



BOTSWANA INTERNATIONAL UNIVERSITY
OF SCIENCE & TECHNOLOGY

**THE IMPACT OF CLIMATE VARIABILITY AND CLIMATE CHANGE ON
SORGHUM GRAIN YIELD IN THE GOODHOPE SUB DISTRICT OF BOTSWANA**

by

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**A Thesis Submitted to the Faculty of Science in Fulfilment of the Requirements for the
Award of the Degree of Master of Science in Environmental Science at BIUST**

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June, 2018

DECLARATION

I, _____, declare that this thesis is my own original work and that it has not been presented and will not be presented to any other university for a similar or any other degree award.

Signature

CERTIFICATION

The undersigned certifies that she has read and hereby recommends for acceptance by the College of Sciences a thesis titled: The impact of climate variability and climate change on sorghum grain yield in the Goodhope Sub District of Botswana in fulfilment of the requirements for the degree of Master of Science in Environmental Science at BIUST.

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Dr. S. Tirivarombo

Date:

DEDICATION

This piece of work is dedicated to my family for the support and love they gave me during my studies.

ACKNOWLEDGEMENT

Foremost, I would like to thank my supervisor; Dr Sithabile Tirivarambo for the continuous support and guidance of my research, for her motivation, patience and knowledge. Sincere thanks also goes to the following institutions that have supported this work by providing me with the data and information that I needed to fulfil the requirements of my research; Department of Meteorological Services, Department of Agricultural Research and Department of Crop Production. I also extend my gratitude to all those who assisted me in writing this thesis. Lastly I would like thank my family for their moral support during the course of my study.

ABSTRACT

In Botswana crop production has been the most vulnerable component of the agricultural sector due to its heavy reliance on rainfed agriculture. At the same time, the availability of rainfall is uncertain due to natural climatic variability which is worsened by climate change. Already the local farmers have knowledge of the climatic conditions around them, and from time to time, they have been adjusting their farming practices in line with the prevailing climatic conditions. Climate change is already imposing threats to most social- economic livelihoods including agriculture. Therefore this study focuses on the impact of climate variability and climate change on dry land crop productivity within Barolong Farms located in the Goodhope Sub District of Botswana. In order to understand and quantify changes in the future, knowledge of the historical (baseline) climate is important as such the initial component of the study involved historical analyses of precipitation and temperature for the period 1979-2014. A relatively low variability (3.8%) in the mean annual temperature is observed, but with a warming of 0.03 oC/year and 0.05 oC/year respectively in the average maximum and minimum temperatures. Contrary to temperature, historical rainfall exhibited high variability ranging from 59% to 91% for the wet seasons. Projected sorghum yield for the period 2030-2060 under the Representative Concentration Pathway (RCP) scenario of RCP 4.5 was simulated using the AquaCrop model which was calibrated and validated based on observed sorghum yields of the Goodhope Agricultural Experimental Station and Barolong Farms respectively. For calibration, the model performed well for the study area as indicated by the coefficient of determination (R^2) of 0.77, a root mean square error (RMSE) of 0.41 and a Nash Sutcliffe Coefficient of Efficiency (CE) of 0.78. Using five selected GCMs the calibrated model was then used to simulate sorghum yields under the projected climate of 2030-2060. The mean average temperature for the cropping season is projected to increase through a range of +5% to +20%, while the rainfall may change by +5% to -25% across all the GCMs under the climate scenario of RCP 4.5. The future yield based on the projected temperature and rainfall is expected to decrease by -5% to -15%. This study concludes that there is a need to explore adaptation strategies under different climate scenarios that are climate smart and tailor made for the local situation.

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THESIS OUTLINE

Chapter 1 introduces the research in a broad context, statement of the problem as well as the significance behind the research including the objectives and the research questions, chapter 2 presents the scientific opinions of other studies in the form of literature review and chapter 3 describes the study area characteristics, data and methods including analysis of the data. Chapter 4 presents the results on variability and trends analysis of the historical rainfall and temperature, chapter 5 involves the calibration and validation of the AquaCrop model, chapter 6 presents the climate change impact projections on future rainfall, temperature and sorghum grain yield for the period of 2030-2060. The conclusions and recommendations of this study are presented in chapter 7.

CHAPTER 1

INTRODUCTION

1.1 Background of study

Agriculture plays a major role in sustaining livelihoods globally while at the same time it is highly vulnerable to climate variability (Murphy et al, 2016). In Sub-Saharan Africa, rainfed agriculture which takes up 95% of agricultural land and upon which a larger proportion of the region's population depends for livelihood is particularly vulnerable to changes in climate (Serdeczny et al, 2017). The African continent is rendered most vulnerable to climate variability and change due to low adaptive and coping capacities (Tumushabe, 2018). In Botswana for instance, about 70% of rural livelihoods depend entirely on subsistence farming which is dominated by small communal farms, (Statistics Botswana, 2012). At the same time, the arid to semi-arid climatic conditions in Botswana have rendered crop production the most vulnerable component of the agricultural sector due to limited soil moisture which in turn reduces crop production and increases production risk. In the past, Botswana has experienced increasing variability in rainfall, high average temperatures, and increased frequency of extreme hydrological events, as a result, the production of cereal grains such as sorghum and maize varies considerably from year to year (FAO, 2006). It is expected that in developing countries where the use of improved technologies is still low, the impacts of climate variability and change are likely to be severe (Hatfield et al, 2011).

Vulnerability in crop production as a result of natural climatic variability is likely to be amplified by the impacts of climate change. Changes in precipitation patterns as a result of climate change will significantly increase the likelihood of crop failures (Nelson et al, 2009). Furthermore increasing temperatures combined with decreasing precipitation have major implications for crop production by negatively affecting all stages of crop growth and production particularly the reproductive stage which is most sensitive to drought stress (Cairns et al, 2012). Scientific evidence proves that there will be gains in some crops in some regions of the world where the climate has shifted towards favorable conditions, however, the overall impacts of climate change on agriculture are expected to be negative, threatening global food security. For example, a study conducted by Adhikari et al. (2015) indicated that in East Africa, climate change was likely to

have negative impacts on the yield of major crops. The same study showed that wheat was the most vulnerable crop in the region, where, up to 72% of the current yield was projected to decline by the end of the 21st century. At the same time sorghum and millet were reported to be more resilient to climate change, with less than 20% reduction in crop yield by the end of 21st century. Gebrekiros et al. (2016) carried out a study on the impact of climate change and variability on sorghum production in Ethiopia and the results suggested that future sorghum yield was likely to decrease through a range of 5% to 24% by 2080. A study carried out in Benin by Dossou-Aminon, et al. (2016) concluded that poor adaptability of sorghum cultivars to climate variability was the most important reason for loss (39.6%) of crop diversity. Msongaleli, et al. (2015) conducted a study on the impacts of climate variability and change on rainfed sorghum and maize in Tanzania and the results suggest that maize and sorghum yields may decline by up to 25% and 21% respectively under three different scenarios (near-term, mid-century and end-century). In another study on the effect of inter-annual variability of climate on crop-related green and blue water footprints in China (1978–2008), Zhuo, et al. (2016) revealed that temperature is a dominant driver of the global climate change influencing future sorghum productivity. The results of the study also suggest that an increase in water demand for sorghum production should be anticipated in future due to high CO₂ concentration. Based on the different studies, there is need to evaluate the sustainability and resilience of different systems of crop production under future climate. Therefore a comprehensive accounting of the response of crops to temperature and rainfall is required (Asseng et al., 2013). Understanding and quantifying the effects of climate variability and climate change on crop production should thus be prioritized in order to develop effective adaptation and mitigation strategies (Godfray et al., 2010; IPCC 2014).

1.2 Statement of the problem

Climate risk assessment points out how the climate has been changing in current years and estimates what might take place in the years to come (IPCC 2014). According to Team (2017) climate risk assessment should include analysis of climate risks due to latest climate condition, trends and long-term climate projections. According to IPCC (2014) knowledge gaps exist concerning climate risk assessment on food security. To some extent, farmers in developing countries are aware of the risks and uncertainties of their local climate. They manage the risks

based on indigenous knowledge and years of experience, and this knowledge is passed from one generation to the next through oral history. However, changing climatic conditions and the need to increase agricultural production impress upon the need for improved climate risk management and decision support systems that enable relevant and timely management strategies in the face of climate change (Bruinsma 2017). Moreover, the fact that agriculture is exposed to the impending threats of climate change implies that farmers have to continuously adapt their farming activities to match the new climatic conditions.

To evaluate the risk of climate on crops, crop simulation models which are conceptualized on the interaction of different climate variables with the crop growth and crop yield processes are used (Rosenzweig et al., 2014; Maiorano et al., 2017). The impact of climate change on crop production is assessed through the use of dynamic crop growth simulation models which are driven with projected scenarios of future climates (Shackley, et al, 2008). Most studies on crop modelling have been performed at global and regional level. In spite of the fact that large scale impacts and adaptation studies provide important knowledge of the effects of regional climate change on agriculture, these studies are limited in understanding the impacts and adaptation needs of farming communities at local scales (Ewert et al., 2015; Challinor et al., 2018). In order to understand impacts of climate change and adaptation options at local scales, the crop models require more detailed location specific input variables such as local soils, climate, agricultural practices, and crop cultivars (Lobell et al., 2008; Thornton et al., 2011). Although studies have been conducted in Botswana on the impacts of various aspects of climate change on agriculture (e.g. Chinpansi et al., 2003; Batisani and Yarnal, 2010; Kenaabatho et al., 2012; Driver and Reason, 2017; Kenabatho et al., 2018), these studies are limited in terms of the diversity of biophysical conditions, climate scenarios, soil physical characteristics, agronomic management strategies and crops being investigated (Morton, 2007). In Botswana, dryland farmers operate at the local scale and make decisions based on local conditions thus there is a need to clearly understand the local scale impacts of climate variability and climate change on the yields of key food security crops. Hence this study assesses the local scale impacts of climate change on sorghum grain yield in the Goodhope Sub District of Botswana. The AquaCrop model is used to simulate crop yield under the present and projected scenario conditions.

1.3 Significance of the study

Climate change is already taking place while food security on the other hand is becoming uncertain (De Trinchieria et al., 2015). Today's changing climate requires improved adaptation and mitigation measures and these bring along opportunities for and enhancement of the current existing knowledge of climate related risks learning (IPCC 2014). Moreover, knowledge of how temperature and rainfall interact and impact agricultural yield is important to inform decision making in the face of climate change (Godfray et al., 2010). Despite the fact that Botswana is a semi-arid country, the crop sector is dominated by subsistence farmers who mostly depend on traditional knowledge in order to adapt to the changing climate as shown in Table 1. In order to implement appropriate adaptation strategies it is essential to quantify the contributions of different climate variables on crop yield in the sub-district. The preliminary results of this study are meant to provide information that policy makers can make use to inform decision making for improved adaptation and resilience to climate change. It is also expected that the findings of the study will provide basic information that will complement the traditional or indigenous knowledge that local farmers use in making decisions.

Table 1: **Agricultural farming statistics for Botswana from 2012 to 2014**

	2012		2013		2014	
Indicators	Subsistence	Commercial	Subsistence	Commercial	Subsistence	Commercial
Holdings Planted	34 976	35	39 434	20	42 466	-
Area Planted (ha)	51 795	11 223	61 877	5 675	65 053	-
Holdings Harvested	14 537	33	17 220	19	32 859	-
Area Harvested (ha)	24 231	11 203	33 680	5 615	50 198	-
Production	7 461	16 560	4 401	5,830	14 310	-
Yield Per Hectare Harvested	308	1 478	131	1 038	285	-

Source: (Statistics Botswana, 2014)

1.4 Aims and objectives

This study aims to assess the impacts of climate change on the yield of sorghum under dryland farming within the Barolong Farms in the Goodhope Sub District of Botswana. The specific objectives are:

1. To examine variability and trends in historical rainfall and temperature in the Good Hope sub-district of Botswana, focusing on the Barolong Farms.
2. To determine the expected change in the cropping season temperature for the future period of 2030-2060 under RCP 4.5 climate scenario.
3. To explore the change in average seasonal rainfall for the future period of 2030-2060 in the study area under RCP 4.5 climate scenario.
4. To determine the future sorghum yield expected under RCP 4.5 climate scenario.

