of on-going projects.

6.4.3. Uncertainties in modelling climate change impacts on crop growth

Agricultural impact projections are subject to uncertainty (Yao et al., 2011; Rötter et al., 2012a) which arises from the various tools used in impact assessment such as: (i) climate models, (ii) emission scenarios, (iii) down-scaling of climate scenario data and (iv) impact models (e.g. crop models). Global climate models, also known as Global Circulation Models (GCMs) typically represent complex interactions of the earth-atmospheric system – the way these interactions have been captured in the models differs to some extent between the different GCMs, leading to different projections. These differences might be interpreted as uncertainties, as the correct representation of the interactions remains unknown. Scenario-based impact studies also inherit uncertainties in GHG trajectories and their impacts on the climate system (Challinor et al., 2009b), because emission scenarios comprise assumptions on future population growth, economic development and technological progress, which determines the sources of energy used (Müller, 2013). Various downscaling techniques are applied to derive GCM projections at a more detailed spatial resolution (regional or local scale) and the downscaling techniques may inherit uncertainties. Furthermore, crop growth simulation models add uncertainties due to their structure or measurement or estimation errors as to input values. Cascading of uncertainties in climate change prediction and impact analysis are presented in Figure 6.2. Due to such uncertainties, the literature commonly shows a wide range of potential impacts of climate change for the same region. For example, Reilly and Schimmelpfennig (1999) estimated that maize yields in Africa may change between -98% and +16% due to the impacts of climate change and elevated CO_2 concentration, while Thornton et al. (2010) estimate a much smaller range from -6 to -25%.

Quantifying uncertainty is, therefore, an important effort in climate impact studies (Challinor et al., 2005; Eitzinger et al., 2008; Yao et al., 2011). However, there is no consensus in the literature on how best to quantify these uncertainties (Challinor et al., 2005). There are two main schools of thought to deal with climate change uncertainty in adaptation under which the various decision making analyses can fit into: prediction-oriented and resilience-oriented (Berkes, 2007). Prediction-oriented thoughts came from decision making and risk analysis literatures and as well as from the IPCC. They argue that uncertainty needs to be characterized, reduced and managed and communicated, which leads to sophistication of modelling tools and techniques to describe the future climate and impacts. The resilience-oriented school of thought originates from the fields of societal and policy learning and complex adaptive systems research, which accept that some uncertainties associated with climate change are irreducible and emphasize learning from the past, i.e. they believe that learning to live with uncertainty requires building a memory of past events, expecting the unexpected and increasing the capability to learn from crises. In this thesis, we follow the prediction-oriented approach.

The recommended approach by IPCC (IPCC, 2001) is to use ranges of multiple climate change scenarios. Most of the climate change impact studies adopt this approach and use ensembles of GCMs, however, the use of multiple crop models has been very limited (Chapter 3 and 5) but is getting recognition recently (Rötter et al., 2011a; Asseng et al., 2013; Rosenzweig et al., 2013b). We applied two well-accepted crop models and multiple climate models for the analysis of impacts of climate variability and change (Chapter 3 and 5). Use of multiple models provided insights on the possible range of outcomes as a measure of uncertainties. In Chapter 3, we observed that the inter-annual yield variability simulated with DSSAT and WOFOST models differed, i.e., CV 9-26% for DSSAT and CV 19-35% for WOFOST. This difference comes due to different approaches of the two crop models in characterizing important components of crop growth, for instance, DSSAT calculates evapotranspiration using the Priestley-Taylor approach while WOFOST uses the penman method.

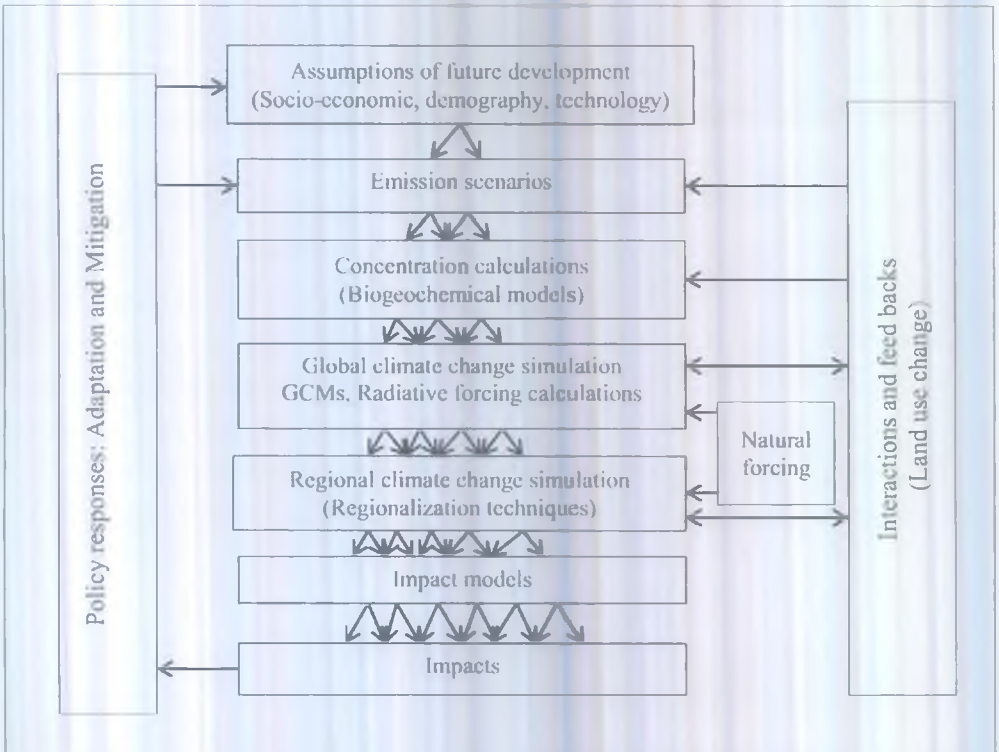

Fig. 6.2. Cascade of uncertainties in climate change impact analysis (Modified after Giorgi, 2005).

In Chapter 5, we showed that climate change will affect maize yield negatively in the CRV, while the extent of the negative impact is more uncertain with estimates ranging from -2 to -29% depending on crop model, GCM and RCPs. The share in uncertainties of impact projections is higher for GCMs (-8 to -28%, average over RCPs and crop models) than it is for the RCPs (-17 to -22%, average over GCMs and crop models) and crop models (-19 to -20%, average over GCMs and RCPs). Thus, from the selection of models we used, it can be deduced that GCMs are the most important source of uncertainties, which is consistent with the observations that uncertainties from GCMs dominate regional impact assessments for mid-century (Hawkins and Sutton, 2011), although on larger scales this may not be necessarily the case (Rosenzweig et al., 2013a). If effective and appropriate agricultural adaptation is to happen in the next decades, such uncertainties need to be communicated and understood by agricultural researchers and policy makers (Ramirez-Villegas et al., 2013). However, the uncertainty in the magnitude of climate change impacts does not take away the certainty that adapting to climate change is needed.

6.5. Methodological strengths and limitations, and implications for future research

6.5.1. Strengths of the methodology

The study reported in this thesis applied a combination of complementary approaches such as an agro-climatic index-based analysis (Chapter 2), farming systems survey tools (Chapter 4) and a crop and climate modelling approach (Chapters 3 and 5). Agro-climatic index-based analysis provided insights on main characteristics of agriculturally relevant climate resources. The farm household survey adds a participatory component to the study by involving farmers and extension workers through questionnaires, in-depth interviews and focus group discussions, which enabled to gain insights on local perceptions and adaptive responses. Furthermore, the study compared farmers' perceptions with climate data analysis and discussed why some of farmers' perceptions diverged from observed climate trends. This approach provides relevant lessons for better integration of local knowledge and scientific-based information to avoid counterproductive adaptation planning or to put specific effort in awareness raising, e.g. when it comes to actual versus perceived changes in rainfall.

Crop growth simulation was done using two well-accepted crop models (Chapter 3 and 5), which is an innovative feature of the methodology used in this thesis. To date, most research efforts on modelling crop-climate interactions used a single crop model to simulate crop growth processes. However, crop growth is a very complex process involving a series of interactions of soil, crop and weather and a crop model, being representative for parts of reality, may not accurately reproduce the dynamic processes of crop growth and development in the field (Rötter et al., 2011a). Outputs from a single crop model simulation are, therefore, not sufficient to indicate uncertainties (Rosenzweig et al., 2013b). Using several models, also known as ensemble modelling (Challinor et al., 2009c), if suitable for the aim and domain of application, enables to better represent uncertainty emanated from the crop models. In Chapter 3, we showed that the two used crop models differed in capturing inter-annual variability of maize yield in the CRV and hence ranges of outcomes from the two models were used to characterize yield variability. This could provide important lessons to other researchers on the added value of using more than a single crop model in simulation studies.

For the analysis of climate change impacts and adaptation, we used the latest GCMs and Representative Concentration Pathways (RCPs) released by the Coupled Model Comparison Project phase5 (CMIP5). Compared to the CMIP3, the new CMIP5 models have higher horizontal and vertical resolution in the atmosphere and ocean and a more complete representation of the Earth system such as the carbon cycle (Taylor et al., 2012) which leads to a better projection of climate. The IPCC Fifth Assessment Report, AR5 (under way, expected to be published in 2014) uses a new set of scenarios, called Representative Concentration Pathways (RCPs) replacing the Special Report on Emission Scenarios (SRES) standards employed in the two previous reports. These new generation of GCMs and RCPs are expected to be the basis for climate change impact studies over the coming few decades (Ramirez-Villegas et al., 2013). The methodology applied in future climate change impact analysis is therefore up-to-date.

6.5.2. Capturing all relevant bio-physical processes

Crop models and climate scenarios used in various impact studies, including this thesis, lack addressing indirect impacts of climate change such as changes in the incidence of pests and diseases as well as extreme weather events. Climatic factors determine the spatial and temporal distribution of pests and disease and increases in climate extremes due to climate change may have serious implications for population dynamics of pests and diseases and altering their geographical distribution, thereby possibly leading to increased crop losses (Gregory et al., 2009). In such cases, the actual impacts of climate variability and change on yields at farmers' fields may be different from those simulated by the crop models. Thus, effects of pests and disease in climate change impact study could lead to more realistic projection of impacts on yield and thereby help developing appropriate adaptation strategies.

Climate change impact analysis reported in this thesis applied a delta method approach for creating climate change scenarios (Chapter 5), which has a drawback in that it assumes that the behavior of current climate variability stays the same in the future. However, extreme weather events such as spells of very high temperature and intense rains are expected to increase with climate change (IPCC, 2012) thereby affecting agricultural productivity beyond the impacts of mean climate change. Hence, including impacts of extreme weather events under climate change may complement analysis of climate change impacts on agriculture.

6.5.3. Integrated assessment of climate change and adaptation

The study reported in this thesis provided useful insights on bio-physical impacts, however, it does not quantify the socio-economic aspects of climate change adaptation, nor does it analyze impacts and evaluates adaptation options at farm level. The challenges for agro-ecosystem modelling in supporting farm level analysis of adaption options have recently been described (e.g. by Rötter et al., 2013b). For example, in our study, farmers indicated that the current land tenure system does not encourage investing in long-term adaptation strategies (Chapter 4). Future research should focus on how land use rights could be secured so as to enhance adaptation planning. Other socio-economic issues such as market infrastructure, access to credit system and agricultural inputs (seed, fertilizer, pesticides) and institutional arrangements for effective extension services also need attention in research and policy for improving adaptation planning and implementation. A modelling approach that integrates the biophysical, economic, social and institutional aspects of a system under study (Van Ittersum et al., 2008) could be helpful to assess and explore more appropriate adaptation strategies. According to Weyant et al. (1996), integrated assessment provides three main purposes: (i) to assess the potential impacts and responses to climate change by integrating physical, ecological, economic and social factors; (ii) to provide coherent systematic frameworks that may facilitate more systematic searching for possible responses; (iii) to help addressing the most fundamental policy questions on climate change. Moreover, an integrated assessment of climate change at farm level (Reidsma et al., 2010) allows accounting for resource heterogeneity and differences in socio-economic contexts to come to farm-scale adaptations.

6.5. Conclusions and recommendations for research and development

Climate-crop simulation in combination with agro-climatic index analysis and farming systems survey approaches provided relevant information on risks of current climate variability and potential impacts of future climate change. Crop production has already been challenged with climate variability, and climate change is projected to affect it negatively. In response to perceived risks, farmers are implementing various adaptive strategies; however, such responses are relatively low cost changes in farm practices and may not be adequate for future climate change adaptation. Investment in more appropriate adaptation options such as more heat tolerant crop breeds, increased level of agricultural inputs (e.g. fertilizer), and irrigation are highly needed to reduce climate change impacts and adapting cropping systems. Research could play significant role by providing scientific evidence and more reliable information about climate change and its impacts, and by developing and disseminating improved adaptive technologies. The following actions should be given priority to enhance climate adaptation and improve resilience of crop production systems in Ethiopia:

- Mainstreaming and strengthening climate change and adaptation research in the National Agricultural Research System (NARS) towards developing adaptive technologies for managing climate risk and uncertainty. Mainstreaming climate change and adaptation refers to a process of integrating climate research into on-going research projects and adjusting research activities and approaches to address climate risks and explore adaptation options.

- Building institutional memory for relevant data (climate, soil, agronomic, socio-economic data) to facilitate research on climate change impacts and adaptations;
- Strengthening the knowledge base (capacity) on using advanced tools and approaches (e.g. crop-climate simulation models) for climate change and adaptation assessment;
- Communicating projected climate change impacts and possible management strategies effectively among farmers and decision makers;
- Improving institutional arrangements towards enhancing the adaptive capacity of farmers through providing agricultural credit and effective extension services.

References

Abdelkadir, A., Yimer, F., 2011. Soil water property variations in three adjacent land use types in the Rift Valley area of Ethiopia. Journal of Arid Environments 75, 1067-1071.

Abebe, G., Assefa, T., Harrun, H., Mesfine, T., 2005. Participatory selection of drought tolerant maize varieties using mother and baby methodology: A case study in the semi arid zones of the central rift valley of Ethiopia. African Crop Science Conference Proceedings, pp. 1479-1485.

Abegaz, A., van Keulen, H., 2009. Modelling soil nutrient dynamics under alternative farm management practices in the Northern Highlands of Ethiopia. Soil and Tillage Research 103, 203-215.

Adger, W.N., Agrawala, S., Mirza, M.M.Q., Conde, C., O'Brien, K., Puhlin, J., Pulwarty, R., Smit, B., Takahashi, K., 2007: Assessment of adaptation practices, options, constraints and capacity. Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [M.L. Parry, O.F. Canziani, J.P. Palutikof, P.J. van der Linden and C.E. Hanson (eds.)], Cambridge University Press, Cambridge, UK, 717-743.

Adger, W. N., Arnell, N.W., Tompkins, E.L., 2005. Successful adaptation to climate change across scales. Global Environmental Change 15, 77-86.

Aggarwal, P. K., 1995. Uncertainties in crop, soil and weather inputs used in growth models: Implications for simulated outputs and their applications. Agricultural Systems 48, 361-384.

Agrawal, P. K., Mall, R., 2002. Climate change and rice yields in diverse agro-environments of India. II. Effects of uncertainities in scenarios and crop models on impact assessment. Climatic Change 52, 331-343

Alem, Y., Bezabih, M., Kassie, M., Zikhali, P., 2010. Does fertilizer use respond to rainfall variability? Panel data evidence from Ethiopia. Agricultural Economics 41, 165-175.

Alexander, L.V., Arblaster, J.M., 2009. Assessing trends in observed and modelled climate extremes over Australia in relation to future projections. International Journal of Climatology 29, 417-435.

Alexandrov, V., Hoogenboom, G., 2000a. The impact of climate variability and change on crop yield in Bulgaria. Agricultural and Forest Meteorology 104, 315-327.

Alexandrov, V., Hoogenboom, G., 2000b. Vulnerability and adaptation assessments of agriculturalcrops under climate change in the Southeastern USA. Theoretical and Applied Climatology 67, 45-63.

Allen, R.G., Pereira, L.S., Raes, D., Smith, M., 1998b. Crop evapotranspiration: Guidelines for computing crop water requirements, Irrigation and Drainage Paper No. 56. FAO, Rome, Italy.

Almorox, J., 2011. Estimating global solar radiation from common meteorological data in Aranjuez, Spain. Turkish Journal of Physics 35, 53-64.

Amsalu, A., Stroosnijder, L., de Graaff, J., 2007. Long-term dynamics in land resource use and the driving forces in the Beressa watershed, highlands of Ethiopia. Journal of Environmental Management 83, 448-459.

Annandale, J., Jovanovic, N., Benade, N., Allen, R., 2002. Software for missing data error analysis of Penman-Monteith reference evapotranspiration. Irrigation Science 21, 57-67.

Araus, J.L., Slafer, G.A., Royo, C., Serret, M.D., 2008. Breeding for yield potential and stress adaptation in cereals. Critical Reviews in Plant Science 27, 377-412.

Araya, A., Stroosnijder, L., 2010. Effects of tied ridges and mulch on barley (Hordeum vulgare) rainwater use efficiency and production in Northern Ethiopia. Agricultural Water Management 97, 841-847.

Araya, A., Stroosnijder, L., 2011. Assessing drought risk and irrigation need in northern Ethiopia. Agricultural and Forest Meteorology 151, 425-436.

Arndt, C., Robinson, S., Willenbockel, D., 2011. Ethiopia's growth prospects in a changing climate: A stochastic general equilibrium approach. Global Environmental Change 21, 701-710.

Asseng, S., Ewert, F., Rosenzweig, C., Jones, J., Hatfield, J., Ruane, A., Boote, K., Thorburn, P., Rötter, R. P., Cammarano, D., and others, 2013. Uncertainty in simulating wheat yields under climate change. Nature Climate Change 3, 827-832.

Asseng, S., Pannell, D.J., 2013. Adapting dryland agriculture to climate change: Farming implications and research and development needs in Western Australia. Climatic Change 118, 167-181.

Ayenew, T., 2004. Environmental implications of changes in the levels of lakes in the Ethiopian Rift since 1970. Regional Environmental Change 4, 192-204.

Bannayan, M., Eyshi Rezaei, E., Hoogenboom, G., 2013. Determining optimum planting dates for rainfed wheat using the precipitation uncertainty model and adjusted crop evapotranspiration. Agricultural Water Management 126, 56-63.

Barron, J., Rockström, J., Gichuki, F., Hatibu, N., 2003. Dry spell analysis and maize yields for two semi-arid locations in East Africa. Agricultural and Forest Meteorology 117, 23-37.

Below, T., Artner, A., Siebert, R., Sieber, S., 2010. Micro-level practices to adapt to climate change for African small-scale farmers. International Food Policy Research Institute (IFPRI), discussion paper 00953.

Ben Nouna, B., Katerji, N., Mastrorilli, M., 2000. Using the CERES-Maize model in a semi-arid Mediterranean environment: Evaluation of model performance. Europian Journal of Agronomy 13, 309-322.

Benioff, R., Guill, S., Lee, J., 1996. Vulnerability and Adaptation Assessments. An International handbook. Version 1.1. Kluwer Academic Publishers.

Berg, A., de Noblet-Ducoudré, N., Sultan, B., Lengaigne, M., Guimberteau, M., 2013. Projections of climate change impacts on potential C4 crop productivity over tropical regions. Agricultural and Forest Meteorology 170, 89-102.

Berkes, F., 2007. Understanding uncertainty and reducing vulnerability: Lessons from resilience thinking. Natural Hazards 41, 283-295.

Bewket, W., 2008. Rainfall variability and agricultural vulnerability in the Amhara region, Ethiopia. Ethiopian Journal of Development Research 29, 1-34.

Bewket, W., 2012. Climate change perceptions and adaptive responses of smallholder farmers in central highlands of Ethiopia. International Journal of Environmental Studies 69, 507-523.

Bewket, W., Conway, D., 2007. A note on the temporal and spatial variability of rainfall in the drought-prone Amhara region of Ethiopia. International Journal of Climatology 27, 1467-1477.

Biazin, B., Sterk, G., 2013. Drought vulnerability drives land-use and land cover changes in the Rift Valley dry lands of Ethiopia. Agriculture, Ecosystems and Environment 164, 100-113.

Biazin, B., Stroosnijder, L., 2012. To tie or not to tie ridges for water conservation in Rift Valley drylands of Ethiopia. Soil Tillage Research 124, 83-94.

Block, P.J., Strzepek, K., Rosegrant, M.W., Diao, X., 2008. Impacts of considering climate variability on investment decisions in Ethiopia. Agricultural Economics 39, 171-181.

Boberg, F., Christensen, J.H., 2012. Overestimation of Mediterranean summer temperature projections due to model deficiencies. Nature Climate Change 2, 433-436.

Boko, M., Niang, I., Nyong, A., Vogel, C., Githeko, A., Medany, M., Osman-Elasha, B., Tabo, R., Yanda, P., 2007. Africa. In: Climate change 2007: Impacts, adaptation and vulnerability. Contribution of working group II to the fourth assessment report of the Intergovernmental Panel on Climate Change [Parry, M.L., Canziani,O.F., Palutikof,J.P., van der Linden, P.J. and Hanson, C.E.(eds.)], Cambridge University Press, Cambridge UK,. 433-467.

Bondeau, A., Smith, P.C., Zaehle, S., Schaphoff, S., Lucht, W., Cramer, W., Gerten, D., Lotze-Campen, H., Müller, C., Reichstein, M., 2007. Modelling the role of agriculture for the 20th century global terrestrial carbon balance. Global Change Biology 13, 679-706.

Boogaard, H., Van Diepen, C., Rötter, R., Cabrera, J., Van Laar, H., 1998. WOFOST 7.1: User's guide for the WOFOST 7.1 crop growth simulation model and WOFOST control center 1.5. DLO Winand Staring Centre Wageningen, the Netherlands.

Boogaard, H., Wolf, J., Supit, I., Niemeyer, S., van Ittersum, M., 2013. A regional implementation of WOFOST for calculating yield gaps of autumn-sown wheat across the European Union. Field Crops Research 143, 130-142.

Branković, Č. Srnec, L. & Patarčić, M. (2010). An assessment of global and regional climate change based on the EH5OM climate model ensemble. Climatic change 98, 21-49.

Bryan, E., Deressa, T.T., Gbetibouo, G.A., Ringler, C., 2009. Adaptation to climate change in Ethiopia and South Africa: options and constraints. Environmental Science & Policy 12, 413-426.

Burke, M.B., Lobell, D.B., Guarino, L., 2009. Shifts in African crop climates by 2050 and the implications for crop improvement and genetic resources conservation. Global Environmental Change 19, 317-325.

Burney, J.A., Davis, S.J., Lobell, D.B., 2010. Greenhouse gas mitigation by agricultural intensification. Proceedings of the National Academy of Sciences 107, 12052-12057.

Cairns, J.E., Hellin, J., Sonder, K., Araus, J.L., MacRobert, J.F., Thierfelder, C., Prasanna, B., 2013. Adapting maize production to climate change in Sub-Saharan Africa. Food Security 5, 345-360.

Camberlin, P., Okoola, R., 2003. The onset and cessation of the" long rains" in eastern Africa and their interannual variability. Theoretical and Applied Climatology 75, 43-54.

Cammarano, D., Basso, B., Stefanova, L., Grace, P., 2012. Adapting wheat sowing dates to projected climate change in the Australian subtropics: analysis of crop water use and yield. Crop and Pasture Science 63, 974-986.

Cassman, K.G., 1999. Ecological intensification of cereal production systems: Yield potential, soil quality, and precision agriculture. Proceedings of National Acadamic Sciences 96, 5952-5959.

Ceglar, A., Kajfež-Bogataj, L., 2012. Simulation of maize yield in current and changed climatic conditions: addressing modelling uncertainties and the importance of bias correction in climate model simulations. European Journal of Agronomy 37, 83-95.

Challinor, A., Wheeler, T., 2008a. Crop yield reduction in the tropics under climate change: processes and uncertainties. Agricultural and Forest Meteorology 148, 343-356.

Challinor, A., Wheeler, T., 2008b. Use of a crop model ensemble to quantify CO2 stimulation of water-stressed and well-watered crops. Agricultural and Forest Meteorology 148, 1062-1077.

Challinor, A., Wheeler, T., Craufurd, P., Ferro, C., Stephenson, D., 2007a. Adaptation of crops to climate change through genotypic responses to mean and extreme temperatures. Agriculture, Ecosystems & Environment 119, 190-204.

Challinor, A., Wheeler, T., Garforth, C., Craufurd, P., Kassam, A., 2007b. Assessing the vulnerability of food crop systems in Africa to climate change. Climatic Change 83, 381-399.

Challinor, A., Wheeler, T., Hemming, D., Upadhyaya, H., 2009a. Crop yield simulations using a perturbed crop and climate parameter ensemble: sensitivity to temperature and potential for genotypic adaptation to climate change. Climate Research 38, 117-127.

Challinor, A., Wheeler, T., Slingo, J., Hemming, D., 2005. Quantification of physical and biological uncertainty in the simulation of the yield of a tropical crop using present-day and doubled CO2 climates. Philosophical Transactions of the Royal Society B: Biological Sciences 360, 2085-2094.

Challinor, A.J., Ewert, F., Arnold, S., Simelton, E., Fraser, E., 2009b. Crops and climate change: progress, trends, and challenges in simulating impacts and informing adaptation. Journal of experimental botany 60, 2775-2789.

Challinor, A.J., Wheeler, T., Hemming, D., Upadhyaya, H., 2009c. Ensemble yield simulations: crop and climate uncertainties, sensitivity to temperature and genotypic adaptation to climate change. Climate Research 38, 117-127.

Cheung, W.H., Senay, G.B., Singh, A., 2008. Trends and spatial distribution of annual and seasonal rainfall in Ethiopia. International Journal of Climatology 28, 1723-1734.

Chylek, P., Li, J., Dubey, M., Wang, M., Lesins, G., 2011. Observed and model simulated 20th century Arctic temperature variability: Canadian earth system model CanESM2. Atmospheric Chemistry and Physics Discussions 11, 22893-22907. doi: I22810.25194/acpd-22811-22893-22201g.

CIA, 2013. The World Factbook. Available: https://www.cia.gov/library/publications/the-worldfactbook/geos/et.html. [Retrived on 01/08/2013].

Clemente, R.S., Asadi, M.E., Dixit, P.N., 2005. Assessment and comparison of three crop growth models under tropical climate conditions. Journal of Food, Agriculture and Environment 3, 254-261.

Coe, R., Stern, R., 2011. Assessing and addressing climate-induced risk in Sub-Saharan rainfed Agriculture: lessons learned. Experimental Agriculture 47, 395-410.

Collins, W., Bellouin, N., Doutriaux-Boucher, M., Gedney, N., Halloran, P., Hinton, T., Hughes, J., Jones, C., Joshi, M., Liddicoat, S., 2011. Development and evaluation of an Earth-system model–HadGEM2. Geoscientific Model Development Discussions 4, 997-1062.

Conway, D., 2000. Some aspects of climate variability in the North-East Ethiopian highlands-Wollo and Tigray. Sinet: Ethiopian Journal of Science 23, 139-161.

Conway, D., 2011. Adapting climate research for development in Africa. Wiley Interdisciplinary Reviews: Climate Change 2, 428-450.

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

Conway, D., Schipper, E.L.F., 2011. Adaptation to climate change in Africa: Challenges and opportunities identified from Ethiopia. Global Environmental Change 21, 227-237.

Cooper, P. J. M., Coe, R., 2011. Assessing and addressing climate-induced risk in Sub-Saharan rainfed agriculture. Experimental Agriculture 47, 179.

Cooper, P. J. M., Dimes, J., Rao, K. P. C., Shapiro, B., Shiferaw, B., Twomlow, S., 2008. Coping better with current climatic variability in the rainfed farming systems of Sub-Saharan Africa: An essential first step in adapting to future climate change. Agriculture, Ecosystems & Environment 126, 24-35.

Cooper, P. J .M., Dimes, J., Rao, K. P. C., Shapiro, B., Twomlow, S., 2006. Coping better with current climate variability in the rainfed farming systems of Sub-Saharan Africa: A dress rehearsal for adapting to future climate change. Global Theme on Agroecosystems Report, No. 27.

Cooper, P. J. M., Rao, K. P. C., Singh, P., Dimes, J., Traore, P., Dixit, P., Twomlow, S. J., 2009. Farming with current and future climate risk: Advancing a'Hypothesis of Hope'for rainfed agriculture in the semi-arid tropics. Jounal of SAT Agricultural Research 7, 1-19.

Cooper, P. J. M., Stern, R., Noguer, M., Gathenya, J., 2013. Climate change adaptation strategies in Sub-Saharan Africa: Foundations for the future. In: Singh, B.R. (ed.), Realities, impacts over ice cap, sea level and risks. InTech Open, pp. 327-356. ISBN 9789535109341. doi:10.5772/55133

Coumou, D., Rahmstorf, S., 2012. A decade of weather extremes. Nature Climate Change 2, 491-496.

CSA, 2008. Agricultural sample survey report on area and production of crops (private peasant holdings, meher season). Statistical bulletin 417. Federal Democratic Republic of Ethiopia, Central Statistical Agency (CSA), Addis Abeba.

CSA, 2013. Agricultural sample survey report on area and production for major crops (private peasant holding meher season). Statistical Bulletin 532, Federal Democratic Republic of Ethiopia, Central Statistical Agency (CSA), Addis Ababa, Ethiopia.

Cuculeanu, V., Tuinea, P., Balteanu, D., 2002. Climate change impacts in Romania: Vulnerability and adaptation options. GeoJournal 57, 203-209.

Davidson, O., Halsnaes, K., Huq, S., Kok, M., Metz, B., Sokona, Y., Verhagen, J., 2003. The development and climate nexus: the case of Sub-Saharan Africa. Climate Policy 3, S97-S113.

Debelle, T., Bogale, T., Negassa, W., Workayehu, T., Liben, M., Mesfin, T., Mekonen, B., Mazengia, W., 2001. A review of fertilizer management research on maize in Ethiopia. Nigussie, M., Tanner, D., Twumasi-Afriyie, S. (Eds.), Enhancing the contribution of maize to food security in Ethiopia, Proceedings of the second national maize workshop of Ethiopia 12–16 November, 2001. Addis Ababa, Ethiopia, pp. 46-55.

De Jonge, K., Ascough II, J., Andales, A., Hansen, N., Garcia, L., Arabi, M., 2012. Improving evapotranspiration simulations in the CERES-Maize model under limited irrigation. Agricultural Water Management 115, 92-103.

Demeke, A.B., Keil, A., Zeller, M., 2011. Using panel data to estimate the effect of rainfall shocks on smallholders food security and vulnerability in rural Ethiopia. Climatic Change 108, 185-206.

Dercon, S., 2004. Growth and shocks: evidence from rural Ethiopia. Journal of Development Economics 74, 309-329.

Deressa, T., Hassan, R., Ringler, C., 2011. Perception of and adaptation to climate change by farmers in the Nile basin of Ethiopia. The Journal of Agricultural Science 149, 23-31.