1.5 Research questions

This study addresses the following research questions:

1. Are there any patterns of variability and trends in the historical climate data for the Barolong Farms?
2. What is the change in the cropping season temperature for the future period of 2030-2060 RCP 4.5 climate scenario?
3. What is the change in mean seasonal rainfall for the future period of 2030-2060 under RCP 4.5 climate scenario?
4. What is the percentage change in the expected sorghum grain yield for the future period of 2030-2060 under RCP 4.5 climate scenario?

CHAPTER TWO

LITERATURE REVIEW

2.1 Impacts of climate variability and climate change on dryland agriculture

Agricultural productivity is primarily dependent on favorable climatic conditions which are crucial in generating optimal crop yield. Although climate influences crop growth in various ways, rainfall and temperature are the major climatic factors that drive crop growth (Schmidhuber and Tubiello, 2007) and recently, rising atmospheric CO₂ concentration has become another factor of concern in the development of a crop (Wheeler and von Braun, 2013; Rosenzweig et al., 2014; Antle et al., 2017). Of these factors, temperature increase is reported to have the greatest negative impact on crop yields (Ottman et al., 2012). A warmer climate will most likely accelerate the growth and development of plants while extremely cold or hot weather conditions may negatively affect crop productivity (Bita and Gerats, 2013). Risks associated with weather are likely to have an effect on the plant chemical processes and also cause physiological damage hence posing a challenge to field management practices (Mahdi et al, 2015). Although change in year-to-year variability of climate is a threat to agriculture, climate change; as a result of increased temperature and increased frequency of occurrence of hydrologically extreme flood and drought events is likely to have more significant threats to agriculture and food security (Walthall et al., 2013). With low to medium confidence Pachauri et al. (2014) concluded that by the year 2100, relative to the 1990-2000 period, and a for global mean temperature increase of about a 1 °C to 3 °C cereal production would decrease in low latitudes and increase in high latitudes.

Climate change is regarded as an important risk factor which contributes to significant loss of yield of various crops, increased vulnerability on the farming communities (Davis and Vincent, 2017; Mahmoudi and Knierim, 2015) as well as elevated levels of poverty especially for subsistence farming communities (Kurukulasuriya and Rosenthal, 2003). Studies carried out in in Sub-Saharan Africa show that climate change will have negative impacts on the yield of cereal crops (Lobell et al., 2008; Challinor et al., 2014), however, different species require different optimum temperatures for development and therefore the direction and nature of change in crop yield is largely guided by the physiology of the particular crop as well as the prevailing climatic conditions in the crop environment (Msongaleli et al., 2015). The total stress on the crop is a combination of

changes in rainfall and temperature, with various forms of stress depending on the stage of crop development (FAO, 2016).

Increasing temperatures combined with decreasing precipitation have implications for crop productivity by negatively affecting all stages of crop growth and production particularly the reproductive stage which is most sensitive to drought stress (Deryng et al., 2014). For example the temperatures above threshold coupled with low rainfall, result in heat stress and drought, which have negative effects on the processes of photosynthesis (Martre et al., 2015). Rising temperatures, changes in precipitation patterns and increasing drought stress as a result of climate change may alter the functioning of plants at the molecular level and developmental stages as well as causing changes in the morphological and physiological traits of the plant (Gray and Brady, 2016). Changes in temperature and rainfall as a result of global warming have direct effects on soil moisture and groundwater level which in turn reduce the amount of crop water (Klove et al., 2014). Moreover, high temperatures and low rainfall may lead to an increased outbreak of pests and diseases as well as complete crop failure (Glaser et al., 2016). Given that various climatic conditions such as rainfall, relative humidity, temperature and sunlight control disease development in plants, any change in some of these factors is likely to promote disease prevalence and outbreak in crops (Wu et al., 2016). This implies that more methods of disease control must be put in place, yet at the same time there may be increased resistance to the control methods (Lawal and Omonona, 2014).

2.1.2 Effects of rainfall

Water acts as a medium for transporting nutrients within a crop; this water is obtained from rainfall thus demonstrating the importance of water availability as a driver for sustaining crop productivity in rainfed agriculture (Conway et al., 2015). However, Lobell and Burke, (2008) state that due to high variability, rainfall is not necessarily a good predictor of crop yield at the broader scales. In addition, Thornton et al. (2015) demonstrated that crop yield response to climatic variability was insensitive to increase in rainfall. Rainfall has an indirect impact on plant growth and developmental processes since decreased amounts of rainfall can either increase or decrease the plant developmental rates subject to the species or cultivar and the stage of development (Tardieu

et al., 2018). In Sub-Saharan Africa most small holder farmers rely entirely on rainfed crop production such that crops are vulnerable to rainfall variability and uncertainty. At the same time extreme floods and droughts can impact productivity which will in turn impose direct effects on people's lives (Ndamani and Watanabe, 2015). Rainfall characteristics that influence crop yield include; the amount of effective rainfall, the timing of the rainfall event, the distribution and duration of rainfall within a season (FAO 2016). According to Davis and Vincent (2017), high temporal variation of rainfall increases crop susceptibility to disease and other risks. Also heavy rainfall, floods and hail storms can cause physical damage to crops while extremely wet conditions may result in the delay of management practices including planting and harvesting (Tubiello and van der Velde, 2010; Rao et al., 2016).

2.1.3 Effects temperature on crop productivity

Temperature influences the germination, vegetative and reproductive stages of a crop and thus it determines the length of the growing season (FAO, 2009). Likewise, water shortage and heat stress are two of the most important environmental factors limiting crop growth, development, and yield (Reynolds et al., 2016). It is also noted that cereal crops are more susceptible to slight changes in temperature (Trnka et al., 2014). Crops are sensitive to high temperatures at both the reproductive and fruit stages (Hatfield and Prueger, 2015). Different plant tissues and developmental stages are affected by heat stress in different ways depending on the metabolic processes that are active at the time of the stress (Tripathi et al, 2016). Temperature has a greater impact on crop production than rainfall and increased temperature as a result of climate change will negatively impact crop production (Bilham, 2011; Ochieng et al., 2016). Higher temperatures are often associated with early flowering and maturity while increased maximum temperatures can cause reproductive failure and highly reduced crop yields (Elias et al., 2017). During droughts for example, a maize crop yield reduction of about 1.7% can be experienced for each degree day spent above 30 °C (Lobell et al., 2015). According to FAO (2016) extremely high temperatures of more than 30°C can lead to permanent crop failure, with the effect being more severe above 37°C. This causes damage to stored seeds, increased soil evaporation and transpiration leading to crop water stress, reduced crop yields and high incidences of pest proliferation (Kaur et al., 2017). At the developmental stage and across all plant species pollination is reported to be one of the most sensitive stages to temperature extremes (Hatfield and Prueger, 2015).

High temperatures may induce a shortened life cycle of the plant resulting in reduced time for the cropping season and a shortened grain-filling period for cereal crops. Other impacts include reduced light interception and increased sterility (Tripathi et al., 2016). During the growing stage, temperatures higher than 32 °C result in loss of grain yield especially in tropical areas while an increase of 2°C may cause more than 10% yield loss (Mathobo et al., 2017). At the same time elevated temperatures can negatively affect protein synthesis at the seedling and vegetative stages of the crop. Various other significant physiological changes of crops have been reported (Zandalinas et al., 2018) which include; changes in carbon utilization as well as decreases in leaf elongation rate, leaf area, shoot biomass and photosynthetic CO₂ assimilation rate. Increased temperatures result in higher evapotranspiration which in turn affects water availability and has effects on the photosynthesis process (Frank et al., 2015). Generally high temperatures have an effect on chloroplasts which are the sites of photosynthetic activity and where reactive oxygen species are generated (Zandalinas et al., 2018). High temperature decreases grain yield while starch quality is affected through decreased starch granule size and amylase content. Also heat stress due to elevated temperature may affect the number of grains, weight and size of the kernel that may result in decreased number of fertilized ovules which develop into grain (Shim et al., 2017).

2.2 Climate scenarios and models

Climate change is expected to have important adverse consequences on regional water resources (Chiew et al., 2009) which will in turn impact human health, water supply, food security and energy. To ensure the sustainability of livelihoods in the future there is need to understand and quantify the impacts of potential climate change on various resources including agriculture (Kundzewicz et al., 2010). A climate scenario is a description of the climate in the future based on a variety of climatological relationships together with assumptions of radioactive forcing (IPCC 2007). Global Climate Models (GCMs) and Regional Climate Models (RCMs) are used to create the climate scenarios. It is important to note that climate projections should be used as means to find out the possible futures under different emission scenarios, rather than as a forecasting tool (Suppiah et al., 2011). Due to the fact that we are not sure how the climate is going to be like in the future and by how much it is going to change if it does, there is some degree of uncertainty in quantifying the changes in the future climate. To deal with the uncertainty, the Intergovernmental

Panel on Climate Change (IPCC) published the Special Report on Emission Scenarios (SRES) consisting of a set emission scenarios which can be used to assess the sensitivity of the global system to climatic changes (Thuiller, 2014). The emission scenarios project how greenhouse gas emissions may change in the period 2000-2100. They are based on various hypotheses of how the different climates as a result of different greenhouse gas concentrations in the future may have effects in different regions (Mainali, et al., 2015). These concentrations are guided by factors including social and economic development as well as people's lifestyles.

Initially the Fourth Assessment Report (AR4) of IPCC published four groups of emission scenarios were developed based on a family of story lines, namely the A1, A2, B1 and B2 scenarios (IPCC, 2007). The A1 scenario describes a future of rapid economic growth, increase in population growth that decrease after the midcentury, rapid development and spread of new and efficient technologies. This scenario consists of three sub-groups that describe the different ways of technological change in the energy system. A1F1 with intensive use of fossil fuel energy, A1T which uses non-fossil energy and A1B which balances across all sources of energy meaning that it is not relying too much on one particular energy source. The A2 scenario is characterized by self-reliant nations operating in an independent world, with a population that continues to increase and economic development that is regionally oriented. Like A1, the B1 scenario also has rapid economic growth, with resources that are efficient in technology and emphasizing on global solutions to social, economic and environmental stability but with changes observed towards information and service economy, a rising population rising that decreases in the midcentury. The B2 scenario includes continuous increase of the population, with a slower rate than A2, putting emphasis on local solutions to social, economic and environmental stability. The levels of economic development are intermediate and technological change is less rapid and more continuous than in A1 and B1.

Lately, Representative Concentration Pathway (RCP) scenarios consisting of greenhouse gas concentrations (IPCC, 2014) rather than emissions have been adopted. The RCP scenarios are based on different greenhouse gas concentrations based on the concept variable radiative forcing; each RCP describes specific emissions trajectory and the subsequent radiative forcing. In general the RCPs contain quantitative descriptions of the different concentrations of pollutants in the

atmosphere over time together with their radiative forcing by the year 2100. Radiative forcing is the extra energy in use by the earth system because of improved greenhouse effect (Solomon, et al., 2007, Von Schuckmann et al., 2016) and is expressed as watts per square meter. The four RCPs include the RCP2.6 consisting of very low emissions, RCP4.5 and RCP6 which are both of intermediate emissions and RCP8.5 of high emissions IPCC (2013). The RCP projections for three greenhouse gases carbon dioxide (CO₂), methane (CH₄) and nitrous oxide (N₂O) are presented in Figure 1 (van Vuuren et al., 2011). In the figure, the light grey area indicates the 98th percentile and the dark grey represents the 90th percentiles of the literature values (Clarke et al. 2010).