Deressa, T., Hassan, R.M., Ringler, C., 2008. Measuring Ethiopian farmers' vulnerability to climate change across regional states. IFPRI discussion paper No. 806. Available: http://www.ifpri.org/pubs/dp/ifpridp00806.asp. [Retrieved on 10/03/2013].

Deressa, T.T., 2007. Measuring the economic impact of climate change on Ethiopian agriculture: Ricardian approach. World Bank Policy Research Working Paper 4342.

Deressa, T.T., Hassan, R.M., 2009. Economic impact of climate change on crop production in Ethiopia: Evidence from cross-section measures. Journal of African Economies 18, 529-554.

Deressa, T.T., Hassan, R.M., Ringler, C., 2010. Factors affecting the choices of coping strategies for climate extremes: The case of farmers in the Nile Basin of Ethiopia, IFPRI Discussion Paper 01032.

Deressa, T.T., Hassan, R.M., Ringler, C., Alemu, T., Yesuf, M., 2009. Determinants of farmers' choice of adaptation methods to climate change in the Nile Basin of Ethiopia. Global Environmental Change 19, 248-255.

Desanker, P.V., Justice, C.O., 2001. Africa and global climate change: critical issues and suggestions for further research and integrated assessment modelling. Inter-research Nordbunte 23, D-21385 Oldendorf Luche, Germany.

Dickmann, F., 2012. Data practices of agricultural scientists: Results from an exploratory study. Journal of Agricultural & Food Information 13, 14-34.

Dixit, P., Cooper, P., Dimes, J., Rao, K., 2011. Adding value to field-based agronomic research through climate risk assessment: A case study of maize production in Kitale, Kenya. Experimental Agriculture 47, 317-338.

Dow, K., Berkhout, F., Preston, B.L., Klein, R.J., Midgley, G., Shaw, M.R., 2013. Limits to adaptation. Nature Climate Change 3, 305-307.

Downing, T.E., Ringius, L., Hulme, M., Waughray, D., 1997. Adapting to climate change in Africa. Mitigation and Adaptation Strategies for Global Change 2, 19-44.

Eitzinger, J., Formayer, H., Thaler, S., Trnka, M., Zdenek, Z., Alexandrov, V., 2008. Aspects on results and uncertainties of climate change impact simulation studies for agricultural crop production in Europe. Die Bodenkultur 131, 1-4.

Eitzinger, J., Thaler, S., Schmid, E., Strauss, F., Ferrise, R., Moriondo, M., Bindi, M., Palosuo, T., Rötter, R., Kersebaum, K., 2012. Sensitivities of crop models to extreme weather conditions during flowering period demonstrated for maize and winter wheat in Austria. The Journal of Agricultural Science 1, 1-23. doi: 10.1017/S0021859612000779.

Eitzinger, J., Trnka, M., Hösch, J., Žalud, Z., Dubrovský, M., 2004. Comparison of CERES, WOFOST and SWAP models in simulating soil water content during growing season under different soil conditions. Ecological modelling 171, 223-246.

EPA, 2011. Ethiopia's Vision for a Climate Resilient Green Economy. Federal Democratic Republic of Ethiopia, Environmental Protection Authority. Available on line via http://go.nature.com/pqPcg4 (Accessed on 25 Aug. 2013)

Eriksen, S., Lind, J., 2009. Adaptation as a political process: Adjusting to drought and conflict in Kenya's drylands. Environmental Management 43, 817-835.

FAO, 2007. The social dimension of adaptation to climate change in Ethiopia. Discussion paper 14, the World Bank, Wahington, DC.

Feenstra, J.F., Burton, I., Smith, J.B., Tol, R.S., (eds.). 1998. Handbook on methods for climate change impact assessment and adaptation strategies. United National Environment Programme and the Institute for Environmental Studies, vrije Universiteit amsterdam.

Finger, R., Hediger, W., Schmid, S., 2011. Irrigation as adaptation strategy to climate change—a biophysical and economic appraisal for Swiss maize production. Climatic Change 105, 509-528.

Forster, P., Ramaswamy, V., Artaxo, P., Berntsen, T., Betts, R., Fahey, D.W., Haywood, J., Lean, J., Lowe, D.C., Myhre, G., 2007. Changes in Atmospheric Constituents and in Radiative Forcing. In: Climate Change 2007: The Physical Science Basis . Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [Solomon, S., D.

Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA., Climate change.

Fosu-Mensah, B., MacCarthy, D., Vlek, P.L.G., Safo, E., 2012. Simulating impact of seasonal climatic variation on the response of maize (Zea mays L.) to inorganic fertilizer in sub-humid Ghana. Nutrient Cycling in Agroecosystems 94, 255–271.

Fowler, H., Blenkinsop, S., Tebaldi, C., 2007. Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modelling. International Journal of Climatology 27, 1547-1578.

Frere, M., Popov, G., 1979. Agrometeorological crop monitoring and forecasting. Plant production and protection division, no 17. Food and Agriculture Organization of the United Nations (FAO), Rome, Italy, pp. 64

Frere, M., Popov, G., 1986. Early agrometeorological crop yield assessment. FAO Plant Production and Protection Paper No. 73, 144. Food and Agriculture Organization of the United Nations (FAO), Rome, Italy.

Fritzsche, F., Zech, W., Guggenberger, G., 2007. Soils of the Main Ethiopian Rift Valley escarpment: A transect study. Catena 70, 209-219.

Fufa, B., Hassan, R.M., 2006. Determinants of fertilizer use on maize in Eastern Ethiopia: A weighted endogenous sampling analysis of the extent and intensity of adoption. Agrekon 45, 38–49.

Funk, C., Asfaw, A., Steffen, P., Senay, G., Rowland, J., Verdin, J., 2009. Estimating Meher Crop Production Using Rainfall in the 'Long Cycle'Region of Ethiopia. FEWS NET Special Report.

Funk, C., Dettinger, M.D., Michaelsen, J.C., Verdin, J.P., Brown, M.E., Barlow, M., Hoell, A., 2008. Warming of the Indian Ocean threatens eastern and southern African food security but could be mitigated by agricultural development. Proceedings of the National Academy of Sciences 105, 11081.

Funk, C., Rowland, J., Eilerts, G., Kebebe, E., Biru, N., White, L., Galu, G., 2012. A Climate Trend Analysis of Ethiopia: Famine Early Warning Systems Network-Informing Climate Change Adaptation Series. U.S. Geological Survey, Fact Sheet 2012–3053

Garedew, E., 2010. Land-use and land-cover dynamics and rural livelihood perspectives in the semi-arid areas of Central Rift Valley of Ethiopia. Doctoral thesis. Swedish University of Agricultural Sciences, Umeå, p. 89.

Garedew, E., Sandewall, M., Söderberg, U., Campbell, B.M., 2009. Land-use and land-cover dynamics in the Central Rift Valley of Ethiopia. Environmental Management, 44, 683-694.

Gbetibouo, G.A., Hassan, R., 2005. Measuring the economic impact of climate change on major South African field crops: a Ricardian approach. Global and Planetary Change 47, 143-152.

Gebre, T., Nigussie, M., Tanner, D., Twumasi-Afriyie, S., 2002. Maize technology adoption in Ethiopia: Experiences from the Sasakawa-Global 2000 agriculture program. Nigussie, M., Tanner, D., Twumasi-Afriyie, S. (Eds.), Enhancing the contribution of maize to food security in Ethiopia, Proceedings of the second national maize workshop of Ethiopia 12–16 November, 2001. Addis Ababa, Ethiopia, pp. 153-156.

Gebremedhin, B., Jaleta, M., Hoekstra, D., 2009. Smallholders, institutional services, and commercial transformation in Ethiopia. Agricultural Econnomics 40, 773-787.

Georgis, K., Temesgen, M., Goda, S., 2004. On-farm evaluation of soil moisture conservation techniques using improved germplasm. Seventh Eastern and Southern Africa Regional maize conference. International Maize and Wheat Improvement Center (CYMMIT) and Kenya Agricultural Research Institute (KARI), Kenya, Nairobi, pp. 313-316.

Giorgi, F., 2005. Climate change prediction. Climatic Change 73, 239-265.

Glantz, M.H., Gommes, R., Ramasamy, S., 2009. Coping with a changing climate: considerations for adaptation and mitigation in agriculture. Environment and Natural Resources Management Series, Monitoring and Assessment-Food and Agriculture Organization of the United Nations.

Gordon, H.B., Rotstayn, L., McGregor, J., Dix, M., Kowalczyk, E., O'Farrell, S., Waterman, L., Hirst, A., Wilson, S., Collier, M., 2002. The CSIRO Mk3 climate system model. CSIRO Atmospheric Research, Technical Paper No. 60 Victoria, Australia.

Gray, C., Mueller, V., 2012. Drought and Population Mobility in Rural Ethiopia. World Development 40, 134-145.

Gregory, P.J., Johnson, S.N., Newton, A.C., Ingram, J.S., 2009. Integrating pests and pathogens into the climate change/food security debate. Journal of Experimental Botany 60, 2827-2838.

Haile, M., 2005. Weather patterns, food security and humanitarian response in Sub-Saharan Africa. Philosophical Transactions of the Royal Society B: Biological Sciences 360, 2169-2182.

Haileslassie, A., Priess, J., Veldkamp, E., Teketay, D., Lesschen, J.P., 2005. Assessment of soil nutrient depletion and its spatial variability on smallholders' mixed farming systems in Ethiopia using partial versus full nutrient balances. Agriculture, Ecosystems & Environment 108, 1-16.

Hansen, J., Jones, J., 2000. Scaling-up crop models for climate variability applications. Agricultural Systems 65, 43-72.

Hansen, J.W., Baethgen, W., Osgood, D., Ceccato, P., Ngugi, R.K., 2007. Innovations in climate risk management: protecting and building rural livelihoods in a variable and changing climate. Journal of Semi-Arid Tropical Agricultural Research 4, 1-12.

Hansen, J.W., Mason, S.J., Sun, L., Tall, A., 2011. Review of seasonal climate forecasting for agriculture in Sub-Saharan Africa. Experimental Agriculture 47, 205.

Hargreaves, G.H., Samani, Z.A., 1982. Estimating potential evapotranspiration. Journal of the Irrigation and Drainage Division 108, 225-230.

Hawkins, E., Sutton, R., 2011. The potential to narrow uncertainty in projections of regional precipitation change. Climate Dynamics 37, 407-418.

Hellmuth, M.E., Moorhead, A., Thomson, M.C., Williams, J., 2007. Climate risk management in Africa: Learning from practice. International Research Institute for Climate and Society (IRI), Columbia University, New York, USA.

Hengsdijk, H., Van Keulen, H., 2002. The effect of temporal variation on inputs and outputs of future-oriented land use systems in West Africa. Agriculture, Ecosystems & Environment 91, 245-259.

Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G., Jarvis, A., 2005. Very high resolution interpolated climate surfaces for global land areas. International Journal of Climatology 25, 1965-1978.

Hochman, Z., Gobbett, D., Holzworth, D., McClelland, T., van Rees, H., Marinoni, O., Garcia, J.N., Horan, H., 2013. Reprint of "Quantifying yield gaps in rainfed cropping systems: A case study of wheat in Australia". Field Crops Research 143, 65-75.

Hoogenboom, G., 2000. Contribution of agrometeorology to the simulation of crop production and its applications. Agricultural and Forest Meteorology 103, 137-157.

Hoogenboom, G., Jones, J., Wilkens, P., Porter, C., Batchelor, W., Hunt, L., Boote, K., Singh, U., Uryasev, O., Bowen, W., 2004. Decision support system for agrotechnology transfer version 4.0. University of Hawaii, Honolulu, HI (CD-ROM).

Hoogenboom, G., Jones, J.W., Wilkens P.W, Porter, C.H., Boote, K.J., Hunt, L.A., Singh, U., Lizaso, J., White, J.W., Uryasev, O., Royce, F.S., Ogoshi, R., Gijsman, A.J., Tsuji, G.Y., 2010. Decision support system for agrotechnology transfer version 4.5 [CD-ROM]. University of Hawaii, Honolulu, Hawaii.

Howard, J., Crawford, E., Kelly, V., Demeke, M., Jeje, J.J., 2003. Promoting high-input maize technologies in Africa: the Sasakawa-Global 2000 experience in Ethiopia and Mozambique. Food Policy 28, 335-348.

Howden, S.M., Soussana, J.-F., Tubiello, F.N., Chhetri, N., Dunlop, M., Meinke, H., 2007. Adapting agriculture to climate change. Proceedings of the National Academy of Sciences 104, 19691-19696.

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

Huq, S., Reid, H., Konate, M., Rahman, A., Sokona, Y., Crick, F., 2004. Mainstreaming adaptation to climate change in least developed countries (LDCs). Climate Policy 4, 25-43.

IPCC, 2001. Climate Change 2001: The Scientific Basis. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change [Houghton, J.T., Y.

Ding, D.J. Griggs, M. Noguer, P.J. van der Linden, X. Dai, K. Maskell, and C.A. Johnson (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York. NY, USA, 881pp.

IPCC, 2007. Summary for policy makers. In: Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of working group II to the Fourth assessment report of the Intergovernmental Panel on Climate Change [Parry, M.L., Canziani,O.F., Palutikof, J.P., van der Linden, P.J. and Hanson, C.E. (eds)]. Cambridge University Press, Cambridge, UK, 7-22.

IPCC, 2012. Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change [Field, C.B., V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor, and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, UK, and New York, NY, USA, pp 582

Jaetzold, R., Kutsch, H., 1982. Agro-ecological zones of the tropics with a sample from Kenya. Tropenlandwirt 83, 15-34.

Jame, Y., Cutforth, H., 1996. Crop growth models for decision support systems. Canadian Journal of Plant Science 76, 9-19.

Jansen, H., Hengsdijk, H., Legesse, D., Ayenew, T., Hellegers, P., Spliethoff, P., 2007. Land and water resources assessment in the Ethiopian Central Rift Valley Alterra Report 1587. Wageningen, the Netherlands.

Jones, J., Keating, B., Porter, C., 2001. Approaches to modular model development. Agricultural Systems 70, 421-443.

Jones, J.W., Hoogenboom, G., Porter, C., Boote, K., Batchelor, W., Hunt, L., Wilkens, P., Singh, U., Gijsman, A., Ritchie, J., 2003. The DSSAT cropping system model. European Journal of Agronomy 18, 235-265.

Jones, P.G., Thornton, P.K., 2003. The potential impacts of climate change on maize production in Africa and Latin America in 2055. Global Environmental Change 13, 51-59.

Jones, P.G., Thornton, P.K., 2009. Croppers to livestock keepers: livelihood transitions to 2050 in Africa due to climate change. Environmental Science Policy 12, 427-437.

Kahiluoto, H., Rimhanen, K., Rötter, R., Tseganeh, B., 2012. Mitigation of climate change to enhance food security: An analytical framework. Forum for Development Studies 39, 51-73.

Kandji, S.T., Verchot, L., Mackensen, J., 2006. Climate Change and Variability in the Sahel Region: Impacts and Adaptation Strategies in the Agricultural Sector. United Nations Environment Program (UNEP) and World Agroforestry Center (ICRAF) , Nairobi, Kenya

Karaburun, A., Demirci, A., Kara, F., 2011. Analysis of spatially distributed annual, seasonal and monthly temperatures in Istanbul from 1975 to 2006. World Applied Sciences Journal 12, 1662-1675.

Kassie, B.T., Hengsdijk, H., Rötter, R., Kahiluoto, H., Asseng, S., Ittersum, M.V., 2013a. Adapting to Climate Variability and Change: Experiences from Cereal-Based Farming in the Central Rift and Kobo Valleys, Ethiopia. Environmental Management 52, 1115-1131. doi: 10.1007/s00267-013-0145-2.

Kassie, B.T., Rötter, R.P., Hengsdijk, H., Asseng, S., Van Ittersum, M.K., Kahiluto, H., Van Keulen, H., 2013b. Climate variability and change in the Central Rift Valley of Ethiopia: Challenges for rainfed crop production. Journal of Agricultural Science 52, 58-74.

Kato, E., Ringler, C., Yesuf, M., Bryan, E., 2011. Soil and water conservation technologies: a buffer against production risk in the face of climate change? Insights from the Nile basin in Ethiopia. Agricultural Economics 42, 593-604

Keating, B., McCown, R., Wafula, B., 1993. Adjustment of nitrogen inputs in response to a seasonal forecast in a region of high climatic risk. In: F.W.T. Penning de Vries, P.T.K.Metselaar. (Ed.), Systems approaches for agricultural development, Vol. 2, Kluwer, Dordrecht, The Netherlands, pp. 233-252.

Kendall, M.G., 1975. Rank correlation methods, 4th ed. Charles Griffin, London.

Kersebaum, K.C., Hecker, J.-M., Mirschel, W., Wegehenkel, M., 2007. Modelling water and nutrient dynamics in soil–crop systems: a comparison of simulation models applied on common data sets.

In: Kersebaum, K.C. (Ed.), Modelling water and nutrient dynamics in soil–crop systems. Springer, Dordrecht, the Netherlands, pp. 1-17.

Kidanu, A., Rovin, K., Hardee-Cleaveland, K., 2009. Linking population, fertility and family planning with adaptation to climate change: Views from Ethiopia. Population Action International (PAI), Washington, DC.

Kimball, B., 2010. Lessons from FACE: CO2 effects and interactions with water, nitrogen, and temperature. In: The Handbook of Climate Change and Agroecosystems [Hillel D, Rosenzweig C., (eds.)], Imperial College Press, Singapore.), pp. 87-107

Kipkorir, E.C., Raes, D., Bargerei, R.J., Mugalavai, E.M., 2007. Evaluation of two risk assessment methods for sowing maize in Kenya. Agricultural and Forest Meteorology 144, 193-199.

Kizza, M., Rodhe, A., Xu, C.Y., Ntale, H.K., Halldin, S., 2009. Temporal rainfall variability in the Lake Victoria Basin in East Africa during the twentieth century. Theoretical and applied climatology 98, 119-135.

Knutti, R., Sedláček, J., 2012. Robustness and uncertainties in the new CMIP5 climate model projections. Nature Climate Change 3, 369-373.

Kurukulasuriya, P., Mendelsohn, R., 2006. Crop selection: Adapting to climate change in Africa. Pretoria: Centre for Environmental Economics and Policy in Africa, University of Pretoria.

Laux, P., Jäckel, G., Tingem, R.M., Kunstmann, H., 2010. Impact of climate change on agricultural productivity under rainfed conditions in Cameroon—A method to improve attainable crop yields by planting date adaptations. Agricultural and Forest Meteorology 150, 1258-1271.

Leemans, R., Eickhout, B., 2004. Another reason for concern: regional and global impacts on ecosystems for different levels of climate change. Global Environmental Change 14, 219-228.

Lehmann, N., Finger, R., Klein, T., Calanca, P., Walter, A., 2013. Adapting crop management practices to climate change: Modelling optimal solutions at the field scale. Agricultural Systems 117, 55-65.

Liang, W., Carberry, P., Wang, G., Lü, R., Lü, H., Xia, A., 2011. Quantifying the yield gap in wheat–maize cropping systems of the Hebei Plain, China. Field Crop Research 124, 180-185.

Liu, J., Fritz, S., Van Wesenbeeck, C., Fuchs, M., You, L., Obersteiner, M., Yang, H., 2008. A spatially explicit assessment of current and future hotspots of hunger in Sub-Saharan Africa in the context of global change. Global and Planetary Change 64, 222-235.

Lobell, D.B., Burke, M.B., 2010. On the use of statistical models to predict crop yield responses to climate change. Agricultural and Forest Meteorology 150, 1443-1452.

Lobell, D.B., Cassman, K.G., Field, C.B., 2009. Crop yield gaps: their importance, magnitudes, and causes. Annual Review of Environment and Resources 34, 179.

Lobell, D.B., Field, C.B., 2007. Global scale climate–crop yield relationships and the impacts of recent warming. Environmental Research Letters 2, 014002.

Lobell, D.B., Field, C.B., Cahill, K.N., Bonfils, C., 2006. Impacts of future climate change on California perennial crop yields: Model projections with climate and crop uncertainties. Agricultural and Forest Meteorology 141, 208-218.

Lobell, D.B., Hammer, G.L., McLean, G., Messina, C., Roberts, M.J., Schlenker, W., 2013. The critical role of extreme heat for maize production in the United States. Nature Climate Change 3, 497-501.

López-Cedrón, F.X., Boote, K.J., Ruíz-Nogueira, B., Sau, F., 2005. Testing CERES-Maize versions to estimate maize production in a cool environment. Europian Journal of Agronomy 23, 89-102.

Luo, Q., Bellotti, W., Williams, M., Wang, E., 2009. Adaptation to climate change of wheat growing in South Australia: analysis of management and breeding strategies. Agriculture, Ecosystems & Environment 129, 261-267.

Mamo, G., 2005. Using Seasonal Climate Outlook to Advice on Sorghum Production in the Central Rift Valley of Ethiopia. PhD thesis, University of the Free State, Bloemfontein, South Africa, pp.181.

Mann, H.B., 1945. Nonparametric tests against trend. Econometrica: Journal of the Econometric Society, 245-259.

Martin, R.V., Washington, R., Downing, T.E., 2000. Seasonal maize forecasting for South Africa and Zimbabwe derived from an agroclimatological model. Journal of Applied Meteorology 39, 1473-1479.

Matthews, R.B., Rivington, M., Muhammed, S., Newton, A.C., Hallett, P.D., 2012. Adapting crops and cropping systems to future climates to ensure food security: The role of crop modelling. Global Food Security 2, 24-28.

Meehl, G.A., Stocker, T.F., Collins, W.D., Friedlingstein, P., Gaye, A.T., Gregory, J.M., Kitoh, A., Knutti, R., Murphy, J.M., Noda, A., 2007. Global climate projections. In: Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller (Ed.), Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 747-845.

Mehari, A., Van Steenbergen, F., Schultz, B., 2011. Modernization of spate irrigated agriculture: A new approach. Irrigation and Drainage 60, 163-173.

Mersha, E., Boken, V.K., 2005. Agricultural drought in Ethiopia. In: Vijendra K. Boken, Arthur P. Cracknell, Heathcote, R.L. (Eds.), Monitoring and Predicting Agricultural Drought: A Global Study. Oxford University Press,Inc., New York, p. 227.

Mertz, O., Mbow, C., Reenberg, A., Diouf, A., 2009. Farmers' perceptions of climate change and agricultural adaptation strategies in rural Sahel. Environmental Management 43, 804-816.

Meza, F.J., Silva, D., 2009. Dynamic adaptation of maize and wheat production to climate change. Climatic change 94, 143-156.

Meze-Hausken, E., 2004. Contrasting climate variability and meteorological drought with perceived drought and climate change in northern Ethiopia. Climate Research 27, 19-31.

Mideksa, T.K., 2010. Economic and distributional impacts of climate change: The case of Ethiopia. Global Environmental Change 20, 278-286.

Mitchell, T.D., Carter, T.R., Jones, P.D., Hulme, M., New, M., 2004. A comprehensive set of high-resolution grids of monthly climate for Europe and the globe: the observed record (1901–2000) and 16 scenarios (2001-2100). Working paper, Tyndall Centre

Moges, G., Hengsdijk, H., Jansen, H., 2011. Review and quantitative assessment of ex situ household rainwater harvesting systems in Ethiopia. Agricultural Water Management 98, 1215-1227.

Monod, H., Naud, C., Makowski, D., 2006. Uncertainty and sensitivity analysis for crop models. In: D. Wallach, D. Makowski and J.W. Jones (eds): Working with Dynamic Crop Models, Elsevier, Amsterdam, The Netherlands, 55-100.

Morton, J.F., 2007. The impact of climate change on smallholder and subsistence agriculture. Proceedings of the National Academy of Sciences 104, 19680-19685.

Moss, R.H., Edmonds, J.A., Hibbard, K.A., Manning, M.R., Rose, S.K., van Vuuren, D.P., Carter, T.R., Emori, S., Kainuma, M., Kram, T., 2010. The next generation of scenarios for climate change research and assessment. Nature 463, 747-756.

Mugalavai, E.M., Kipkorir, E.C., Raes, D., Rao, M.S., 2008. Analysis of rainfall onset, cessation and length of growing season for western Kenya. Agricultural and Forest Meteorology 148, 1123-1135.

Müller, C., 2009. Climate change impact on Sub-Saharan Africa: an overview and analysis of scenarios and models. German Development Institute/Deutsches Institut für Entwicklungspolitik (DIE), Discussion paper, ISSN 1860-0441.

Müller, C., 2013. African Lessons on Climate Change Risks for Agriculture. Annual Review of Nutrition 33, 395-411.

Müller, C., Cramer, W., Hare, W.L., Lotze-Campen, H., 2011. Climate change risks for African agriculture. Proceedings of the National Academy of Sciences 108, 4313-4315.

Nakicenovic, N., Alcamo, J., Davis, G., de Vries, B., Fenhann, J., Gaffin, S., Gregory, K., Grubler, A., Jung, T.Y., Kram, T., 2000. Special report on emissions scenarios: a special report of working group III of the Intergovernmental Panel on Climate Change. Cambridge University Press, p. 599.

Ngigi, S.N., 2009. Climate Change Adaptation Strategies: Water Resources Management Options for Smallholder Farming Systems in Sub-Saharan Africa. The MDG Centre for East and Southern Africa, The Earth Institute at Columbia University, New York. 189.

Nhemachena, C., Hassan, R., 2007. Micro-Level Analysis of Farmers Adaption to climate change in Southern Africa, IFPRI Discussion Paper 00714. International Food Policy Research Institute (IFPRI), Washington, DC

Nigussie, M., Tanner, D., Twumasi-Afriyie, S., 2002. Enhancing the Contribution of Maize to Food Security in Ethiopia: Proceedings of the Second National Maize Workshop of Ethiopia: 12-16 November 2001, Addis Ababa, Ethiopia.

NMA, 2001. Initial National Communication of Ethiopia to the United Nations Framework Convention on Climate Change (UNFCCC), Addis Ababa, Ethiopia, pp. 113.

NMA, 2007. Climate change national adaptation programme of action (NAPA) of Ethiopia:Technical Report, National Metorological Agency, Addis Abeba, pp. 85

Oliver, J.E., 1980. Monthly precipitation distribution: a comparative index. The Professional Geographer 32, 300-309.

Osbahr, H., Dorward, P., Stern, R., Cooper, S., 2011. Supporting agricultural innovation in Uganda to respond to climate risk: linking climate change and variability with farmer perceptions. Experimental Agriculture 47, 293.

Osborne, T., Rose, G., Wheeler, T., 2013. Variation in the global-scale impacts of climate change on crop productivity due to climate model uncertainty and adaptation. Agricultural and Forest Meteorology 170 183-194.

Osman, M., Sauerborn, P., 2002. A preliminary assessment of characteristics and long term variability of rainfall in Ethiopia–Basis for sustainable land use and resource management. Challenges to organic farming and sustainable land use in the tropics and subtropics, Deutscher Tropentag 2002, Witzenhausen.

Oteng-Darko, P., Yeboah, S., Addy, S., Amponsah, S., Danquah, E.O., 2012. Crop modelling: A tool for agricultural research - A review. Journal of Agricultural Research and Development 21, 001-006.

Palosuo, T., Kersebaum, K.C., Angulo, C., Hlavinka, P., Moriondo, M., Olesen, J.E., Patil, R.H., Ruget, F., Rumbaur, C., Takác, J., 2011. Simulation of winter wheat yield and its variability in different climates of Europe: A comparison of eight crop growth models. Europian Journal Agronomy 35, 103-114.

Parry, M.L., O.F. Canziani, J.P. Palutikof and Co-authors. 2007. Technical Summary. Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [M.L. Parry, O.F. Canziani, J.P. Palutikof, P.J. van der Linden and C.E. Hanson (eds.)], Cambridge University Press, Cambridge, UK, 23-78.

Parry, M.L., Rosenzweig, C., Iglesias, A., Livermore, M., Fischer, G., 2004. Effects of climate change on global food production under SRES emissions and socio-economic scenarios. Global Environmental Change 14, 53-67.

Popova, Z., Kercheva, M., 2005. CERES model application for increasing preparedness to climate variability in agricultural planning–calibration and validation test. Physics and Chemistry of the Earth 30, 125-133.

Potter, P., Ramankutty, N., Bennett, E.M., Donner, S.D., 2010. Characterizing the spatial patterns of global fertilizer application and manure production. Earth Interactions 14, 1-22.

Raes, D., Sithole, A., Makarau, A., Milford, J., 2004. Evaluation of first planting dates recommended by criteria currently used in Zimbabwe. Agricultural and Forest Meteorology 125, 177-185.

Räisänen, J., Räty, O., 2012. Projections of daily mean temperature variability in the future: cross-validation tests with ENSEMBLES regional climate simulations. Climate Dynamics, 1-16.

Ramirez-Villegas, J., Challinor, A., 2012. Assessing relevant climate data for agricultural applications. Agricultural and Forest Meteorology 161, 26-45.

Ramirez-Villegas, J., Challinor, A.J., Thornton, P.K., Jarvis, A., 2013. Implications of regional improvement in global climate models for agricultural impact research. Environmental Research Letters 8, 024018.

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

Reidsma, P., Ewert, F., Lansink, A.O., Leemans, R., 2010. Adaptation to climate change and climate variability in European agriculture: The importance of farm level responses. European Journal of Agronomy 32, 91-102.

Refsgaard, J.C., Arnbjerg-Nielsen, K., Drews, M., Halsnæs, K., Jeppesen, E., Madsen, H., Markandya, A., Olesen, J.E., Porter, J.R., Christensen, J.H., 2013. The role of uncertainty in climate change adaptation strategies—A Danish water management example. Mitigation and Adaptation Strategies for Global Change 18, 337-359.

Reilly, J.M., Schimmelpfennig, D., 1999. Agricultural impact assessment, vulnerability, and the scope for adaptation. Climatic Change 43, 745-788.

Robinson, S., Willenbockel, D., Strzepek, K., 2012. A Dynamic General Equilibrium Analysis of Adaptation to Climate Change in Ethiopia. Review of Development Economics 16, 489-502.

Rockström, J., Kaumbutho, P., Mwalley, J., Nzabi, A., Temesgen, M., Mawenya, L., Barron, J., Mutua, J., Damgaard-Larsen, S., 2009. Conservation farming strategies in East and Southern Africa: yields and rain water productivity from on-farm action research. Soil and Tillage Research 103, 23-32.

Rosell, S., 2011. Regional perspective on rainfall change and variability in the central highlands of Ethiopia, 1978-2007. Applied Geography 31, 329-338.

Rosenzweig, C., J.W. Elliott, D. Deryng, A.C. Ruane, A. Arneth, K.J. Boote, C. Folberth, M. Glotter, C. Müller, K. Neumann, F. Piontek, T. Pugh, E. Schmid, E. Stehfest, J.W. Jones, 2013a. Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison PNAS, in press.