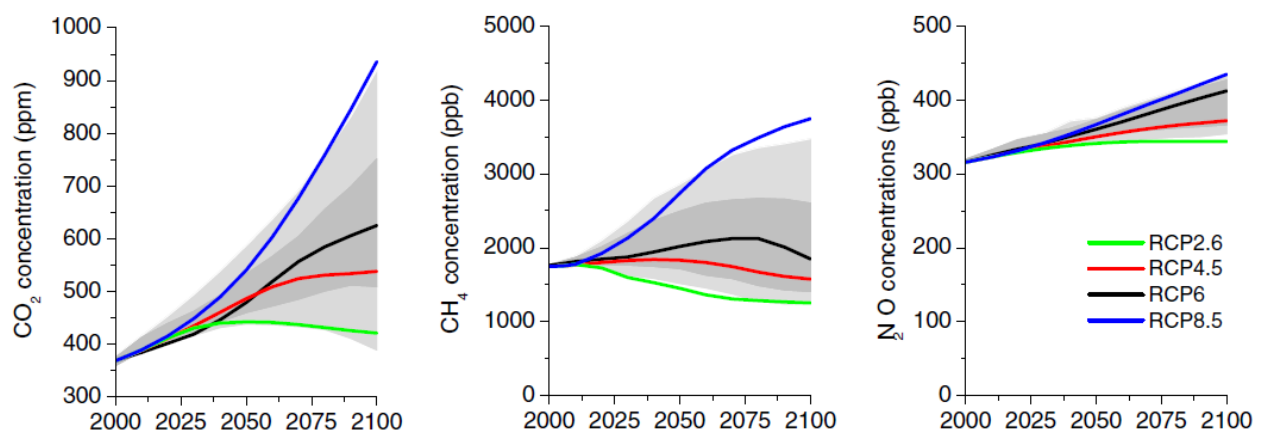


Figure 1 Emissions of main greenhouse gases across the RCPs. Source: van Vuuren et al. (2011).

2.3 Downscaling of GCMs

So far GCMs are the most common tool for predicting of climate change; however, due to their coarse spatial resolution of hundreds of kilometers they are only good at predicting continental or large scale conditions which cannot be used for local scale studies (Carter et al., 1994; Fatichi et al., 2011). Environmental impact models are sensitive to local climate features yet the drivers of local climate variation are not taken into consideration at the coarse scales of GCMs (Maurer and Hidalgo, 2008). The issue of scale can be solved by downscaling the GCM to a finer resolution which is compatible with the local scale (Jones et al., 2003). There are two basic approaches to downscaling which are; statistical downscaling and dynamical downscaling (Mizukami et al., 2016).

Statistical downscaling (Hewitson and Crane, 1996) establishes relationships between the observed large-scale atmospheric and local climate variables after which the relationships are used to predict future local climate variables (Trzaska and Schnarr, 2014). This technique creates site-specific climate projections, and it is dependent on the assumption that the relationship between existing large scale transmission and local climate remains valid under different conditions of forcings for possible future climates (Zorita and von Storch, 1999). The method is good for low cost and rapid assessments of climate change impacts and it is preferred where estimation of variables at point locations is required for model input or for decision making purposes (Wilby et al., 2002).

Dynamical downscaling uses data of a regional climate model (RCM) which uses the same principles as those for a GCM, but having a high resolution than GCMs. GCMs provide predictions at a coarse scale of 250 km by 250 km in most cases while RCMs provide a finer resolution of 10 km by 10 km (Jacob and Van den Hurk, 2012). The RCM takes information on a large scale from a GCM and incorporates detailed physical processes of the area in order to produce output at high resolution for the local climate (Seaby et al., 2013). Dynamic downscaling has an advantage over statistical downscaling because it emphasizes more on local feedback processes. This method also uses a systematic method of downscaling the variables, unlike in the statistical method where there is an independent relationship between the observed and simulated variables (Schmidli et al., 2007). Some of the major limitations of this method are that it is computationally and resource intensive and its output is sensitive to the choice of the initial conditions (Wilby et al., 2002).

2.3.1 GCM uncertainty

It is important to acknowledge the model uncertainty and therefore increase confidence in model projections and in decision making guided by the model outputs. A variety of ways are available to address the uncertainty including the use of GCMs to achieve a possible range of future outcomes as a function of emissions scenarios (Alexander, et al., 2006; Moss et al., 2010). Also methods such as the global sensitivity analysis and uncertainty analysis can reduce the degree of uncertainty in model simulations (Saltelli et al., 2004). Another approach towards the improvement

of models is the model-intercomparison technique which was muted through the Coupled Model Inter-comparison Project (Taylor et al., 2012). This method uses reference scenarios to inter-compare model outputs and in so doing improve the models and their performance against the set reference criteria. Researchers have also used model ensembles to characterize and reduce model uncertainty in a bid to improve the performance of crop yield models (Martre et al., 2014). On the other hand probabilistic modelling which incorporates an uncertainty framework within the models is increasingly becoming popular (Uusitalo et al., 2015).

2.4 Crop modelling

The impacts of climate change on crop yield can be quantified by coupling a calibrated crop yield model to the outputs of downscaled GCMs (Gleick, 1989). Coupling of the two models ensures that solutions to climate-induced water stress and consequently crop yield problems are generated at a level appropriate to the local climate (Hertel and Lobell, 2014). Continued pressure on agriculture, food security and the need for appropriate adaptive measures to climate change have resulted in increased use of crop models as a means for projecting future crop yields (IPCC, 2014). Various modelling tools are used to support the decision making and planning in crop production, of which crop growth simulation models are important. These models imitate the growth and development of crops. An understanding of the basic interactions between the soil, plant and atmosphere makes crop modelling useful because it is used to estimate the importance and effect of certain parameters on crops (Hertel and Lobell, 2014). Crop models simulate or mimic the behaviour of a crop by calculating the growth of its components, such as roots, stems, leaves and grains and then estimates crop yield based on biomass accumulation. The models also contain quantitative information about major processes involved in the growth and development of the crop (Rounsevell et al., 2006). The model input parameters normally include temperature, carbon dioxide, solar radiation, and water. One of the advantages of these models is that they help simulate optimum conditions for plant growth which are not easy to figure out in ideal environments (Kpongor, 2007). In general there are two approaches to crop modelling, namely process-based modelling and empirical modelling.

2.4.1 Process-based crop growth simulation model

Process-based crop growth simulation models were developed to simulate crop responses to environmental conditions at the plot and field level (Hertel and Rosch, 2010). The process incorporates crop dynamics based on cause and effect relationships, and simulates the underlying processes at different time scales (Tubiello and Ewert, 2006). These models are based on the concept of radiation-use efficiency, water-use and nitrogen use efficiency (Challinor et al., 2009). Examples of the crop models include the Decision Support System of AgroTechnology Transfer (DSSAT) model (Jones et al., 2003), the Cropping Systems (CropSyst) model (Stockle and Nelson, 1994), the World Food Studies crop growth (WOFOST) model (van Ittersum et al., 2003), the Crop Environment Resource Synthesis (CERES) model (Jones et al., 1986), Hybrid-Maize model (Yang et al., 2004) and the AquaCrop model (Steduto et al., 2009; Raes et al., 2009).

The AquaCrop model was developed by the Land and Water Division of Food Agriculture Organization (FAO), (Steduto et al., 2009; Raes et al., 2009). It is a water-driven crop model that simulates yield response to water. The model was designed to balance simplicity, accuracy and robustness, and is particularly suited to address conditions where water is a key limiting factor in crop production. It was first developed based on herbaceous food crops, and now it also considers forage and feed crops (Abedinpour et al., 2012). The model simulates soil water content, crop water use, crop growth, total biomass production and yield under varying environmental, climatological and management activities (Raes et al., 2009; Steduto et al., 2009). The design of the model (Steduto et al., 2009) assumes that a linear relationship exists between biomass growth rate and transpiration through a water productivity (WP) parameter. The WP parameter for the climate (both the evaporative demand and the atmospheric CO₂ concentration) is normalized and therefore the model has a greater applicability in different locations under varying spatial and temporal settings (Steduto et al., 2012).

The AquaCrop model was initially parameterized and tested on maize by using experimental data for six cropping seasons (Hsiao et al., 2009). Results showed that the model was able to simulate the canopy cover, biomass and grain yield of four maize cultivars over six different cropping seasons that differed in plant density, planting date, and evaporative demands (Hsiao et al., 2012).

Araya et al., (2010) evaluated the AquaCrop model for biomass and yield simulation of water shortage and irrigation of barley in northern Ethiopia. The results showed a good model performance with model efficiency ranging from 0.5 to 0.95 for grain yield under various planting dates. In another study, Stricevic et al., (2011) evaluated the AquaCrop model under rainfed conditions and supplemental irrigation of maize and sugar cane in Serbia, and reported a maximum prediction error of 3.6% for maize while that for sugar cane was 12.2%. The same study concluded that the AquaCrop model could be used in making decisions for the selected crops especially under irrigation in water limited areas.

The CropSyst model is another commonly used process-based model. It is a crop growth simulation model that is designed with the aim of studying cropping management impacts on crop production and the environment (Stockle and Donatelli, 1997). The model simulates the soil water budget, soil-plant nitrogen budget, phenology, canopy cover, development of roots, accumulation of biomass, crop yield, soil erosion by water, use of pesticides, crop residue production and decomposition (ibid). The factors that the model simulates are affected by weather, soil characteristics, crop characteristics, and cropping system management activities including crop rotation, cultivar selection, irrigation, application of fertilizers, pesticide applications, soil and irrigation water salinity, tillage operations, and crop residue management (Stockle et al., 2010). The model comprises of the climate file, crop file, the soil file and the crop management file. The water budget of the model is made up of precipitation, irrigation, runoff, interception, infiltration, water redistribution in the soil profile, crop transpiration, and evaporation, while the nitrogen budget includes transformation of nitrogen (N), absorption of ammonium, symbiotic N fixation, demand of N by the crop uptake of N by the crop (Stockle and Nelson, 2003). The water and nitrogen budgets interrelate to produce a simulation of the transportation of N within the soil. Chemical budgets comprising of pesticide decay, salinity and absorption are also considered and they interact with the water balance.

The WOFOST is also a widely used process-based crop model. It simulates the growth and production of annual field crops under a wide range of weather and soil conditions (Pohlert, 2004). The model is based on the fact that crop growth is driven by photosynthesis, respiration and

environmental conditions (Farshad and Zinck, 1993). The model calculates the amount of water used in crop growth and biomass accumulation for a specific location based on soil, crop type, weather data and crop management activities (Confalonieri et al., 2009). Evett and Tolk (2009) evaluated the performance WOFOST in simulating Water Use Efficiency (WUE) for cotton, maize, sunflower, soybean, dry bean. It was revealed that the WUE was primarily governed by the evaporation (E) and transpiration (T) components of the crop, however, lack of experimental data in separating E and T components limits the investigations to evaluate the model performances on estimation of WUE by using separate E and T values.

Todorovic et al. (2009) compared the performance of the AquaCrop, CropSyst and WOFOST models for sunflower using deficit irrigation methods in Southern Italy. It was observed that although the AquaCrop required less input data than CropSyst and WOFOST, it performed at par with these two models in simulating biomass and yield (Steduto et al., 2009). The study concluded that the AquaCrop model should be preferred because it requires minimum input data. The use of simpler models for yield predictions under different water supply situations and under conditions of limited input parameter data was therefore recommended.