Rosenzweig, C., Jones, J., Hatfield, J., Ruane, A., Boote, K., Thorburn, P., Antle, J., Nelson, G., Porter, C., Janssen, S., 2013b. The agricultural model intercomparison and improvement project (AgMIP): protocols and pilot studies. Agricultural and Forest Meteorology 170, 166-182.

Rötter, R.P., 1993. Simulation of the biophysical limitations to maize production under rainfed conditions in Kenya. Evaluation and application of the model WOFOST. PhD Thesis, Universität Trier, Germany (Materialien zur Ostafrika-Forschung, Heft 12) p. 297.

Rötter, R.P., Carter, T.R., Olesen, J.E., Porter, J.R., 2011a. Crop-climate models need an overhaul. Nature Climate Change 1, 175-177.

R2tter, R.P., Dreiser, C., 1994. Extrapolation of maize fertilizer trial results by using crop-growth simulation: Results for Murang'a District, Kenya. In: L.O. Fresco, L.S., J. Bourne , H. Van Keulen (eds.), The Future of the Land: Mobilising and Integrating Knowledge for Land Use Options. John Wiley & Sons, Chichester, UK, pp. 249-260.

Rötter, R.P, Ewert, F., Palosuo, T., Bindi, M., Kersebaum, K.C., Olesen, J.E., Trnka, M., van Ittersum, M.K., Jansen, S., Rivington, M., Semenov, M., Wallach, D., Porter, J.R., Srewart, D., Verhagen, J., Angulo, C., Gaiser, T., Nendel, C., Martre, P., de Wit, A. 2013b. Challenges for agro-ecosystem modelling in climate change risk assessment for major Europian crops and farming systems. In: Impacts world 2013, international conference on climate change effects , Potsdam, Germany, 27-30 May 2013 : Conference proceedings. Potsdam Institute for Climate Impact Research. pp. 555-564.

Rötter, R.P., Höhn, J.G., Fronzek, S., 2012a. Projections of climate change impacts on crop production: A global and a Nordic perspective. Acta Agriculturae Scandinavica, Section A– Animal Science 62, 166-180, doi: 110.1080/09064702.09062013.09793735.

Rötter, R.P., Höhn, J.G., Trnka, M., Fronzek, S., Salo, T., Carter, T., Kahiluoto, H., 2013a. Modelling shifts in agroclimate and crop cultivar response under climate change. Ecology and Evolution. doi: 10.1002/ece3.782.

Rötter, R.P., Palosuo, T., Kersebaum, K.C., Angulo, C., Bindi, M., Ewert, F., Ferrise, R., Hlavinka, P., Moriondo, M., Nendel, C., 2012b. Simulation of spring barley yield in different climatic zones of Northern and Central Europe: A comparison of nine crop models. Field Crops Research 133, 23-36.

Rötter, R.P., Palosuo, T., Pirttioja, N., Dubrovsky, M., Salo, T., Fronzek, S., Aikasalo, R., Trnka, M., Ristolainen, A., Carter, T., 2011b. What would happen to barley production in Finland if global warming exceeded 4 °C? A model-based assessment. European Journal of Agronomy 35, 205-214.

Rötter, R.P., Van Keulen, H., 1997. Variations in yield response to fertilizer application in the tropics: II. Risks and opportunities for smallholders cultivating maize on Kenya's arable land. Agricultural Systems 53, 69-95.

Rötter, R.P., Van Keulen, H., Jansen, M., 1997. Variations in yield response to fertilizer application in the tropics: I. Quantifying risks and opportunities for smallholders based on crop growth simulation. Agricultural Systems 53, 41-68.

Ruane, A.C., Cecil, L.D., Horton, R.M., Gordón, R., McCollum, R., Brown, D., Killough, B., Goldberg, R., Greeley, A.P., Rosenzweig, C., 2013. Climate change impact uncertainties for maize in Panama: farm information, climate projections, and yield sensitivities. Agricultural and Forest Meteorology 170, 132-145.

Sacks, W.J., Deryng, D., Foley, J.A., Ramankutty, N., 2010. Crop planting dates: an analysis of global patterns. Global Ecology and Biogeography 19, 607-620.

Schaap, B.F., Blom-Zandstra, M., Hermans, C.M., Meerburg, B.G., Verhagen, J., 2011. Impact changes of climatic extremes on arable farming in the north of the Netherlands. Regional Environmental Change 11, 731-741.

Schlenker, W., Lobell, D.B., 2010. Robust negative impacts of climate change on African agriculture. Environmental Research Letters 5, 014010.

Segele, Z., Lamb, P., 2005. Characterization and variability of Kiremt rainy season over Ethiopia. Meteorology and Atmospheric Physics 89, 153-180.

Seleshi, Y., Camberlin, P., 2006. Recent changes in dry spell and extreme rainfall events in Ethiopia. Theoretical and Applied Climatology 83, 181-191.

Seleshi, Y., Zanke, U., 2004. Recent changes in rainfall and rainy days in Ethiopia. International Journal of Climatology 24, 973-983.

Sen, P.K., 1968. Estimates of regression coefficients based on Kendall's tau Journal of the American Statistical Association 63, 1379-1389.

Senay, G.B., Verdin, J., 2003. Characterization of yield reduction in Ethiopia using a GIS-based crop water balance model. Canadian Journal of Remote Sensing 29, 687-692.

Slegers, M. F., 2008a. "If only it would rain": Farmers' perceptions of rainfall and drought in semi-arid central Tanzania. Journal of Arid Environments 72, 2106-2123.

Slegers, M. F., 2008b. Exploring farmers' perceptions of drought in Tanzania and Ethiopia. Available: http://edepot.wur.nl/14361 [Accessed on 20/06/2013]

Slingo, J.M., Challinor, A.J., Hoskins, B.J., Wheeler, T.R., 2005. Introduction: food crops in a changing climate. Philosophical Transactions of the Royal Society. Biological Sciences 360, 1983-1989.

Smit, B., Skinner, M.W., 2002. Adaptation options in agriculture to climate change: a typology. Mitigation and Adaptation Strategies for Global Change 7, 85-114.

Soler, C.M.T., Maman, N., Zhang, X., Mason, S.C., Hoogenboom, G., 2008. Determining optimum planting dates for pearl millet for two contrasting environments using a modelling approach. The Journal of Agricultural Science 146, 445.

Soler, C.M.T., Sentelhas, P.C., Hoogenboom, G., 2007. Application of the CSM-CERES-Maize model for planting date evaluation and yield forecasting for maize grown off-season in a subtropical environment. European Journal of Agronomy 27, 165-177.

Southworth, J., Pfeifer, R.A., Habeck, M., 2002. Crop modelling results under climate change for the upper Midwest USA. In: Doering, O.C., Randolph, J.C., Southworth, J., and Pfeifer, R.A., (eds.), Effects of Climate Change and Variability on Agricultural Production Systems. Kluwer Academic publishers, Dordrecht, the Netherlands, pp.127-157.

Spielman, D.J., 2008. Encouraging economic growth in Ethiopia: Perspectives on agricultural input markets, agricultural extension and advisory services, and agricultural education and training. Briefing note. International Food Policy Research Institute,Washington, DC.

Spielman, D.J., Kelemwork, D., Alemu, D., 2011. Seed, Fertilizer, and Agricultural Extension in Ethiopia. Ethiopian strategy support program (ESSP II), Working Paper 20. International Food Policy Research Institute, Washington, DC.

SPSS Inc., 2007. SPSS Base 16 windows user's guide. SPSS Inc., Chicago.

Steenbergen, F., Haile, A.M., Alemayehu, T., Alamirew, T., Geleta, Y., 2011. Status and Potential of Spate Irrigation in Ethiopia. Water Resources Management 25, 1899-1913.

Stern, N.H., 2007. The economics of climate change: the Stern review. Cambridge University Press, pp.673.

Stern, R., Dennett, M., Dale, I., 1982. Analyzing daily rainfall measurements to give agronomically useful results. I. Direct methods. Experimental Agriculture 18, 223-236.

Stern, R., Rijks, D., Dale, I., Knock, J., 2006. INSTAT climatic guide. Statistical Services Centre, The University of Reading, UK.

Stern, R.D., Cooper, P.J.M., 2011. Assessing climate risk and climate change using rainfall data - a case study from Zambi. Experimental Agriculture 47, 241-266.

Stewart J.I, 1988. Response farming in rainfed agriculture. The Wharf Foundation Press, Davis, CA.

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

Stigter, K., 2008. Agrometeorological services under a changing climate: old wine in new bags. Bulletin of the World Meteorological Organization 57, 114-117.

Sultan, B., Roudier, P., Quirion, P., Alhassane, A., Muller, B., Dingkuhn, M., Ciais, P., Guimberteau, M., Traore, S., Baron, C., 2013. Assessing climate change impacts on sorghum and millet yields in the Sudanian and Sahelian savannas of West Africa. Environmental Research Letters 8, 014040.

Supit, I., 1994. Global radiation. Publication EUR 15745 EN of the Office for Official Publications of the EU, Luxembourg.

Supit, I., Van Diepen, C., De Wit, A., Kabat, P., Baruth, B., Ludwig, F., 2010. Recent changes in the climatic yield potential of various crops in Europe. Agricultural Systems 103, 683-694.

Tachie-Obeng, E., Gyasi, E., Adiku, S., Abekoe, M., Zierrogel, G., 2010. Farmers' adaptation measures in scenarios of climate change for maize production in semi-arid zones of Ghana. 2nd International Conference: Climate Sustainability and Development in Semi-arid Regions,Fortaleza -Ceará, Brazil, pp. 16-20.

Tao, F., Yokozawa, M., Zhang, Z., 2009. Modelling the impacts of weather and climate variability on crop productivity over a large area: a new process-based model development, optimization, and uncertainties analysis. Agricultural and Forest Meteorology 149, 831-850.

Taylor, K.E., Stouffer, R.J., Meehl, G.A., 2012. An overview of CMIP5 and the experiment design. Bulletin of the American Meteorological Society 93, 485-498.

Tebaldi, C., Knutti, R., 2007. The use of the multi-model ensemble in probabilistic climate projections. Philosophical Transactions of the Royal Society. Mathematical, Physical and Engineering Sciences 365, 2053-2075.

Thomas, D., 2005. Adaptations to Climate Change amongst Natural Resource-Dependant Societies in the Developing World: Across the Southern African Climate Gradient. Technical Report 35. Tyndall Centre for Climate Change Research.

Thomas, D.S.G., Twyman, C., Osbahr, H., Hewitson, B., 2007. Adaptation to climate change and variability: farmer responses to intra-seasonal precipitation trends in South Africa. Climatic Change 83, 301-322.

Thornton, P. K., Boone, R.B., Galvin, K.A., BurnSilver, S.B., Waithaka, M.M., Kuyiah, J., Karanja, S., González-Estrada, E., Herrero, M., 2007. Coping strategies in livestock-dependent households in East and southern Africa: a synthesis of four case studies. Human Ecology 35, 461-476.

Thornton, P. K., Jones, P.G., Alagarswamy, G., Andresen, J., 2009. Spatial variation of crop yield response to climate change in East Africa. Global Environmental Change 19, 54-65.

Thornton, P. K., Jones, P.G., Alagarswamy, G., Andresen, J., Herrero, M., 2010. Adapting to climate change: agricultural system and household impacts in East Africa. Agricultural Systems 103, 73-82.

Thornton, P.K., Jones, P.G., Ericksen, P.J., Challinor, A.J., 2011. Agriculture and food systems in Sub-Saharan Africa in a 4 °C+ world. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences 369, 117-136.

Thornton, P. K., Jones, P.G., Owiyo, T.M., Kruska, R.L., Herrero, M., Kristjanson, P., Notenbaert, A., Bekele, N., Omolo, A., Orindi, V., Ochieng, A., Otiende, B., Bhadwal, S., Anantram, K., Nair, S., Kumar, V., Kelkar, U., 2006. Mapping climate vulnerability and poverty in Africa: Report to the department for international development. ILRI, Nirobi, Kenya, pp.171.

Thornton, P. K., Saka, A., Singh, U., Kumwenda, J., Brink, J., Dent, J., 1995. Application of a maize crop simulation model in the central region of Malawi. Experimental Agriculture 31, 213-226.

Tingem, M., Rivington, M., Bellocchi, G., Azam-Ali, S., Colls, J., 2008. Comparative Assessment of Crop Cultivar and Sowing Dates as Adaptation Choice for Crop Production in Response to Climate Change in Cameroon. African Journal of Plant Science and Biotechnology 2, 10-17.

Tittonell, P., Giller, K.E., 2013. When yield gaps are poverty traps: The paradigm of ecological intensification in African smallholder agriculture. Field Crops Research 143, 76-90.

Tittonell, P., Muriuki, A., Shepherd, K., Mugendi, D., Kaizzi, K., Okeyo, J., Verchot, L., Coe, R., Vanlauwe, B., 2010. The diversity of rural livelihoods and their influence on soil fertility in agricultural systems of East Africa-A typology of smallholder farms. Agricultural Systems 103, 83-97.

Tittonell, P., Vanlauwe, B., Corbeels, M., Giller, K.E., 2008. Yield gaps, nutrient use efficiencies and response to fertilisers by maize across heterogeneous smallholder farms of western Kenya. Plant and Soil 313, 19-37.

Tompkins, E.L., Eakin, H., 2011b. Managing private and public adaptation to climate change. Global Environmental Change 22, 3-11.

Trærup, S.L.M., Mertz, O., 2011. Rainfall variability and household coping strategies in northern Tanzania: a motivation for district-level strategies. Regional Environmental Change 11, 471-481.

Trnka, M., Olesen, J.E., Kersebaum, K.C., Skjelvåg, A.O., Eitzinger, J., Seguin, B., Peltonen-Sainio, P., Rötter, R., Iglesias, A., Orlandini, S., 2011. Agroclimatic conditions in Europe under climate change. Global Change Biology 17, 2298-2318.

Tsuji, G.Y., Hoogenboom, G., Thornton, P., 1998. Understanding options for agricultural production. Kluwer Dordrecht,The Netherlands.

Tubiello, F.N., Donatelli, M., Rosenzweig, C., Stockle, C.O., 2000. Effects of climate change and elevated CO_2 on cropping systems: model predictions at two Italian locations. European Journal of Agronomy 13, 179-189.

Tubiello, F.N., Ewert, F., 2002. Simulating the effects of elevated CO_2 on crops: approaches and applications for climate change. European Journal of Agronomy 18, 57-74.

Tukey, J.W., 1977. Exploratory data analysis. Reading, MA: Addison-Wesley.

Turner, N.C., Rao, K., 2013. Simulation analysis of factors affecting sorghum yield at selected sites in eastern and southern Africa, with emphasis on increasing temperatures. Agricultural Systems 121, 53-62.

UN, 2013. World Population Prospects: The 2012 Revision, Key Findings and Advance Tables. Working Paper No. ESA/P/WP.227 United Nations, Department of Economic and Social Affairs, Population Division.

Van de Steeg, J., Herrero, M., Kinyangi, J., Thornton, P., Rao, K., Stern, R., Cooper, P., 2009. The influence of climate variability and climate change on the agricultural sector in East and Central

Africa-Sensitizing the ASARECA strategic plan to climate change. Research Report 22, ILRI. pp 85. ISBN 92-9146-23-1. Nairobi, Kenya.

Van den Berg, H., Jiggins, J., 2007. Investing in farmers-The impacts of farmer field schools in relation to integrated pest management. World Development 35, 663-686.

Van den Berg, M., Driessen, P., 2002. Water uptake in crop growth models for land use systems analysis: I. A review of approaches and their pedigrees. Agriculture, Ecosystems & Environment 92, 21-36.