2.4.2 Empirical crop modelling

The structure of an empirical model is determined by observed relationships among experimental data. The Ricardian approach focuses on the economic impact of climate change on agriculture and considers that farmers are economically prudent and therefore select farming activities which give the highest return on any given piece of land (Mendelson et al., 1994). This method relates climate variation or change with fluctuations in land value. The other method uses use historical data on crop yields and climate to develop statistical relationships (Lobell and Burke, 2010), it was designed to operate at the multi-seasonal and regional scales, and is thus best suited for analyzing inter-annual variability in regional crop production (Hertel and Rosch, 2010). The model can be used as alternative to process-based methods when assessing climate change impacts at larger scales. The main advantages of empirical models include little reliance on field calibration data, as well as their transparent assessment of model uncertainties through the use of coefficients of determination and confidence intervals (ibid). Nonetheless, these models are not based on cause

and effect but on predicting future responses based on past relationships such that it is possible that the past relationships may not be a true reflection of the future. Past relationships are hard to validate in countries like Botswana where an extensive part of historical data may not exist. Another limitation of these models for future crop response projection is the absence of adaptation responses because changes in varieties grown, planting, harvesting dates and other management practices are not taken into consideration (Lobell and Burke, 2010).

2.5 Projecting climate change impacts on crop yield

The relationship between the climate and crop yield is important to understand and to improve resilience of crop production systems to climate change. In assessing the impact of climate change on crops, projected climate data from GCMs is used to drive crop models in order to simulate yield under future climate scenarios. Generalized data validations established during the design of the GCM do not consider that modelled conditions are different from one place to another due to climatic conditions at given time (Zhao et al., 2015), therefore it is necessary that location specific calibrations be performed for each area. Furthermore there is need for local calibration because soil characteristics are also influenced by land use and management practices. Localized calibration is also important because experimental trials during the development of the model provide location specific validations which are practiced under managed conditions hence not representing dry land conditions under which farmers operate (Twomlow et al., 2008). According to Easterling et al. (2000) crop models should also be assessed on their ability to simulate the impact of extreme events because extreme events such as floods, droughts and high temperature episodes may become more frequent and this could have large impacts on crop productivity.

Although with uneven spatial effects, the impacts of climate change on agriculture are already being felt worldwide and it is important to note that the effects of climate change on agriculture are a result of variable local climates and not due to global climate patterns (Porter et al., 2014). Changes in climate shorten the growing season due to increased temperatures and reduced rainfall amounts. For example Belay et al. (2017) carried out a study on the adaptation of smallholder farmers to climate change and determinants of their adaptation decisions in the Central Rift Valley of Ethiopia. The study revealed that 90% of farmers had already experienced climate variability,

and 85% of them were adapting using different farming practices like crop diversification, changing planting dates, soil and water conservation and management, increasing the intensity of input use, integrated farming, and tree planting. Another study conducted by Ochieng et al. (2017) found out that change of crop varieties was being used as an adaptation measure to climate variability, and that lack of finances and knowledge reduced adaptation measures within the smallholder farming sector.

CHAPTER 3

MATERIALS AND METHODS

3.1 Description of the study area

The specific study area is Barolong Farms (Figure 2) which are located in the Southern District of Botswana between latitudes 25.27 °S to 25.45 °S and longitudes 24.85 °E to 25.45 °E. The climate is suitable for the production of a wide range of field crops including maize, sorghum, beans and groundnuts but the area mainly produces maize and sorghum.

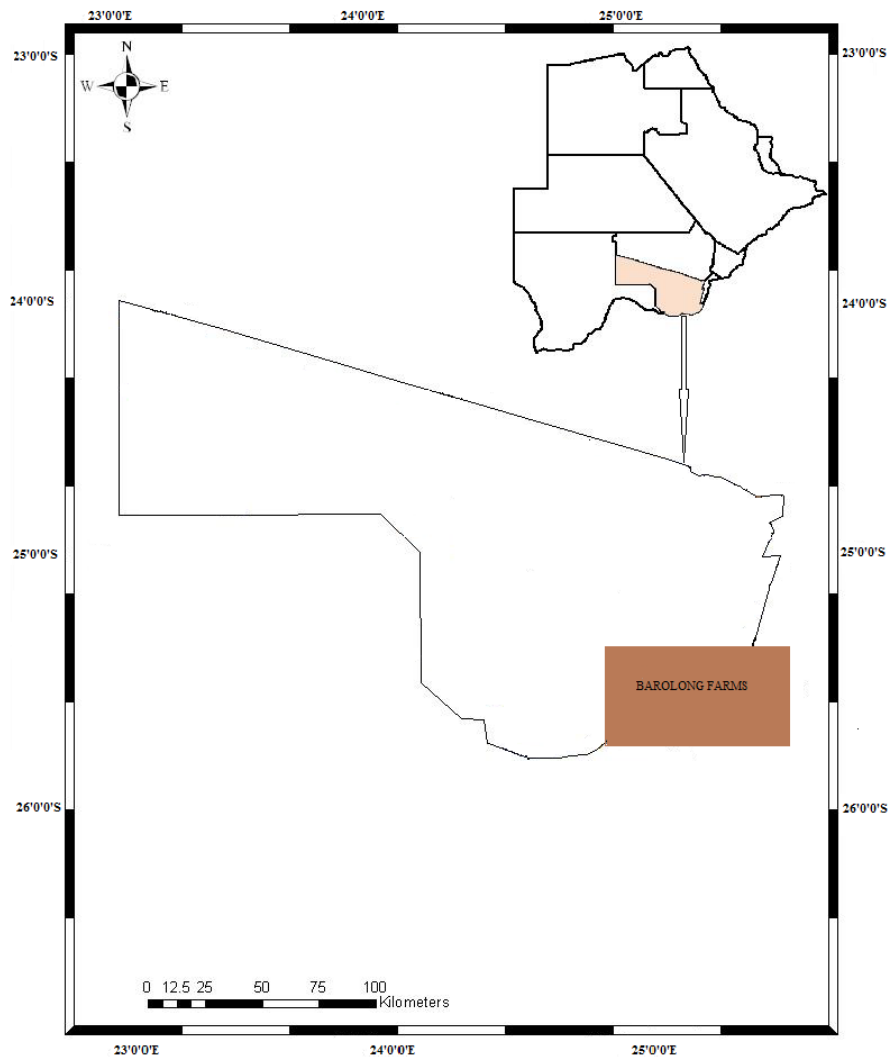


Figure 2: Location of Study area in Botswana

Source: modified from Adelabu (2010)

Sorghum is a native crop to Africa and comes second after maize in terms of production both in the region and in Botswana. It is a crop that is drought tolerant and well adapted to the climate in the tropics. It thrives well under adverse climatic conditions with low input management practices. The optimum growth conditions for sorghum are; deep well drained fertile soil and medium to good and fairly stable rainfall pattern during the cropping season. The crop requires a temperate to warm weather of 20 °C to 30 °C and reaches maturity between 110 days to 140 days (Steduto et al., 2012). In Botswana sorghum is grown under rainfed conditions at the beginning of the rainy season which is usually in October to early December and the growing cycle varies depending on the cultivar as presented in Table 2. According to the Department of Agricultural Research (DAR), in Botswana, the climatic and soil requirements for sorghum are rainfall (total growing season): ≥ 250 mm, temperature: up to 33 °C and a soil pH of 5.2 to 7.5. The plant spacing is 0.75 m x 0.3 m, plant density of 40 000 plants/ha with a seed rate of 5-10 kg/ha for the broadcasting method and 1-2 kg/ha for row planting (DAR, 2010).

Table 2: Recommended sorghum cultivars in Botswana Source: DAR (2010)

Cultivar	Days to 50% flowering	Maturity (days)	Yield potential (ton/ha)
Phofu	60-65	112-125	1.5-3.5
Mahube	52-63	100-125	1.0-3.0
Mmabaitse	60-70	125-130	1.0-3.0
Segaolane	60-65	110-140	1.0-3.5
Town	65-70	130-135	1.5-3.5
BSH1	68-78	120-130	3.0-6.0
Marupantse	65-70	125-130	1.5-3.5
65D	55-62	65-100	1.0-3.0

3.1.1 Climate

Botswana is characterized by an arid to semi-arid climate and receives erratic rainfall patterns which show a marked spatial variation in average annual rainfall ranging from 650 mm in the north to 250 mm in the southwestern parts of the country. Under normal conditions the wet season months extend from October to March. The Southern District is mostly semi-arid in nature and receives an annual rainfall of 500 mm. Very few cloudy days are experienced in the area, with around 290-300 sunshine days per year, as such humidity is extremely low particularly in the dry months and it rises to an average of about 65 % in the rainy season. The annual evaporation rates

of about 2000 mm are very high and far exceed the average annual rainfall (FAO 2009) of the study area. The study area experiences mean monthly maximum temperatures ranging from 29.5 °C to 33 °C in summer and from 19.8 °C to 28 °C in winter, while the mean monthly minimum temperature ranges between 14.6 °C and 20.8 °C in summer and from 2.9 °C to 11.6 °C in winter (Department of Meteorological Services, 2014).

3.2 Data and methods

3.2.1 Meteorological data

Historical rainfall and temperature data sets covering a period of 35 years and extending from 1979 to 2014 were obtained from the Goodhope Meteorological Station which is located within the study area at 25.28 °S to 25.46 °S latitude and 25.26 °E to 25.43 °E longitude. These datasets were used to assess the historical climatic variability in the study area and also as the baseline upon which changes in the future would be assessed.

3.2.2 Sorghum grain yield data and field characteristics

Sorghum grain yield data and soil characteristics for the Goodhope Agricultural Experimental Station for the period of 1979 to 1982 were obtained from the annual reports and hand books of Department of Agricultural Research (DAR). The data sets were used to calibrate the AquaCrop model. For validating the crop model, sorghum grain yield data for the Barolong Farms was used, it was obtained from Statistics Botswana. This data covers the period 1979 to 2012.

3.2.3 Climate change data

Climate scenario data is required to quantify changes in the future climate variables with respect to the historical climate. The data is then used as input data to the crop model in order to simulate crop yield under future climate change. The Global Climate Model (GCM) data used for this study was statistically downscaled to the Goodhope station location by the Climate Systems Analysis Group (CSAG) at the University of Capetown (<http://cip.csag.uct.ac.za/webclient2/datasets/africa-merged-cmip5>). The projected climate data consists of the CMIP5 GCMs for the RCP 4.5 Representative Concentration Pathway (RCP). The advantage of statistical downscaling is that it is capable of establishing quantitative relationships between the global scale circulations and the

local climate. The method also has an upper hand in that it can remove constraints by deriving direct mathematical relationships between the global circulations and the local climate characteristics. In addition this method is able to capture some of the non-linear relationships that exist between the global and local climates (Wilby et al., 2004).

The method of Hewitson and Crane (2006) developed at CSAG is used to downscale the GCM data to a resolution of 0.25°. Here, a self-organizing map (SOM) which is a data description and visualization tool that extracts and displays the major characteristics of the multidimensional data distribution function is used. In the downscaling approach the SOM is employed to characterize the atmospheric circulation on a localized domain around the target location, and probability density functions (PDFs) are generated for the rainfall distribution associated with each atmospheric state. Downscaling is then performed by matching the GCM data to the SOM characterization of the atmospheric states, while precipitation values from the associated PDF are randomly selected for each circulation state in the GCM data. For purposes of this study five statistically-downscaled GCMs consisting of rainfall and temperature data for the future period of 2030-2060 were used. The data was downscaled under RCP 4.5 climate scenario. A summary of the five selected is provided in Table 3.

Table 3: Global climate models (GCMs) used in the study

Name	Originating group(s)	Country	Model full name	Reference
GFDL	US Dept. of Commerce / NOAA	USA	Geophysical Fluid Dynamics Laboratory	Delworth et al. (2006)
MRI- CGMC	Meteorological Research Institute	Japan	Meteorological Research Institute Coupled Atmosphere-Ocean General	Yukimoto et al.(2001)
BNU- ESM	Beijing Normal University	China	Beijing Normal University Earth System Model	Whang et al. (2014)
MIROC 5	Center for Climate System Research, The	Japan	Model for Interdisciplinary Research on Climate	Watanabe et al. (2010)
CanESM2	Los Alamos National Laboratory,	USA	Canadian Earth System Model	Chylek et al. (2011)

3.3 Statistical methods of data analysis

First quality assurance was performed on the climate data sets before using the data for trend and variability and change analysis.

3.3.1 Quality assurance

A homogeneity test was performed to make sure that the rainfall and temperature data sets are consistent and fit to be used for use in the study. The test examines how much the data varies throughout the time series and also assesses if the time series is significant or not. The Analysis of Variance (ANOVA) test using a one way factor was used to test for the homogeneity; this method determines whether the means between three or more independent variables are statistically significant (Andrea, 2007). The F value which is a ratio of two variances is used with the p-value in deciding the significance of the results. The variance gives a description of how far the data is scattered from the mean. The results are significant if the F value is larger than the p-value, and not significant if the p-value is smaller than the alpha level.

3.3.2 Trends and variability

Analysis for variability and trends in the historical climate time series data is important in understanding their impact on various sectors such as agriculture, water resources and health. For this purpose the Mann-Kendall test and Sen' slope estimator were used to test for trends in the climate data while the coefficient of variation was used to assess variability in the time series.

3.3.2.1 Mann-Kendall test

The Mann-Kendall test is a nonparametric rank-based method which is used to detect the presence or absence of trends in time series data (Kendall, 1975). This approach is robust in the sense that it is capable of dealing with extremes and outliers and can also be applied to skewed variables and to non-normally distributed data (Burns et al., 2007). A standard normal variance, Z and a test statistic, S , are used to estimate the significance of a trend slope of a linear trend model and $\text{var}(S)$ is the variance in S . Z is given as

$$Z = \frac{S - 1}{\sqrt{\text{var}(S)}} \quad \text{if } S > 0 \quad (1)$$

$$Z = 0 \quad \text{if } S = 0$$

$$Z = \frac{S + 1}{\sqrt{\text{var}(S)}} \quad \text{if } S < 0 \quad (2)$$

where S is presented by

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^n \text{sgn}(x_j - x_k) \quad (3)$$

and n represents the total number of elements in the time series and the sign function is given as

$$\text{sgn}(x_j - x_k) = 1 \quad \text{if } x_j - x_k > 0$$

$$\text{sgn}(x_j - x_k) = 0 \quad \text{if } x_j - x_k = 0$$

$$\text{sgn}(x_j - x_k) = -1 \quad \text{if } x_j - x_k < 0$$

A positive S value indicates that there is an upward trend while a negative value signifies a decreasing trend. Based on whether the calculated Z is greater or less than the critical Z- statistic, the null hypothesis H0, which states that there is no trend in the data, is either rejected or accepted. The variance of S is calculated as

$$\text{Var}(S) = \frac{1}{18} \left[n(n-1)(2n+5) - \sum_{p=1}^q t_p(t_p-1)(2t_p+5) \right] \quad (4)$$

where, n is the number of data points, tp is the number of ties for the pth value and q is the number of tied values. A tie is a subset of the ordered data that comprises a sequence of the same value. $\sum tp$ represents the summation over all ties.

3.3.2.2 Sen's slope estimator

Sen's test (Sen, 1968) is used to estimate the value and confidence interval for a trend and is normally used in conjunction with the Mann-Kendall's test. Time series of equally spaced data are

required and the method makes no assumptions about the distribution of data, it is also not affected by outliers. In this method, slope is calculated as a measure of change with time and is given as:

$$Q_i = \frac{X_{i+t} - X_i}{t} \quad (5)$$

where, Q_i is the slope between data points X_i and X_{i+t} and t is the time interval.

Sen's estimator of the slope, Q , is given by the median slope as shown below, where, N is the number of calculated slopes:

$$\begin{aligned} Q &= Q[(N+1)/2] && \text{if } N \text{ is odd and} \\ Q &= (Q[N/2] + Q[(N+2)/2])/2 && \text{if } N \text{ is even} \end{aligned} \quad (6)$$

Sen's Method also allows determination of whether the median slope is statistically different from zero. To develop a confidence interval, the rank for the upper and lower confidence interval is estimated. The slopes corresponding to these ranks are used to define the actual confidence interval for Q' . For a two-sided confidence interval about the median slope, the Z statistic is first established for the required confidence level (e.g. $Z=1.96$ at 95 % confidence interval). The variance, $\text{Var}(S)$ of the Mann-Kendall statistic is then calculated as given in equation 4.

The range of ranks for the specified confidence interval, C_α is estimated

$$C_\alpha = Z_{1-\alpha/2} * \sqrt{\text{Var}(S)}$$

(7) Using the value of C , the ranks of the lower ($M1$) and upper ($M2+1$) confidence limits are calculated using the following equations:

$$M1 = \frac{N' - C_\alpha}{2} \quad (8)$$

$$M2 = \frac{N' + C_\alpha}{2} \quad (9)$$

The slope corresponding to the ranks $M1$ and $M2+1$ as the lower and upper confidence limits respectively is then calculated. This slope is defined as statistically significant if zero (for the selected confidence interval) does not lie between the upper and lower confidence limits.

3.3.2.3 Coefficient of variation

The coefficient of variation (CV) is used for determining variability in rainfall and temperature for the baseline period of 1979 to 2014 used in this study. CV is calculated as follows:

$$CV = \sigma / \bar{x} \quad (10)$$

where σ is the standard deviation and $\bar{x}$ is the mean

3.3.3 Evaluation of model performance

This study uses the AquaCrop model to simulate crop yield under historical and projected future climates. The model is described below. The performance of the model during calibration is assessed based on the goodness of fit between observed yield and simulated yield. Statistical objective functions of the root mean square error (RMSE), the model coefficient of efficiency (CE) and coefficient of determination (R²) were used. The RMSE (equation 11) represents the measure of the overall mean deviation between observed and simulated values. Values of error close to zero indicate small differences between observed and simulated values thus representing a better model fit (Legates et al., 1999).

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (O_i - S_i)^2}{N}} \quad (11)$$

where N is number of observations, S_i are simulated values, O_i are observed values.

CE determines how much the overall deviation between simulated and observed values differs from the total deviation between observed values and their mean values. The efficiency lies between negative infinity and 1, where 1 indicates a perfect match between the model and the observations, while 0 means that model predictions are as accurate as represented by the average of the observed data. A negative CE indicates that the mean of the observations is a better predictor than the model or simply it indicates poor model performance (McCuen et al., 2006). The coefficient of efficiency is calculated as:

$$CE = 1 - \frac{\sum_{i=1}^n (O_i - S_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2} \quad (12)$$

where, CE is the coefficient of efficiency, n represents the number of observations, S_i are the simulated values, O_i the observed values and $\bar{O}$ is the mean of the observed values.

The squared value of correlation coefficient gives the coefficient of determination (R^2) which ranges from 0 to 1. R^2 estimates the combined dispersion of observed and simulated values (Taylor, 1990). The correlation coefficient (R) is a statistical relationship between the observed and the simulated values. An R value of +1 indicates a perfect positive correlation while a value of -1 indicates a very weak negative correlation. The correlation, R, is calculated as

$$R = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 (y_i - \bar{y})^2}} \quad (13)$$

where n = number of values or elements, y = simulated values and x = observed values

3.3.4 Future climate and crop yield analysis under climate change

Projected changes in temperature, rainfall and sorghum yield for the future period of 2030-2060 relative to the historical period of 1979-2014 are obtained as the percentage (%) difference between the projected future values and the historical values using the formula below.

$$\% \text{ change} = \frac{\text{projected value} - \text{historical average}}{\text{historical average}} \times 100 \quad (14)$$

3.4 The AquaCrop Model

For this study the AquaCrop model was used to simulate the historical and future yield of sorghum. The AquaCrop model is a crop water productivity model that was developed by FAO to be used under a wide range of conditions where water is a limiting factor. The model is conceptualized (Doorenbos and Kassam, 1979) based on the linear relationship between yield and water; water being considered as a specific function of the crop to the total evapotranspiration over the cropping season. The soil water balance, crop growth and development processes are simulated as a function

of crop, soil, weather, and management input data, on a daily time step. Also the model simulates soil evaporation and crop transpiration as individual processes. Transpiration is used to determine biomass accumulated each day, using a crop-specific water productivity parameter that is normalized for reference evapotranspiration (Steduto et al., 2009) this makes the parameter applicable to a wide range of climates. The accumulated biomass that becomes harvestable yield is calculated using a harvest index, that responds to water and temperature stress over the cropping season. The model separates evapotranspiration (ET) into soil evaporation (E) and crop transpiration (Tr) components as follows:

$$ET = E + Tr \quad (15)$$

The final yield (Y) is also separated into biomass (B) and harvest index (HI) and given as:

$$Y = HI(B) \quad (16)$$

The core equation for the Aqua crop model is presented as:

$$B = WP \cdot \Sigma Tr \quad (17)$$

where,

WP is the parameter of water productivity in kg of biomass produced per m² per mm of total water transpired.

WP values are normalized for evaporative demand and CO₂ concentration to allow the model to be applied in diverse locations, seasons and different climates including future climate scenarios. Simulations are performed on growth degree days but can also be based on calendar days in daily time-steps. The model uses canopy cover instead of leaf area index (LAI) as the basis to calculate transpiration and to separate soil evaporation from transpiration. Crop yield is calculated as the product of above-ground dry biomass and harvest index (HI). Starting at flowering, HI increases linearly with time until it nears complete physiological maturity. A schematic representation of the conceptualization of the model is presented in Figure 3.

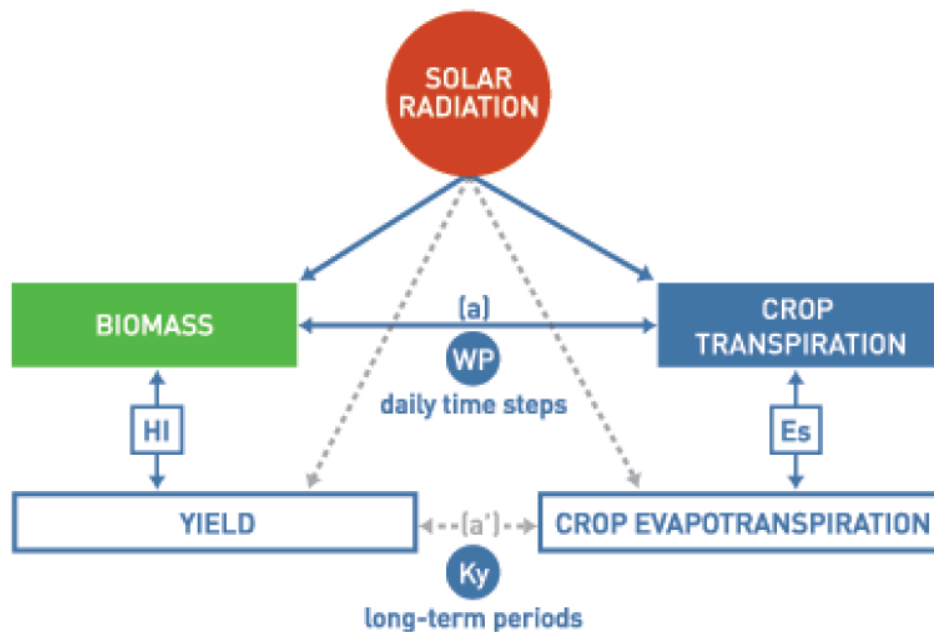


Figure 3: Schematic conceptualization of the AquaCrop model Source: Raes et al. (2009)

The model consists of four components; the climate, the crop, the soil and management practices. These components also have sub components as shown in Figure 4 and outlined below: The climate component incorporates daily maximum and minimum temperature, daily rainfall, daily evapotranspiration (ET_o) and CO₂ concentration. The soil component consists of the soil profile and ground water table while the crop profile is made up of development, growth and yield. The management component includes agronomic practices such as irrigation and field management as well as fertilization and use of bands.