Van den Berg, M., Driessen, P., Rabbinge, R., 2002. Water uptake in crop growth models for land use systems analysis: II. Comparison of three simple approaches. Ecological Modelling 148, 233-250.

Van Diepen, C., Wolf, J., Van Keulen, H., Rappoldt, C., 1989. WOFOST: a simulation model of crop production. Soil Use Management 5, 16-24.

Van Halsema, G., Keddi Lencha, B., Assefa, M., Hengsdijk, H., Wesseler, J., 2011. Performance assessment of smallholder irrigation in the Central Rift Valley of Ethiopia. Irrigation and Drainage 60, 622-634.

Van Ittersum, M. K., Cassman, K.G., Grassini, P., Wolf, J., Tittonell, P., Hochman, Z., 2013. Yield gap analysis with local to global relevance—A review. Field Crops Research 143, 4-17.

Van Ittersum, M. K., Ewert, F., Heckelei, T., Wery, J., Alkan Olsson, J., Andersen, E., Bezlepkina, I., Brouwer, F., Donatelli, M., Flichman, G., 2008. Integrated assessment of agricultural systems–A component-based framework for the European Union (SEAMLESS). Agricultural Systems 96, 150-165.

Van Ittersum, M. K., Leffelaar, P., Van Keulen, H., Kropff, M., Bastiaans, L., Goudriaan, J., 2003. On approaches and applications of the Wageningen crop models. Europian Journal of Agronomy 18, 201-234.

Van Ittersum, M. K., Rabbinge, R., 1997. Concepts in production ecology for analysis and quantification of agricultural input-output combinations. Field Crops Research 52, 197-208.

Van Vuuren, D.P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., Hurtt, G.C., Kram, T., Krey, V., Lamarque, J.-F., 2011. The representative concentration pathways: an overview. Climatic change 109, 5-31.

Ventrella, D., Charfeddine, M., Moriondo, M., Rinaldi, M., Bindi, M., 2012. Agronomic adaptation strategies under climate change for winter durum wheat and tomato in southern Italy: irrigation and nitrogen fertilization. Regional Environmental Change 12, 407-419.

Verdin, J., Funk, C., Senay, G., Choularton, R., 2005. Climate science and famine early warning. Philosophical Transactions of the Royal Society B: Biological Sciences 360, 2155-2168.

Vergni, L., Todisco, F., 2011. Spatio-temporal variability of precipitation, temperature and agricultural drought indices in central Italy. Agricultural and Forest Meteorology 151, 301-313.

Vermeulen, S.J., Challinor, A.J., Thornton, P.K., Campbell, B.M., Eriyagama, N., Vervoort, J.M., Kinyangi, J., Jarvis, A., Läderach, P., Ramirez-Villegas, J., 2013. Addressing uncertainty in adaptation planning for agriculture. Proceedings of the National Academy of Sciences 110, 8357-8362.

Viste, E., Korecha, D., Sorteberg, A., 2013. Recent drought and precipitation tendencies in Ethiopia. Theoretical and Applied Climatology 112, 537-551.

Wafula, B.M., 1995. Applications of crop simulation in agricultural extension and research in Kenya. Agricultural Systems 49, 399-412.

Waha, K., Müller, C., Bondeau, A., Dietrich, J., Kurukulasuriya, P., Heinke, J., Lotze-Campen, H., 2013. Adaptation to climate change through the choice of cropping system and sowing date in Sub-Saharan Africa. Global Environmental Change 23, 130-143.

Waha, K., van Bussel, L., Müller, C., Bondeau, A., 2012. Climate-driven simulation of global crop sowing dates. Global Ecology and Biogeography 21, 247-259.

Walker, W.E., Harremoës, P., Rotmans, J., van der Sluijs, J.P., van Asselt, M.B., Janssen, P., Krayer von Krauss, M., 2003. Defining uncertainty: a conceptual basis for uncertainty management in model-based decision support. Integrated Assessment 4, 5-17.

Wang, T., Lu, C., Yu, B., 2011. Production potential and yield gaps of summer maize in the Beijing-Tianjin-Hebei Region. Journal of Geographical Sciences 21, 677-688.

Washington, R., Kay, G., Harrison, M., Conway, D., Black, E., Challinor, A., Grimes, D., Jones, R., Morse, A., Todd, M., 2006. African climate change: taking the shorter route. Bulletin of the American Meteorological Society 87, 1355-1366.

Webb, N., Stokes, C., 2012. Climate change scenarios to facilitate stakeholder engagement in agricultural adaptation. Mitigation and Adaptation Strategies for Global Change 17, 957-973.

Weyant, J., Davidson, O., Dowlabathi, H., Edmonds, J., Grubb, M., Parson, E., Richels, R., Rotmans, J., Shukla, P., Tol, R., 1996. Integrated assessment of climate change: an overview and comparison of approaches and results. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Wheeler, T., von Braun, J., 2013. Climate Change Impacts on Global Food Security. Science 341, 508-513.

White, J.W., Hoogenboom, G., Kimball, B.A., Wall, G.W., 2011. Methodologies for simulating impacts of climate change on crop production. Field Crops Research 124, 357-368.

Whitfield, S., 2013. Uncertainty, ignorance and ambiguity in crop modelling for African agricultural adaptation. Climatic Change 120, 325-340.

Wilby, R., Charles, S., Zorita, E., Timbal, B., Whetton, P., Mearns, L., 2004. Guidelines for use of climate scenarios developed from statistical downscaling methods. IPCC task group on data and scenario support for impacts and climate analysis.

Willmott, C.J., 1981. On the validation of models. Physical Geography 2, 184-194.

Williams, A.P., Funk, C., 2011. A westward extension of the warm pool leads to a westward extension of the Walker circulation, drying eastern Africa. Climate Dynamics 37, 2417-2435.

Wokabi, S., 2003. Effectiveness of WOFOST Simulation Model to predict maize yield gaps on the eastern slopes of Mt Kenya. Sustainable use of land resources to alleviate poverty in the new millennium, 18, Mombasa (Kenya), 4th-8th December 2000. Soil Science Society of East Africa.

Wolf, J., Hessel, R., Boogaard, H., de Wit, A., Akkermans, W., van Diepen, K., 2011. Modelling winter wheat production across Europe with WOFOST-The effect of two new zonations and two newly calibrated model parameter sets. In: Ahuja, L.R., Ma, L. (eds.), Methods of Introducing System Models into Agricultural Research. Advances in Agricultural Systems Modelling 2: Trans-disciplinary Research, Synthesis, and Applications. ASA-SSSA-CSSA Book Series, pp. 297-326.

Wolf, J., Mandryk, M., Kanellopoulos, A., van Oort, P., Schaap, B., Reidsma , P., van Ittersum, M., 2010. Methodologies for analyzing future farming systems in Flevoland as applied within the AgriAdapt project. AgriAdapt project report no.1, Wageningen UR.

Worku, M., Twumasi Afriyie, S., Wolde, L., Tadesse, B., Demisie, G., Bogale, G., Wegary, D., Prasanna, B., 2012. Meeting the challenges of global climate change and food security through innovative maize research. Proceedings of the third national maize workshop, Ethiopia, Addis Ababa.

World Bank, 2006. Managing water resources to maximize sustainable growth: A country water resources assistance strategy for Ethiopia. World Bank, Washington, DC.

Yao, F., Qin, P., Zhang, J., Lin, E., Boken, V., 2011. Uncertainties in assessing the effect of climate change on agriculture using model simulation and uncertainty processing methods. Chinese Science Bulletin 56, 729-737.

Yengoh, G.T., Armah, F.A., Onumah, E.E., Odoi, J.O., 2010. Trends in agriculturally relevant rainfall characteristics for small-scale agriculture in northern Ghana. Journal of Agricultural Science 2, 1-16.

Yesuf, M., Bluffstone, R., 2007. Risk Aversion in Low Income Countries: Experimental Evidence from Ethiopia, IFPRI Discussion paper 715, Washington, DC.

Žalud, Z., Dubrovský, M., 2002. Modelling climate change impacts on maize growth and development in the Czech Republic. Theoretical and Applied Climatology 72, 85-102.

Zewdie, E., 2004. Characterization and genesis of some soils of the Ethiopian rift valley showing andic properties. Ethiopian Journal of Natural Resources 6, 215-235.

Summary

Climate change is one of the most serious environmental threats facing mankind in the 21st century. There is also general consensus that poor countries, particularly in the Sub-Saharan region, are most vulnerable and Ethiopia is often cited as an example. Ethiopia heavily depends on agriculture which (i) provides a living for about 85% of the population, (ii) contributes about 50% to the national GDP and (iii) generates 88% of the export earnings. This vital socio-economic sector is, however, highly vulnerable to climate variability and change mainly due to heavily dependence on rainfall and lack of investments to better exploit the good seasons and use limited water more efficiently. For decades, smallholder farmers in Ethiopia have been facing severe climate related hazards, in particular highly variable rainfall and severe droughts that negatively affect their livelihoods. Particularly, semi-arid regions such as the Central Rift Valley, are prone to climate-induced risks and production uncertainty. Anticipated climate change is expected to aggravate some of the existing challenges and impose new risks beyond the range of current experiences.

Despite the fact that agriculture is the backbone of the country's economic development and climate-induced risks are already challenging and expected to have adverse impacts, research on impacts of climate variability and change, and adaptation options carried out so far are rather limited. Thus, studying the impacts of climate variability and change and investigating adaptation options is important to Ethiopia's agricultural production and food security. Helping farmers to cope better with current climate variability is a prerequisite for adapting to future climate change. Depending on their long-term observations and subjective assessments of risks, farm households use certain adaptive strategies. A better understanding of the local practices in response to the current climate variability is important for policy makers to shape conditions for future adaptation. This study was, therefore, aimed at understanding current and future climate characteristics and associated risks/impacts and providing insights in current climate risk management strategies and future potential adaptation options for adapting agriculture, particularly maize-based production. The study was conducted in the Rift Valley of Ethiopia, which is part of the great East African Rift Valley system and divides Ethiopia into north-western and south-eastern highlands. The study focused on the central part of the rift valley (CRV), however, a second case study area, Kobo valley was also used in Chapter 4, for additional analysis on farmers' perceptions and current adaptation practices.

These two case study areas represent major cereal-based farming systems in the semi-arid environments of Ethiopia and are hotspots for climate induced risks. Maize (*Zea mays*), an important staple crop in the livelihoods of smallholders, is the main focus of the study.

Chapter 2 presents historical trends and projected changes of agro-climatic indices with respect to implications to rainfed crop production in the Central Rift Valley of Ethiopia. Temporal variability and extreme values of selected rainfall and temperature indices were analyzed and trends were evaluated. Projected future changes in rainfall and temperature for the 2080s relative to the 1971-1990 baseline period were determined based on four General Circulation Models (CSIRO2, CGCM2, HadCM3 and PCM) and two emission Scenarios (SRES, A2 and B1). The analysis for observed historical climate data (1977-2007) revealed that total rainfall did not change significantly, but exhibited high inter-annual variability (CV 15-40%). The number of rainy days decreased, and was associated with an increase (statistically not significant) in the rainfall intensity for the main rainy season. The mean annual temperature exhibited a significant warming trend of 0.12 to 0.54 °C per decade. The crop growing period is characterized by late start and early cessation of rainfall, erratic rainfall distribution and frequent intermittent dry spells leading to moisture stress and reduction in crop yield. The length of the growing period also exhibited high inter-annual variability, ranging from 76 to 239 days. Projections from the GCMs suggested that future annual rainfall will change in the range of -40 to +10% and the annual temperature is expected to increase in the range of 1.4 to 4.1 °C by 2080s. Also the length of the growing season is expected to be reduced by 12-35%. The past and future climate trends, especially in terms of rainfall and its variability and the increasing temperature pose major risks to rainfed agriculture implying that specific adaptation strategies are needed to cope with the risks, sustain farming and improve food security.

In Chapter 3, a multi-model crop growth simulation approach using two crop models (DSSAT and WOFOST) was applied to characterize climate-induced yield variability; and yield gaps for maize cultivars in the CRV. The models were calibrated and evaluated with experimental data and subsequently, a simulation experiment was carried out for early and late maturing maize cultivars using historical weather data of three representative stations. The results revealed that potential yield is about 7.0 Mg/ha for the early maturing cultivar and between 8 to 9 Mg/ha for a late maturing cultivar. Simulated water-limited yield is 6.0 to 7.0 Mg/ha for the early maturing and 7.0 to 8.0 Mg/ha for the late maturing cultivars. The simulated water-limited yields are characterized by higher inter-annual yield variability (CV 36%) than the potential yield (CV 7-14%) showing the effect of rainfall variability. About 60% of the yield variability of simulated water-limited yield is explained by rainfall variability during the growing season. Actual yields of maize in the CRV are only 28-30% of the simulated water limited yield and 44-65% of on-farm trial yields. Existing yield gaps between actual and simulated yields indicate that recommended production technologies (e.g. fertilizer and pesticides) are not fully adopted at farmers' fields. The yield gaps also indicate that there is scope to significantly increasing maize yields in the CRV and other similar agro-ecological zones, through improved crop and climate risk management strategies. The study also demonstrated the usefulness of crop simulation modelling in characterizing yield variability and yield gaps, which is not yet a common research tool in Ethiopia. The two crop models applied differed in capturing yield variability, i.e. the inter-annual variability of simulated yield is higher for WOFOST than DSSAT. Differences in simulated yields between WOFOST and DSSAT were 0.4 to 1.6 and 0.4 to 1.0 for the potential yield and water-limited yields, respectively. As the crop models differ in details of describing dynamic processes of crop growth, water use and soil water balance, the multi-model approach provides better information on the uncertainty in simulating crop-climate interactions. It was not possible to judge which model is superior, since detailed sequential measurements (e.g. above ground crop growth and soil moisture during the season) were not available for comparison with the simulations.

Chapter 4 analyses local community perceptions on current climate variability and long-term changes, current adaptation practices, needs for future adaptation, and barriers for successful adaptation. The study was based on a household questionnaire, interviews with key stakeholders and focus group discussions in two selected case study areas, i.e., Central Rift and Kobo valleys, both representing semi-arid vulnerable regions with some contrasting agricultural potential. The results showed that farmers perceived climate variability and change, and they are concerned about the impacts on their agricultural production and livelihoods. In their opinion, annual rainfall has decreased and temperature has increased over the last 20-30 years. Inter-annual and intra-seasonal rainfall variability also has increased according to farmers. Perceptions on increasing temperature and variable rainfall are supported by observed climate, however, some perceptions (e.g. a decrease in rainfall amount) are not confirmed by observed climate trends. Reduced water availability to crops due to the increased hot spells and the interaction of climate with other environmental changes such as a decline in soil fertility and land cover changes may influence the perception of farmers as to declining rainfall. The discrepancy between farmers' perceptions and observed climate trends implies that misconceptions require attention to avoid maladaptation. It also indicates that communication between climate scientists and farmers need to be improved through participatory-based information exchange platforms such as "Climate Field Schools". Farmers mentioned various aspects of climate induced risks which in general reduced agricultural productivity and consequently increasing food insecurity. The study revealed that in response to the perceived climate variability and change, farm households are implementing various coping and adaptation strategies. The most important current adaptive strategies include crop selection, adjusting planting time, various *in situ* moisture conservation techniques such as shilshalo, tied-ridges, spate irrigation and income diversification. For future adaptation, farmers need adequate access to agricultural inputs (e.g. fertilizer and seed), improved crop varieties, irrigation, climate risk insurance and effective weather forecast service. Main barriers as to successful adaptation were associated with technological and institutional limitations. Lack of affordable technologies, high costs for agricultural inputs, unstable market prices, lack of reliable information on weather forecasts, and insecure land tenure systems were identified as limiting factors of farmers' adaptive capacity. It is clear from the analysis that enabling strategies, which are among others targeted at agricultural inputs, credit supply, market access and strengthening of local knowledge and information services need to become integral part of government policies to assist farmers adapt to the impacts of current climate variability.

In Chapter 5, impacts of projected climate change and adaptation options under various state-of-the-art climate change scenarios have been explored for maize production in the CRV using two crop models (DSSAT, v4.5 and WOFOST, v7.1) and three GCMs (CanESM2, CSIRO-MK3 and HadGEM2) in combination with two recently released Representative Concentration Pathways (RCP4.5, RCP8.5) for the period 2040-2069 (referred to as 2050s). The results indicate that without adaptation, maize yield will decrease on average by 20% relative to the baseline (1980-2009) due to climate change in the 2050s. The main driving factors for a lower maize yield under climate change scenarios were increased temperature (1.6-3.5 °C during the growing season) and decreased rainfall, particularly during the critical growth stages of maize (June to July) resulting in a shortened growing season (14-33 days across the climate change scenarios). Maize yield is projected to be reduced even for wet scenarios predicting an increase in rainfall which implies that the impact of increase in temperature would be more pronounced than rainfall under climate change. Analysis for adaptation options indicated that use of irrigation, increasing nitrogen fertilization, and changes in planting dates (slightly shifting to late planting by three weeks relative to the baseline planting dates) can reduce the negative impacts of climate change on maize production. Increasing the nitrogen fertilization by 60 kg N/ha increased yield by 78-86% under the various climate change scenarios and irrigation increased yield by 15-39% relative to rainfed production. However, it should be noted that the response of yield to increased nitrogen fertilization and irrigation supply was less under climate change scenarios than under baseline climate; which indicates that these adaptation options will not totally avoid the negative impacts of climate change. The increase in yield with nitrogen and irrigation application under climate change scenarios is also conditional on application of flanking measures, such as adjusted crop protection, to enable realization of the yield increases. Currently available late and early maturing cultivars are likely not suitable under climate change, which implies that plant breeding research in Ethiopia needs to be tailored towards developing high yielding and heat tolerant cultivars, preferably combined with higher disease and pest-resistance, in order to better adapt crop production to future climate.

The multi-model based analysis also allowed estimation of some of the climate change impact and adaptation uncertainties, which can provide valuable insights and guidance for adaptation planning processes. In this study we took into account uncertainties arising from GCMs and emission scenarios by careful selection of GCMs and RCPs combinations that cover a wide window of uncertainty in climate model output; and we applied two crop models that show different strengths regarding simulation of above-ground growth and development processes, and of soil moisture dynamics. Quantifying uncertainty is an important effort in climate impact studies and a recommended approach is to use multiple crop and climate models. In this thesis, the outputs from two crop models and multiple climate models revealed that without adaptation, a negative impact of climate change on maize production in the CRV is very likely, while the magnitude is more uncertain with estimates ranging from -2 to -29% depending on crop model, GCM and RCP. From the selection of models we used, it is concluded that uncertainties caused by different GCMs are larger than those caused by different RCPs and crop models.

Chapter 6 provides a synthesis of the previous chapters. It discusses key findings and scientific insights as well as issues for further research. In conclusion, this research showed that crop production in Ethiopia, particularly in the semi-arid regions, has already been challenged by climate variability and with a business-as-usual development, the progressive climate change is projected to affect it negatively. Farmers are implementing various adaptive strategies to cope with the current climate variability; however, such responses may not be adequate for future climate change adaptation. The study highlighted that farmers are aware of the necessity to make long term adjustments to sustain agricultural production under climate change. However, affordable technology options, strengthening communication between actors, and new policy arrangements to remove institutional barriers are needed to support smallholder farmers in shaping adaptation to current and future climate risks. Investment in more appropriate adaptation options such as more heat tolerant crop breeds, increased level of agricultural inputs (e.g. fertilizer), and irrigation are highly needed to reduce climate change impacts and adapting cropping systems. Research could play an essential role by developing and disseminating improved adaptive technologies. Mainstreaming climate adaptation research, building institutional memory for relevant data as to climate research and capacity building towards using advanced research approaches such as crop and climate modelling need immediate attention to enhance adaptation of agriculture to climate variability and change.

Samenvatting

Klimaatverandering is een van de ernstigste bedreigingen voor de omgeving in de 21ste eeuw. Er bestaat overeenstemming dat arme landen, vooral ten zuiden van de Sahara, het meest kwetsbaar zijn en Ethiopië wordt in dit verband vaak als voorbeeld genoemd. Ethiopië is zeer afhankelijk van de landbouw die (i) werk verschaft aan 85% van de bevolking, (ii) voor ongeveer 50% bijdraagt aan het nationale BBP en (iii) 88% van exportopbrengsten genereert. Deze sociaaleconomisch belangrijke sector is echter zeer kwetsbaar voor klimaatvariabiliteit en -verandering voornamelijk als gevolg van de sterke afhankelijkheid van regenval en het ontbreken van investeringen om goede seizoenen beter te benutten en schaars water efficiënter te gebruiken. Al decennia lang hebben kleine boeren in Ethiopië te maken met klimaatrisico's zoals sterk fluctuerende neerslag en ernstige droogte die hun bestaanszekerheid bedreigen. In het bijzonder semi-aride gebieden zoals de Centrale Rift Vallei zijn gevoelig voor klimaatrisico's en productie-onzekerheden. Klimaatverandering zal naar verwachting een deel van de bestaande problemen verergeren en nieuwe risico's met zich mee brengen waarvoor huidige ervaringen van belanghebbenden geen oplossing bieden.

Ondanks dat landbouw de basis vormt van de economische ontwikkeling in Ethiopië en huidige klimaatrisico's al een grote uitdaging vormen voor de landbouw is het onderzoek naar de gevolgen van klimaatvariabiliteit en -verandering, en naar adaptatiemogelijkheden tot dusverre beperkt. Studie naar de gevolgen van klimaatvariabiliteit en -verandering, en van adaptatiemogelijkheden is belangrijk voor de landbouwproductie en voedselzekerheid van Ethiopië. Ondersteuning van boeren bij het beter omgaan met de huidige klimaatvariabiliteit is een eerste vereiste voor aanpassing aan toekomstige klimaatverandering. Boerenhuishoudens gebruiken al verschillende aanpassingsmaatregelen gebaseerd of lange-termijn waarnemingen en subjectieve beoordelingen van risico's. Een beter begrip van deze lokale maatregelen om met klimaatvariabiliteit om te gaan is belangrijk voor beleidsmakers om voorwaarden te scheppen voor toekomstige aanpassingen. Deze studie is daarom gericht op het begrijpen van huidige en toekomstige klimaatkarakteristieken en gerelateerde risico's en gevolgen, en op het leveren van inzichten van huidig klimaatrisico management en toekomstige adaptatiemogelijkheden voor de landbouw, in het bijzonder voor maïsproductie. De studie is uitgevoerd in de Rift Vallei van Ethiopië, dat in de grotere Oost Afrikaanse Rift Vallei ligt en dat Ethiopië verdeeld in de noordwestelijk en zuidoostelijke hooglanden. De studie richt zich specifiek op het centrale deel van de Rift Vallei (CRV), maar een tweede studiegebied in de Kobo Vallei is gebruikt in Hoofdstuk 4 voor een aanvullende studie naar de perceptie van boeren en huidige adaptatiemaatregelen. De twee studiegebieden vertegenwoordigen belangrijke graan-gebaseerde landbouwsystemen van de semi-aride klimaatzones in Ethiopië en zijn hot spots voor klimaatrisico's. Maïs (*Zea mays*) is een belangrijk voedselgewas voor kleine boeren en daarom onderwerp van deze studie.

Hoofdstuk 2 presenteert historische trends en verwachte veranderingen in agro-klimatologische indices in relatie tot de regenafhankelijke gewasproductie in de Centrale Rift Vallei van Ethiopië. Temporele variabiliteit en extremen van geselecteerde neerslag- en temperatuur-indices worden geanalyseerd en trends geëvalueerd. Verwachte veranderingen in regenval en temperatuur in 2080 zijn gebaseerd op vier globale klimaatmodellen (CSIRO2, CGCM2, HadCM3 en PCM) en twee CO_2 emissiescenario's (SRES, A1 en B1) en vergeleken met de referentieperiode 1971-1990. Analyse van historische klimaatgegevens (1977-2007) toonde aan dat de totale regenval niet significant was veranderd maar dat de jaar tot jaar variabiliteit (CV 15-40%) groot was. Het aantal dagen met regen nam af en dat ging gepaard met een (statistisch niet significante) toename van de regenval intensiteit in het belangrijkste regenseizoen. De gemiddeld jaarlijkse temperatuur vertoonde een significante stijging van 0.12 tot 0.52 °C per decennium. De periode van gewasgroei werd gekenmerkt door een latere start en vroegtijdige beëindiging van de regenval, grillige verdeling van de regenval en frequente droogte die resulteren in droogtestress en vermindering van de gewasopbrengst. De duur van het groeiseizoen varieerde van jaar tot jaar tussen de 76 tot 239 dagen. Voorspelling van de globale klimaatmodellen (GCMs) suggereerde dat toekomstige regenval zal veranderen binnen een bereik van -40 tot +10% en dat de jaarlijkse temperatuur zal toenemen van 1.4 tot 4.1 °C rond 2080. Ook het groeiseizoen wordt naar verwachting verkort met 12 tot 35%. Huidige en toekomstige klimaattrends, in het bijzonder de hoeveelheid en variatie in regenval en de toenemende temperatuur vormen belangrijke risico's voor de regenafhankelijke landbouw. Dit betekent dat specifieke adaptatiemaatregelen nodig zijn om met deze risico's om te gaan en landbouw te ondersteunen en voedselzekerheid te verbeteren.

In Hoofdstuk 3 zijn twee gewasgroeimodellen (DSSAT en WOFOST) toegepast om klimaat-gerelateerde variatie in opbrengsten en opbrengstverschillen ('yield gaps') te karakteriseren van maïsrassen in de Centrale Rift Vallei. De modellen werden gekalibreerd en geëvalueerd aan de hand van experimentele data. Vervolgens werd een simulatie experiment uitgevoerd voor vroege en late maïsrassen met historische weersdata van drie representatieve weerstations. De resultaten toonden aan dat de potentiële opbrengst ongeveer 7.0 Mg/ha was voor vroege rassen en tussen de 8 en 9 t/ha voor late rassen. Gesimuleerde water-beperkte opbrengsten lopen uiteen van 6.0 tot 7.0 Mg/ha voor de vroege rassen en van 7.0 tot 8.0 Mg/ha voor de late rassen. De gesimuleerde water-beperkte opbrengsten worden gekenmerkt door een hogere jaarlijkse variabiliteit (CV 36%) dan de potentiële opbrengsten (CV 7-14%) die samenhangt met variatie in regenval. Ongeveer 60% van de opbrengstvariabiliteit kan worden verklaard door de variatie in regenval gedurende het groeiseizoen. Huidige maïsopbrengsten van boeren in de Centrale Rift Vallei zijn slechts 28-30% van de gesimuleerde water-beperkte opbrengsten en 44-65% van de experimentele opbrengsten die op bedrijven worden behaald. Opbrengstverschillen tussen actuele en gesimuleerde opbrengsten wijzen erop dat aanbevolen productietechnieken (bijvoorbeeld kunstmest en gewasbeschermingsmiddelen) niet op brede schaal worden toegepast door de boeren. De opbrengstverschillen tonen ook aan dat verhoging van maïsopbrengsten mogelijk is in de Centrale Rift Vallei en in andere gebieden met dezelfde agro-ecologische omstandigheden door toepassing van een verbeterd gewas- en risicomanagement. Tevens laat de studie het nut zien van gewasgroeimodellen om opbrengstvariabiliteit en opbrengstverschillen te kenmerken. Gewasgroeimodellen worden momenteel nog niet veel gebruikt als onderzoeksinstrument in Ethiopië. De twee gebruikte gewasgroeimodellen verschilden in het karakteriseren van opbrengstvariabiliteit; de jaarlijkse opbrengstvariatie was hoger in WOFOST dan in DSSAT. Verschillen in gesimuleerde opbrengsten tussen WOFOST en DSSAT varieerden tussen 0.4 en 1.6 Mg/ha en tussen de 0.4 en 1.0 Mg/ha, respectievelijk voor de potentiële en water-beperkte opbrengsten. Gewasgroeimodellen verschillen in de mate van detail waarmee dynamische processen van gewasgroei, watergebruik en de bodem waterbalans worden beschreven. Daarom levert het gebruik van meerdere modellen betere informatie op over onzekerheden in de simulatie van gewas-klimaat interacties. Het was niet mogelijk vast te stellen welk model beter was omdat gedetailleerde en systematische metingen (bijvoorbeeld van de gewasgroei en bodemvocht) niet beschikbaar waren om de simulaties mee te vergelijken.

Hoofdstuk 4 analyseert de perceptie van de lokale bevolking ten aanzien huidige klimaatvariabiliteit en -verandering, huidige aanpassingsmaatregelen, behoeftes voor toekomstige aanpassingen en belemmeringen voor succesvolle aanpassing. De studie was gebaseerd op een vragenlijst voor boerenhuishoudens, interviews met belangrijke belanghebbenden en groepsdiscussies in twee gebieden, de Centrale Rift Vallei en Kobo Vallei, die beiden representatief zijn voor semi-aride en kwetsbare gebieden, maar met contrasterende landbouwpotenties. De resultaten tonen aan dat boeren bewust zijn van klimaatvariabiliteit en -verandering, en dat ze bezorgd zijn over de gevolgen ervan voor hun landbouwproductie en levensonderhoud. Volgens de boeren is de jaarlijkse neerslag afgenomen en de temperatuur toegenomen gedurende de laatste 20-30 jaar. Neerslagvariabiliteit in en tussen jaren is ook toegenomen volgens boeren. Percepties ten aanzien van de stijgende temperatuur en variabele regenval worden ondersteund door klimaatwaarnemingen, maar andere percepties (bijvoorbeeld de afname in regenval) worden echter niet ondersteund door waarnemingen. Verminderde waterbeschikbaarheid voor gewassen ten gevolge van een toename van hittegolven en de interactie van klimaat met andere omgevingsfactoren zoals een afname van de bodemvruchtbaarheid en landgebruiksveranderingen kunnen de perceptie van boeren beïnvloeden. De tegenstrijdigheid in de perceptie van boeren en de waargenomen klimaattrends vereisen aandacht om contraproductieve aanpassingsmaatregelen te voorkomen. Tevens geeft dit aan dat de communicatie tussen klimaatwetenschappers en boeren moet worden verbeterd door participatieve informatieplatforms zoals 'klimaatscholen'. Boeren noemden verschillende klimaatrisico's die de landbouwproductiviteit verminderden en uiteindelijk resulteren in een toenemende voedselonzekerheid. De studie toonde aan dat boerenhuishoudens al verschillende adaptatiemaatregelen gebruiken om met klimaatvariabiliteit en -verandering om te gaan. De belangrijkste adaptatiemaatregelen zijn gewaskeuze, aanpassing van het zaaitijdstip, en verschillende bodem- en waterconserveringstechnieken zoals 'shilshao', kruisruggen en vloed-irrigatie, en inkomensdiversificatie. Om toekomstige aanpassingen mogelijk te maken hebben boeren voldoende toegang nodig tot landbouw-inputs (bijvoorbeeld kunstmest en zaaizaad), verbeterde rassen, irrigatie, gewasverzekeringen en weersvoorspellingen. Belangrijke obstakels voor succesvolle aanpassing hielden verband met technologische en institutionele belemmeringen. Gebrek aan betaalbare technologieën, hoge kosten van inputs, instabiele prijzen, gebrek aan betrouwbare weersvoorspellingen, en een onzeker pachtstelsel beperkten het aanpassingsvermogen van boeren. Op basis van de analyse is duidelijk dat ondersteunende strategieën o.a. gericht op landbouw-inputs, kredietverstrekking, markttoegang en versterking van lokale kennis en informatiediensten integraal onderdeel moeten worden van overheidsbeleid om boeren te helpen om zich aan te passen aan de gevolgen van klimaatvariabiliteit en -verandering.