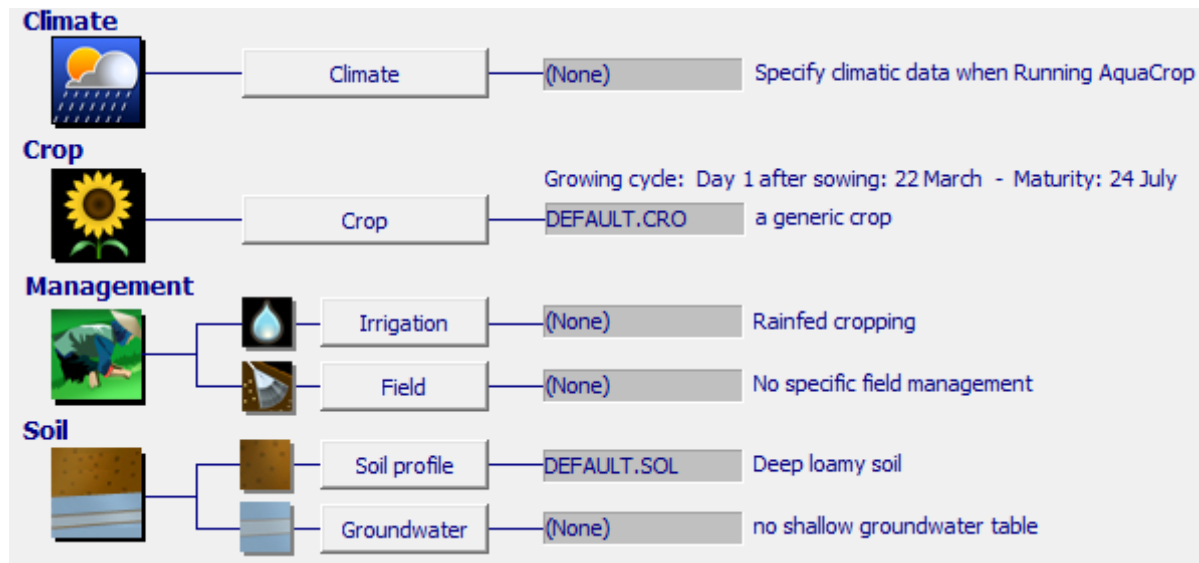


Figure 4: Sub model components of AquaCrop model

Source: Raes et al. (2009)

3.5 Model Parameters

Figure 5 shows the functional relationships between the different model components indicating the soil–plant–atmosphere continuum. The parameters that drive the model include; phenology, canopy cover, transpiration, biomass production, and final yield. In the schematic figure, the different letters represent parameters; (I), minimum air-temperature (T_n), maximum air temperature (T_x), reference evapotranspiration (E_{To}), soil evaporation (E), canopy transpiration (Tr), stomatal conductance (g_s), water productivity (WP), harvest index (HI) and atmospheric carbon dioxide concentration (CO_2). In the same figure, (1), (2), (3), (4) are water stress response functions for leaf expansion, senescence, stomatal conductance and harvest index, respectively. Continuous lines represent direct links between processes and variables while the dashed lines gives feedbacks.

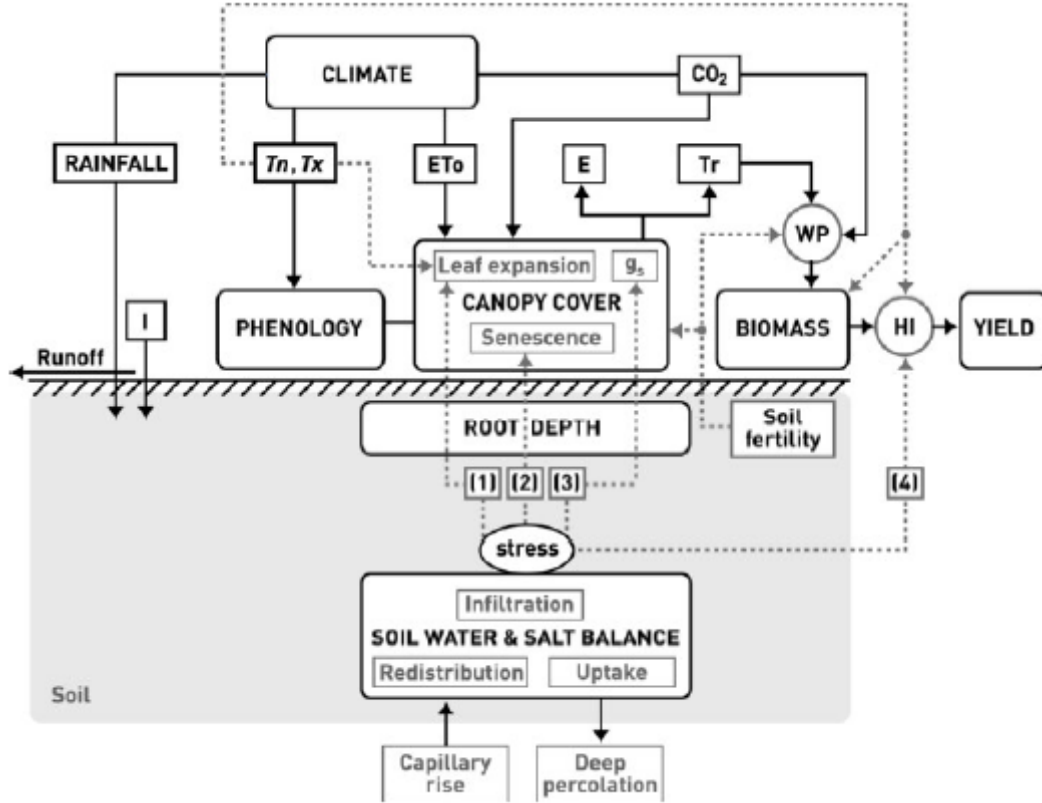


Figure 5: Chart of AquaCrop indicating the main components of the soil–plant–atmosphere Continuum
Source: Raes et al. (2009)

Reference evapotranspiration (ET₀) is calculated from daily maximum and minimum temperature using the FAO-Penman Monteith method (FAO, 2009).

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T + 273} U_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34U_2)} \quad (14)$$

where:

ET₀- reference evapotranspiration (mm/day)

R_n – net radiation (MJ/m²/day)

G – soil heat flux density (MJ/m²/day)

U₂ – wind speed at 2 m height (m/s)

e_a– actual vapour pressure (Kpa)

e_s – saturation vapour pressure (Kpa)

Δ – slope of vapour pressure curve (Kpa/°C)

γ – psychometric constant (Kpa/°C)

T – air temperature at 2 m height (°C)

The model considers 369.47 parts per million by volume as the reference CO₂ concentration (Figure 6) which was measured at the Mauna Loa observatory in Hawaii, from 1970-2013.

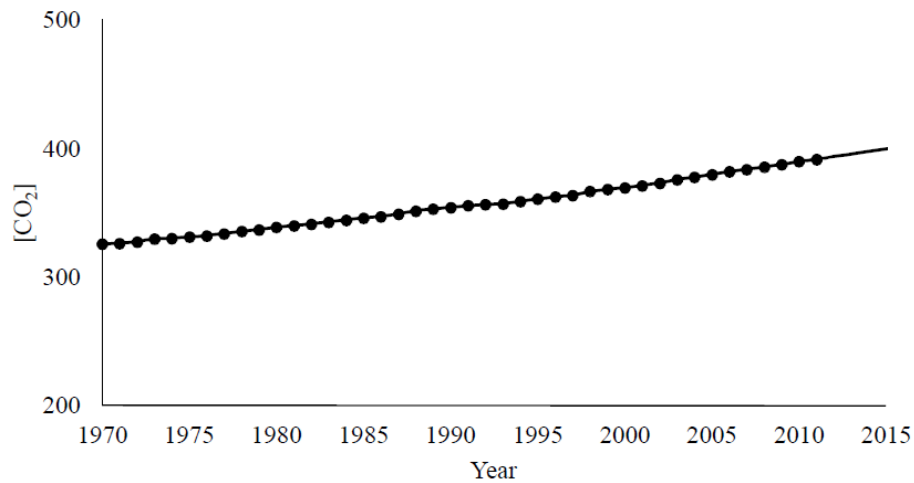


Figure 6: Average atmospheric CO₂ concentration as observed in Mauna Loa observatory (Hawaii, USA)
(2009) Source: Raes et al.

CHAPTER 4

VARIABILITY AND TREND ANALYSIS

4.1 Variability of historical climate data

Under rainfed agriculture plants are particularly sensitive to water availability and therefore knowledge of past trends in the climatic variables is important in order to predict future events and to come up with farming strategies and adaptive plans that are essential for climate change mitigation. This chapter assesses the quality of historical rainfall and temperature data obtained from Meteorological Services as well as the variability and trends in the time series data for the historical period of 1979 to 2014.

It is important to assess the quality of the climate data before it can be used for water resources assessment. Based on the null hypothesis; H_0 : there is homogeneity in the climate data sets, the null hypothesis is rejected if the p-value is less than 0.05 at the 95 % confidence level and in this study the null hypothesis is true. The results in Table 4 demonstrate that since the p-values are larger than 0.05 both the rainfall and temperature data for the Goodhope Metrological Station are homogenous and statistically significant at the 95 % confidence level. Using the f-test, if the f-critical value is smaller than the F-value, null hypothesis is rejected, moreover the null hypothesis for this study is accepted because the F-value is larger than the f-critical value. The p-value and the f-critical values are both large so there is enough evidence to accept the null hypothesis. This implies that the data sets are of reliable quality and can be used for further analyses.

Table 4: Homogeneity of historical climate data

Parameter	F value	p-value	f critical value
Rainfall	30.07	3.4	1.8
Temperature (maximum)	149.16	2	1.8
Temperature (minimum)	395.49	7.9	1.8

4.1.1 Variability of historical temperature

Figure 7 shows the seasonal distribution of temperature during the historical period of 1979-2014 for the Barolong Farms. In general a steady decrease in temperature is observed from March until July with the lowest temperatures in June and July, after which there is a gradual increase from

August onwards and peaking in January. The maximum temperature ranges between 23.39 °C in August to 30.37 °C in January while the values of minimum temperature are in the range of 4.76 °C in July to 18.13 °C in January. The lowest average temperature of 12.62 °C was observed in July while the highest mean temperature of 24.26 °C was experienced in January. Normally the cropping season in Botswana extends from October to March, with September and April considered as the transition months (Adelabu, 2010). Based on the cropping season months the mean values of the highest maximum and lowest maximum temperatures were observed in January at 30.38 °C and in March at 28.47 °C respectively. For the average monthly minimum temperatures, the highest and lowest minimum values were in the order of 18.13 °C and 4.76 °C in January and in October respectively. The mean average monthly maximum and minimum temperature for the cropping months ranged from 21.51 °C in October to 24.26 °C in January.

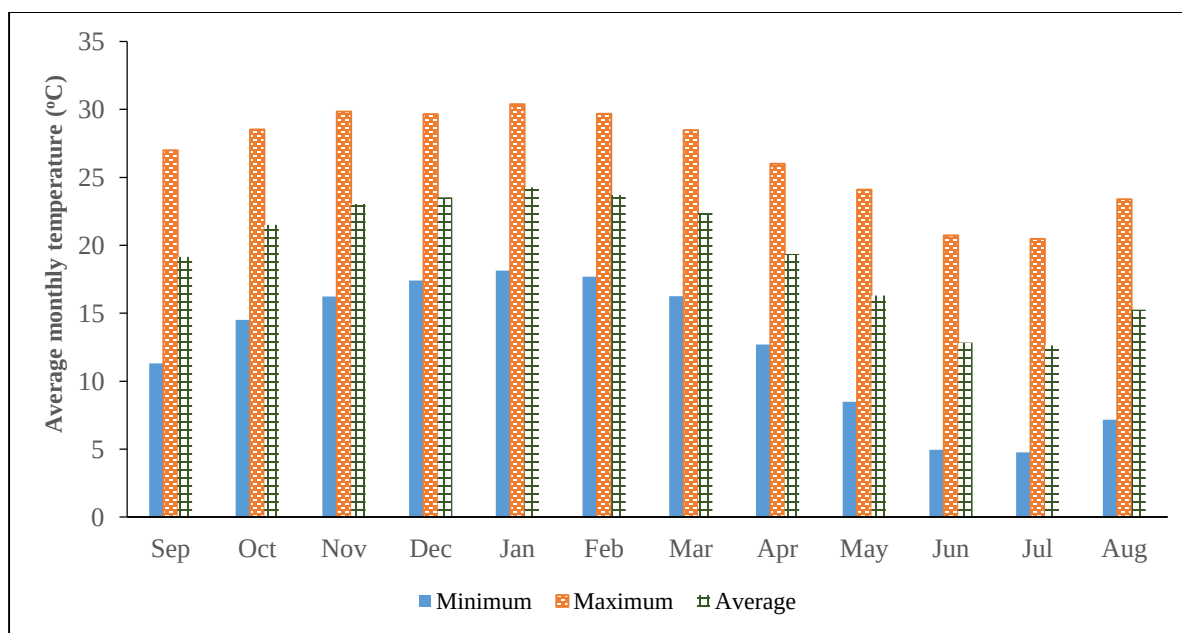


Figure 7: Average monthly temperatures for Barolong Farms from 1979 to 2014

High average monthly maximum temperatures are concentrated in the summer months which extend from October to March (Table 5), coincidentally these are the cropping season months while September and April are considered to be the transition months within the study area. The long term mean temperature ranges from 28.48 °C in March to 30.38 °C in January. Figure 8 shows a generally increasing trend in temperature for the historical period under observation. In addition

Figure 9 an increase in the average mean annual temperature from 19.0 °C pre-2000 to 20.03 °C after the year 2000.

Table 5: Variation in seasonal maximum temperature

	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug
Mean (mm)	26.98	28.54	29.83	29.67	30.38	29.67	28.48	26.01	24.10	20.74	20.48	23.39
SD (mm)	1.67	1.68	1.90	1.76	1.76	1.73	1.6	1.66	1.68	1.42	1.39	1.83
CV (%)	6.19	5.92	6.38	5.92	5.8	5.82	5.62	6.37	6.98	6.83	6.81	7.82

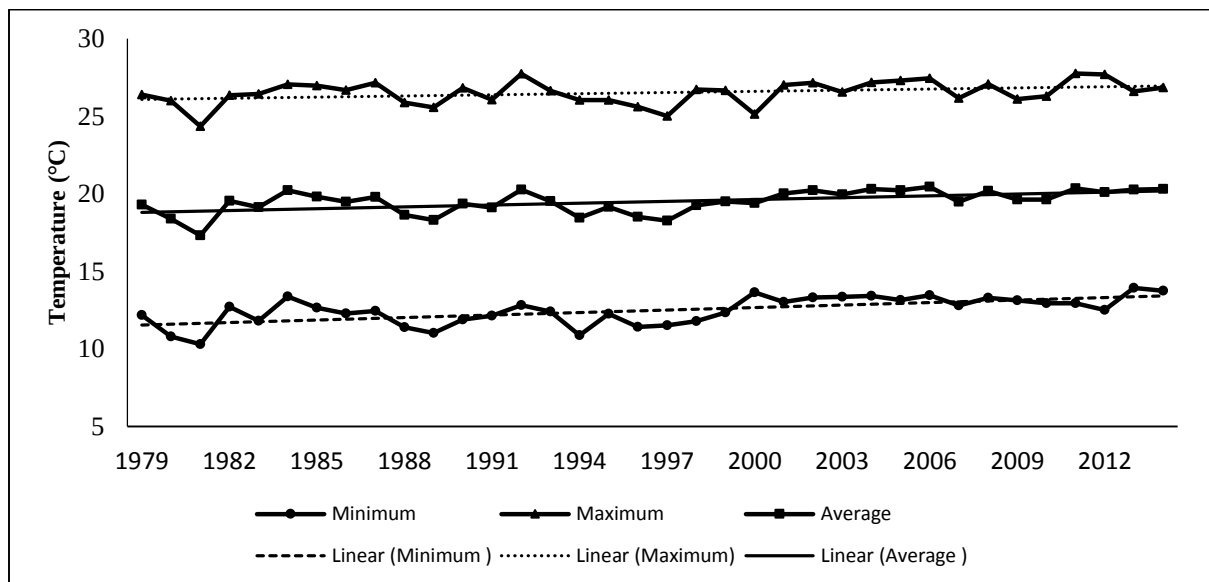


Figure 8: Average mean annual temperatures for Barolong Farms (1979 – 2014)

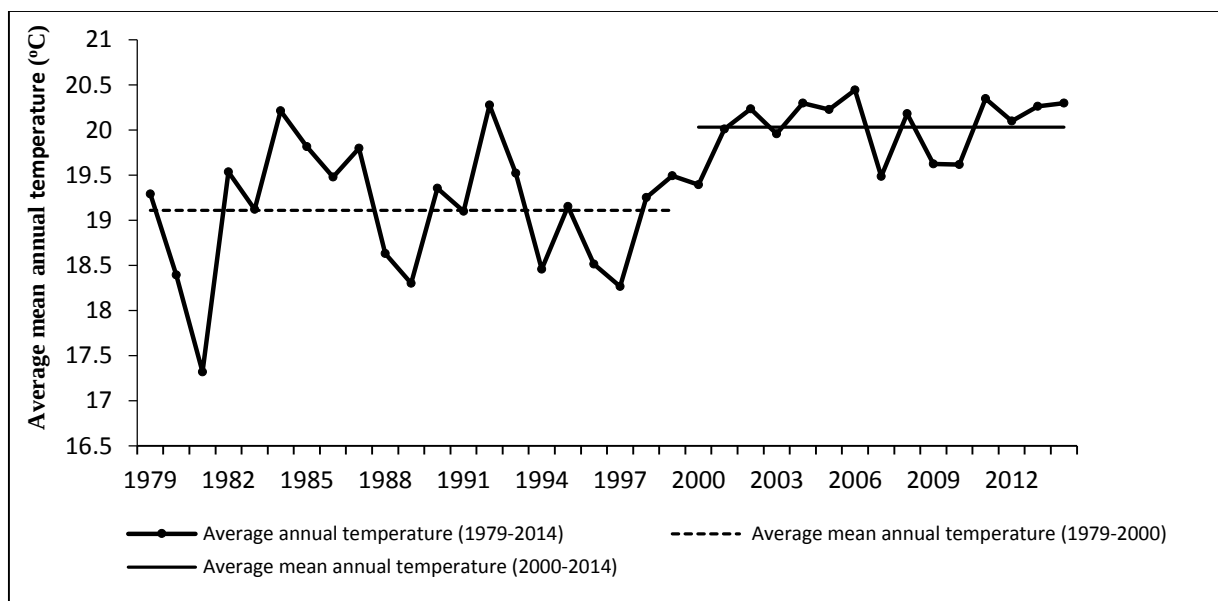


Figure 9: Trend in average annual temperatures for Barolong Farms from 1979 to 2014

The coefficient of variation (CV) was applied to assess variability in the historical temperature. A relatively low CV was observed ranging from 5.62 % in March to 6.38 % in November for the maximum temperature (Table 6). The winter months of May to August experienced average mean temperatures in the range of 20.48 °C in July to 24.10 °C in May, the CV on the other hand ranges between 6.81 % in July and 7.82 % in August. The highest average monthly minimum temperatures are also observed in the summer months ranging from 14.51 °C in October to 18.13 °C in January and with a CV of 5.57 % in January to 10.66 % in October (Table 7). A low degree of variability (3.8 %) is observed in the mean annual temperature (Table 8) for the entire period under study. Also the CVs for the periods 1979-1999 and 2000-2014 were 3.7 % and 1.6 % respectively

Table 6: Variation in seasonal maximum temperature

	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug
Mean (mm)	26.98	28.54	29.83	29.67	30.38	29.67	28.48	26.01	24.10	20.74	20.48	23.39
SD (mm)	1.67	1.68	1.90	1.76	1.76	1.73	1.6	1.66	1.68	1.42	1.39	1.83
CV (%)	6.19	5.92	6.38	5.92	5.8	5.82	5.62	6.37	6.98	6.83	6.81	7.82

Table 7: Variation in seasonal minimum temperature

	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug
Mean (mm)	11.34	14.51	16.24	17.41	18.13	17.70	16.27	12.71	8.5	4.5	4.76	7.16
SD (mm)	1.42	1.55	1.53	1.07	1.00	1.35	1.3	1.75	1.71	1.44	1.66	1.54
CV (%)	12.56	10.66	9.41	6.18	5.57	7.60	7.96	13.79	20.09	29.01	34.96	21.55

Table 8: Variation in average mean annual temperature

	SD (°C)	Mean (°C)	CV (%)
1979-2014	0.74	19.49	3.8
1979-1999	0.71	19.11	3.7
2000-2014	0.33	20.03	1.6

4.1.2 Variability of historical rainfall

The seasonal rainfall distribution for the historical period of study is shown in Figure 10. Clearly there are two distinct seasons; namely the wet season extending from October to March and the dry season for the other months with negligible or no rainfall. The wet season rainfall peaks in January with average monthly amount of 101.36 mm. Figure 11 shows the average annual rainfall for Mosisedi farms during the period 1979-2014. The highest annual rainfall was recorded in 1997 at 847.8 mm and the lowest in 2014 at 259.3 mm. The long term average annual rainfall received was 468.4 mm while the average yearly rainfall ranged from 242 mm in 1983 to 847.8 mm in 1997, however the considerable fluctuations are observed with the time series. The wettest years (annual rainfall exceeding 700 mm) were 1980, 1995, 1997 and 1998. Annual rainfall amounts

below 300 mm were observed in 1983, 1985, 2005 and 2014. In general a decreasing trend is observed for the period under observation. At the same time there is a decrease in mean annual rainfall between the means of 1979-1999 and 2000-2014, in contrast the mean temperature was decreasing for the same period.