In Hoofdstuk 5 zijn de gevolgen van de verwachte klimaatverandering en van adaptatie-opties voor maïsproductie in de Centrale Rift Vallei verkend op basis van verschillende klimaatscenario's. Hierbij werd gebruik gemaakt van twee gewasgroeimodellen (DSSAT, v4.5 en WOFOST, v7.1) en drie GCMs (CanESM2, CSIRO-MK3 en HadGEM2) in combinatie met twee representatieve CO_2 ontwikkelingstrajecten (RCP4.5, RCP8.5) voor de periode 2040-2069. De resultaten tonen aan dat zonder aanpassing maïsopbrengsten zullen afnemen met gemiddeld 20% vergeleken met de uitgangssituatie (1980-2009) ten gevolge van klimaatverandering rond 2050. De belangrijkste factoren die leiden tot lagere maïsopbrengsten waren een toegenomen temperatuur (1.6-3.5 °C in het groeiseizoen) en afgenomen regenval, in het bijzonder gedurende cruciale groeistadia van maïs (juni-juli) resulterend in een verkort groeiseizoen (14-33 dagen afhankelijk van het klimaatscenario). Zelfs in scenario's met een toename in regenval nemen de verwachte maïsopbrengsten af. Dit betekent dat de gevolgen van een toename in temperatuur sterker zijn dan van een toename in regenval onder klimaatverandering. Analyse van adaptatie-opties toonden aan dat gebruik van irrigatie, stikstofkunstmest en verandering in zaai data (3 weken later zaaien dan in de uitgangssituatie) de negatieve gevolgen van klimaatverandering op maïsproductie kunnen verminderen. Verhoging van de stikstofbemesting met 60 kg/ha verhoogde de opbrengsten met 78-86% onder verschillende klimaatscenario's en irrigatie verhoogde de opbrengst met 15-39% vergeleken met regenafhankelijke productie. Behaalde opbrengsten met verhoogde stikstofbemesting en irrigatie zijn echter lager in de klimaatscenario's dan in de uitgangssituatie. Dit wijst erop dat deze adaptatie opties niet volledig de negatieve gevolgen van klimaatverandering kunnen voorkomen. De opbrengstverhoging door stikstofbemesting en irrigatie in de klimaatscenario's is ook afhankelijk van flankerende maatregelen zoals aangepaste gewasbescherming om hogere opbrengsten te kunnen realiseren. Beschikbare late en vroege rassen zijn waarschijnlijk ongeschikt bij klimaatverandering. Dit betekent dat veredelingsonderzoek in Ethiopia moet worden gericht op de ontwikkeling van hoogproductieve en hitte-tolerante rassen, bij voorkeur gecombineerd met goede ziekte- en plaagresistentie, zodat gewasproductie beter is aangepast aan het toekomstig klimaat. De analyse gebaseerd op meerdere modellen bood ook de mogelijkheid om enkele onzekerheden in de gevolgen van klimaatverandering en -adaptatie te schatten. Deze informatie verschaft waardevolle inzichten en richtlijnen voor het plannen van adaptatiemaatregelen. In deze studie is rekening gehouden met onzekerheden die voortvloeien uit GCMs en emissiescenario's door zorgvuldige keuzes en combinaties van GCMs en CO_2 ontwikkelingstrajecten die een breed spectrum van onzekerheid in klimaatmodellen omvatten. Bovendien zijn twee gewasgroeimodellen toegepast die verschillen in de simulatie van bovengrondse biomassa en gewasontwikkeling, en in bodemvochtdynamiek. Het kwantificeren van onzekerheid is belangrijk in klimaatstudies en het wordt aanbevolen om daarvoor meerdere gewas- en klimaatmodellen te gebruiken. De resultaten van twee gewasgroeimodellen en meerdere klimaatmodellen toonden aan dat de negatieve gevolgen van klimaatverandering voor maïsproductie in de Centrale Rift Vallei zeer waarschijnlijk zijn als aanpassing achterwege blijft. De omvang van de gevolgen is meer onzeker met schattingen die uiteenlopen van -2 tot -29% afhankelijk van het gewasgroeimodel, GCM en emissiescenario's. Op basis van de gekozen modellen kan worden geconcludeerd dat onzekerheden veroorzaakt door de GCMs groter is dan die worden veroorzaakt door verschillende emissiescenario's en gewasgroeimodellen.

Hoofdstuk 6 biedt een synthese van de voorafgaande hoofdstukken en bediscussieert de belangrijkste bevindingen, wetenschappelijke inzichten en onderwerpen voor nader onderzoek. Dit onderzoek toonde aan dat gewasproductie in Ethiopië, vooral in semi-aride gebieden, al wordt bedreigd door klimaatvariabiliteit. Met een business-as-usual ontwikkeling zal de voortschrijdende klimaatverandering naar verwachting gewasproductie negatief beïnvloeden. Boeren voeren verschillende maatregelen uit om met de huidige klimaatvariabiliteit om te gaan. Echter dergelijke maatregelen zijn mogelijk onvoldoende voor aanpassing aan toekomstige klimaatverandering. Deze studie maakt duidelijk dat boeren zich er bewust van zijn dat aanpassing nodig is om te blijven produceren onder klimaatverandering. Echter, betaalbare technische opties, versterking van de communicatie tussen actoren, en nieuwe beleidsarrangementen om institutionele belemmeringen weg te nemen zijn nodig om kleine boeren te ondersteunen bij het aanpassen aan huidige en toekomstige klimaatrisico's. Investeringen in geschikte adaptatie-opties zoals hitte-tolerante rassen, meer landbouw inputs (bijv. kunstmest) en irrigatie zijn in het bijzonder noodzakelijk om de gevolgen van klimaatverandering te verminderen en om gewassystemen aan te passen. Onderzoek kan een belangrijke rol spelen bij de ontwikkeling en verspreiding van verbeterde en aangepaste technologieën. Integratie van klimaatadaptatie onderzoek, opbouw van een institutioneel geheugen voor relevante klimaatdata, en capaciteitsopbouw voor toepassing van geavanceerde onderzoekbenaderingen zoals gewas- en klimaatmodellering hebben onmiddellijke aandacht nodig om de landbouw aan klimaatvariabiliteit en -verandering aan te passen.

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Curriculum Vitae

Belay Tseganeh Kassie was born on the 18th of January 1975 in Gojjam, Ethiopia. Belay has obtained his BSc degree in Soil and Water Conservation from Mekelle University in July 1999. During September 1999 to January 2001, he has served Amhara National Regional State Bureau of Agriculture as soil and water conservation expert at Lay Gaint Woreda office of Agriculture. In February 2001, Belay was employed at Amhara Regional Agricultural Research Institute (ARARI) as a researcher in natural resources management. In August 2003, he continued his master's degree in agricultural meteorology at Punjab Agricultural University, India and graduated in July 2005. From August 2005 to October 2009, he served ARARI as a researcher in natural resources management with main focus in agro-climatology.

In September 2009, Belay obtained a PhD scholarship funded by the Academy of Finland (decision no.127405) as part of AlterCLIMA project coordinated by MTT Agrifood Research Finland with Plant Research International and Plant Production Systems Group from Wageningen University as partners. In November 2009, he was admitted to the *C.T. de Wit* graduate school for Production Ecology and Resource Conservation at Wageningen University and did his PhD mainly at the Plant Production Systems Group with extended study periods at MTT Agrifood Research Finland, Mikkeli and the Agricultural and Biological Engineering Department at the University of Florida, USA. His PhD study focuses on climate variability and climate change, impacts, and adaptation options with respect to cereal production in Ethiopia. He acquired basic skills in systems research approaches, particularly in application of crop growth simulation and climate modelling techniques for decision support systems. Belay is interested in working on research and teaching in the domains of climate change, crop modelling and agricultural systems. Recently, he obtained a post-doctoral associate position on crop modelling and climate change research at the University of Florida, USA in the department of Agricultural and Biological engineering.

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List of publications

Journal articles

Kassie, B.T., Hengsdijk, H., Rötter, R., Kahiluoto, H., Asseng, S., Ittersum, M.V., 2013. Adapting to Climate Variability and Change: Experiences from Cereal-Based Farming in the Central Rift and Kobo Valleys, Ethiopia. Environmental Management 52, 1115-1131.

Kassie, B.T., Rötter, R.P., Hengsdijk, H., Asseng, S., Van Ittersum, M.K., Kahiluto, H., Van Keulen, H., 2014. Climate variability and change in the Central Rift Valley of Ethiopia: Challenges for rainfed crop production. Journal of Agricultural Science 52, 58-74.

Helena Kahiluoto, Karoliina Rimhanen, Reimund Rötter & **Belay Tseganeh**. 2012. Mitigation of Climate Change to Enhance Food Security: An Analytical Framework. Forum for development Studies 39, 51-73

Belay Tseganeh, Parmjit Sing Sehra and Anil Sood. 2008. Land suitability analysis for agricultural crops using GIS and remote sensing techniques. Journal of Agrometeorology, Vol. 10, Special issue 2008, Part 1, Pages 67-71, India

Proceedings/posters/presentations

Belay T. Kassie, Huib Hengsdijk, Reimund Rötter. 2011. Strategies for Responding to Current Risk to Crop Production in Ethiopia: In: Conference proceedings. The impacts of and adaptation to climate change in relation to food security in Africa. Scientific Conference of the NASAC-KNAW collaborative initiative, held at Nairobi, 23-25 February 2011, Kenya.

Belay T. Kassie, Reimund Rötter, Huib Hengsdijk, Helena Kahiluoto, 2011. Quantifying current and future climatic risks to cereal production in Ethiopia as a basis for informing adaptation. In: Development on the margin: Tropentag 2011, university of Bonn, October 5-7, 2011. University of Bonn.

Belay T. Kassie, H. Hengsdijk, R. Rötter, H. van Keulen 2010. Adapting to the impacts of climate variability and change on agriculture. Poster presented in a Conference on first-year anniversary of the WUR-Ethio Institutes partnership, 07 July 2010, Holeta, Ethiopia.

Helena Kahiluoto, Karoliina Rimhanen, **Belay Tseganeh**, Reimund Rötter. 2009. Implications of 4+°C global warming on potential of carbon trading for mitigation and food security - analytical framework and an Ethiopian case. In: 4 degrees & beyond : implications of a global climate change of 4+ degrees for people, ecosystems and the earth-system, international climate conference, 28-30 September 2009, Oxford, UK. University of Oxford.

Kiflemariam Yehuala and **Belay Tseganeh**. 2008. Climate change: Conceptual overview and spatio-temporal trends. In: Proceedings of a workshop on climate change and its implication to

sustainable development, organized by Christian Relief and Development Agency (CRDA) , Northern regional office, Bahir Dar, Ethiopia

Belay Tseganeh. 2008. Modelling growth and yield of major crops using Agro-meteorological indices under conditions of Amhara Region: paper presented in Annual research review conference of Amhara Agricultural Research Institute, Bahir Dar, Ethiopia

Belay Tseganeh. 2007. Erratic rainfall and farmer's coping strategies in North Wollo: The case of Kobo District. In: Yihenew G.Selassie (ed.), proceedings of the 2nd Annual Regional Conference on Completed Natural Resources Management Research Activities, 18-19 September 2007, ARARI, Bahir Dar, Ethiopia.

Belay Tseganeh, Sisay Demeku, Belete Birhanu and Gete Zeleke. 2007. Inventory and characterization of potentials and current management of Wetlands in Eastern Amhara Region. In: Yihenew G.Selassie (ed.), proceedings of the 2nd Annual Regional Conference on Completed Natural Resources Management Research Activities, 18-19 September 2007, ARARI, Bahir Dar, Ethiopia

Belay Tseganeh and Adane Tesfaye. 2007. Drought induced disaster risk management for sustainable development: Paper presented on National workshop on Disaster Risk Management, Bahir Dar University, Bahir Dar, Ethiopia

Wondimu Bayu , **Belay Tseganeh** and Tewodros Assefa. 2006. The needs, potentials, constraints and research in Irrigation Agriculture in Eastern Amhara. In: Proceedings of Workshop on Achievements and Priorities in Irrigation Water Management Research in Ethiopia with particular reference to Amhara Region, Bahir Dar.

PE&RC Training and Education Statement

With the educational activities listed below the PhD candidate has complied with the educational requirements set by the C.T. de Wit Graduate School for Production Ecology and Resource Conservation (PE&RC) which comprises of a minimum total of 32 ECTS (= 22 weeks of activities)

Review of literature (6 ECTS)

- Climate variability and change in Ethiopia: exploring impacts and adaptation options for cereal production

Writing of project proposal (4.5 ECTS)

- Climate variability and change in Ethiopia: exploring impacts and adaptation options for cereal production

Post-graduate courses (5.4 ECTS)

- Multivariate analysis; PE&RC (2010)
- Application of Decision Support System for Agro-Technology (DSSAT) to crop growth simulation and climate risk management; University of Georgia, USA (2012)
- The art of crop modelling; PE&RC (2013)
- Introduction to R for statistical analysis; WGS (2013)

Laboratory training and working visits (4.5 ECTS)

- Technical experience and practical training on application of simulation models using WOFOST as an example; MTT Agri-Food Research, Finland (2009)

Invited review of (unpublished) journal manuscript (1 ECTS)

- International Journal of Plant Soil Science: yield of maize (Zea Mays L.) as affected by green manure and nitrogen levels at South-West Ethiopia (2013)

Deficiency, refresh, brush-up courses (3 ECTS)

- Quantitative analysis of land use systems (2010)
- Systems analysis, simulation and systems management (2012)

Competence strengthening / skills courses (3 ECTS)

- Competence assessment; WGS (2010)
- Project and time management; WGS (2010)
- Techniques for writing and presenting a scientific paper; WGS (2012)

PE&RC Annual meetings, seminars and the PE&RC weekend (1.8 ECTS)

- PE&RC Weekend (2010)
- PE&RC Day: exploring life in the extremes and the extremes in life (2012)
- PE&RC Weekend (2013)

Discussion groups / local seminars / other scientific meetings (6.7 ECTS)

- Climate change and soil-water-atmosphere interactions; CSI Wageningen, WUR (2010)
- Spatial Methods (SPAM), WUR (2010)
- Completed research review seminar; Amhara Regional Agricultural Research Institute, Bahir Dar, Ethiopia (2010)
- Project planning workshop on triple win to climate change adaptation in Ethiopia; Addis Ababa, Ethiopia (2010)
- First year anniversary workshop of Ethiopia-WUR collaboration programme on science for impact; Holeta Agricultural Research Centre, Ethiopia (2010)
- National meeting of agrometeorology research review; Addis Ababa, Ethiopia (2011)

International symposia, workshops and conferences (4 ECTS)

- NASAC KNAW and 5th TWAS-ROSSA young scientists conference on climate change in relation to food security; Nairobi, Kenya (2011)
- Agricultural Model Iter-Comparison and Improvement Project (AgMIP) global workshop; San Antonio, USA (2011)
- 1st International Conference on Global Food Security; Noordwijkerhout, the Netherlands (2013)

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