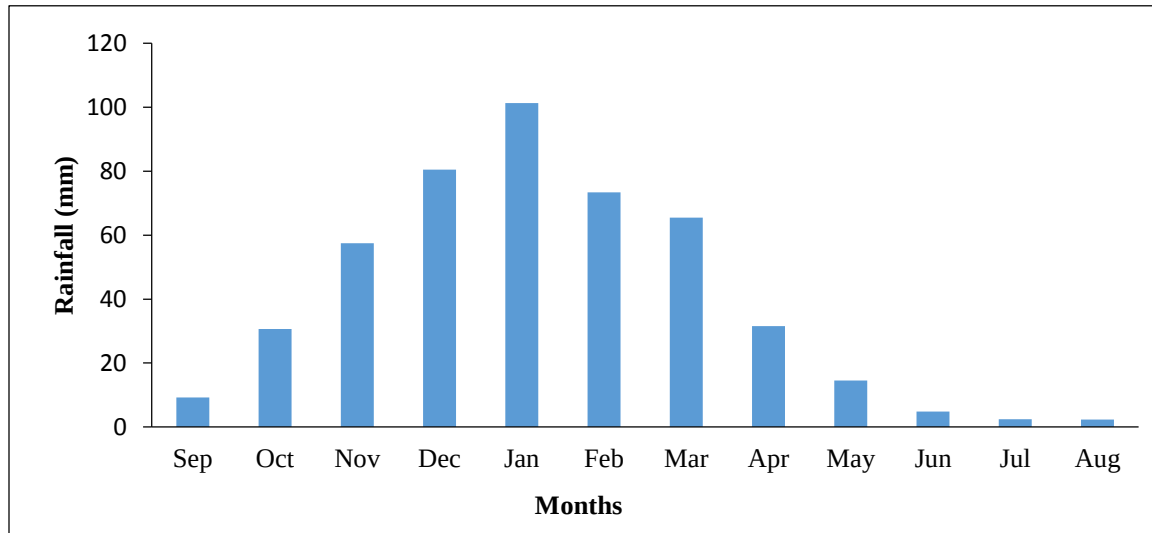


Figure 10: Average monthly rainfall for Barolong Farms from 1979 to 2014

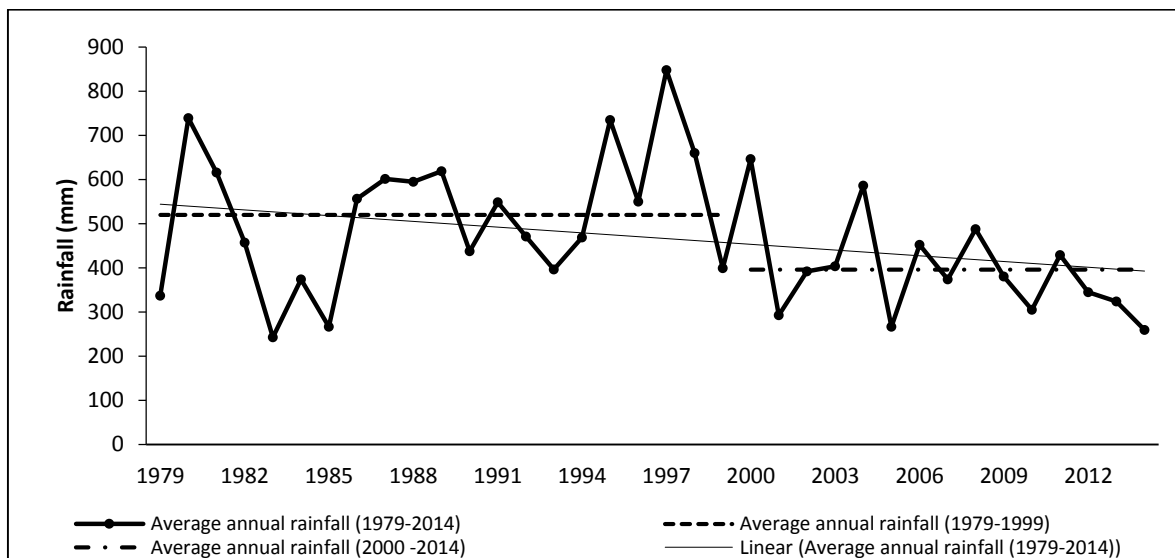


Figure 11: Annual rainfall for Barolong Farms from 1979 to 2014

Unlike temperature there is a high variability in seasonal rainfall ranging between 60 % and 90 % observed within the wet season months (Table 9). Similarly a high degree of inter-annual

variability (31.93 %) is observed in the mean annual rainfall time series of 1979-2014 (Table 10). At the same time the variability was 29.59 % pre-2000 and 27.21 % post 2000.

Table 9: Variability in seasonal rainfall

	Oct	Nov	Dec	Jan	Feb	Mar
MEAN (mm)	30.05	59.96	79.21	98.93	71.48	63.73
SD (mm)	27.32	52.26	46.84	59.64	49.67	44.10
CV (%)	90.90	87.16	59.14	60.28	69.49	69.20

Table 10: variability in mean annual rainfall from 1979-2014

Period	SD (mm)	Mean (mm)	CV (%)
1979-2014	149.56	468.38	31.93
1979-1999	153.85	519.90	29.59
2000-2014	107.82	396.25	27.21

4.2 Trend analysis

Mann-Kendall test and Sen's Slope statistical tests are widely used for trend detection of past climate. Sen's estimate (Q) is used in conjunction with the Mann-Kendall's test (Z) in order to assess the presence of any significant trends in the time series data.

4.2.1 Trend in historical temperature

The Mann-Kendall (MK) test and Sen's slope estimator are used to determine whether there is a significant linear trend in a time series. Sen's test estimates the magnitude of the trend slope (Q) and the confidence interval for the slope. Lower and upper confidence limits (Qmin95 and Qmax95) are used to test the significance of the slope at the 95 % confidence interval. Q is then defined as statistically significant if zero does not lie between the upper and lower confidence limits. For most of months the Mann Kendall test (Table 11) shows statistically insignificant trends in mean temperature at the 95 % confidence level, however, the trend in mean annual temperature is significant while the Sen's slope, Q is also significant at the 95 % confidence level (Figure 12 and Table 11).

Table 11: Mann-Kendall and Sen's statistics for the mean annual maximum temperature (1979-2014)

	MK ((Z)	Significance	Qmin95	Qmax95	Sen's (Q)
September	2.58	*	0.02	0.1	0.07
October	2.47	*	0.01	0.12	0.06
November	2.53	*	0.02	0.14	0.08
December	0.20	no	-0.06	0.06	0.005
January	-0.04	no	-0.07	0.07	0
February	0.26	no	-0.05	0.07	0.008
March	-0.05	no	-0.07	0.05	-0.001
April	-1.36	no	-0.09	0.02	-0.04
May	-0.10	no	-0.06	0.05	-0.001
June	2.44	*	0.01	0.08	0.04
July	0.63	no	-0.03	0.06	0.014
August	1.38	no	-0.01	0.01	0.04
ANNUAL	2.13	*	0.01	0.05	0.03

* Statistically significant at 95 % confidence level

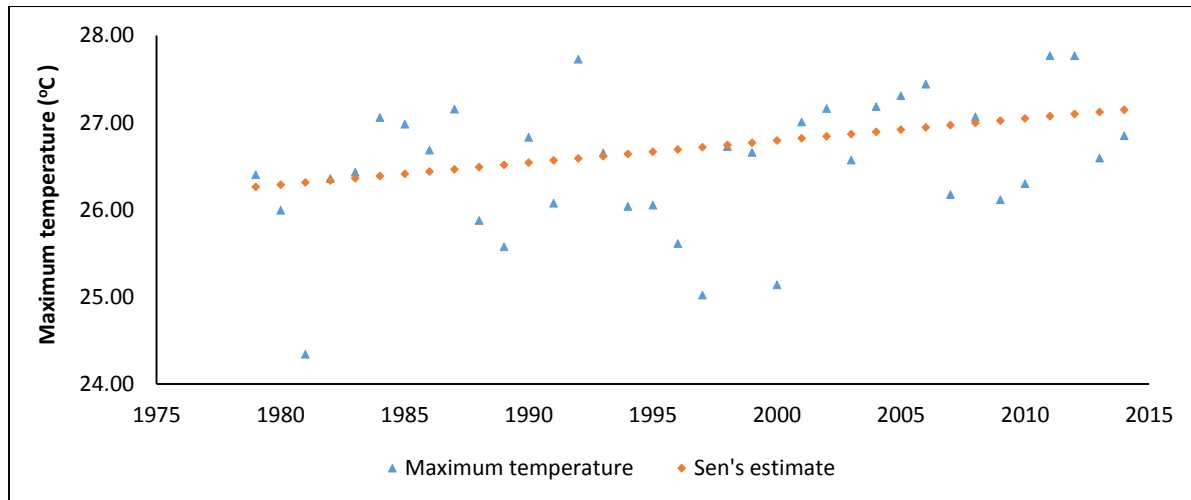


Figure 12: Mean annual maximum temperature for Barolong Farms from 1979 to 2014

Significant trends (Table 12) were observed in the mean annual and average monthly minimum temperatures of the baseline period (1979-2014) except for the month of April at the 95 % confidence level. Sen's slope (Figure 13) also shows a positive slope implying that the increases in the temperature are significant.

Table 12: Mann-Kendall and Sen's statistics for the annual mean minimum temperature (1979-2014)

	MK ((Z)	Significance	Qmin95	Qmax95	Sen's (Q)
September	2.64	*	0.01	0.1	0.06
October	2.37	*	0.01	0.1	0.05
November	3.50	*	0.051	0.1	0.09
December	2.68	*	0.01	0.08	0.04
January	2.89	*	0.02	0.08	0.06
February	2.19	*	0.002	0.08	0.04
March	2.28	*	0.005	0.07	0.05
April	1.64	no	-0.01	0.09	0.03
May	2.33	*	0.01	0.09	0.05
June	2.36	*	0.009	0.10	0.06
July	1.77	*	-0.008	0.10	0.05
August	1.69	*	-0.007	0.09	0.04
ANNUAL	3.62	*	0.03	0.08	0.05

* Statistically significant at 95 % confidence level

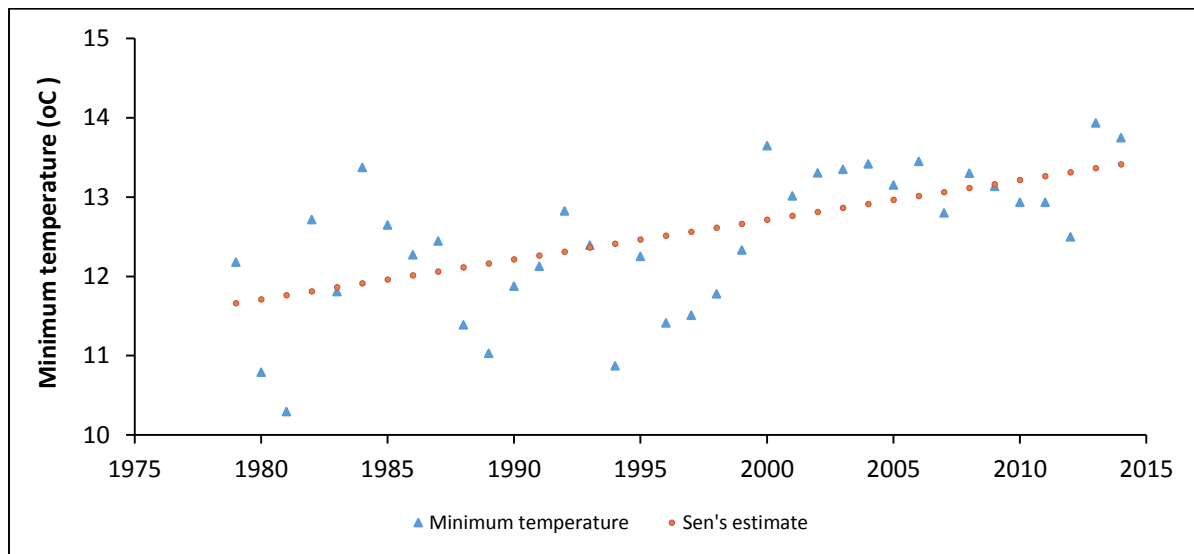


Figure 13: Mean annual minimum temperature for Barolong Farms from 1979 to 2014

4.2.2 Trend in historical rainfall

Table 13 shows statistically significant trends in both the mean annual and the mean monthly rainfall. This is particularly so for most of the wet season months.

Table 13: Mann-Kendall and Sen's statistics for the mean annual rainfall (1979-2014)

	MK ((Z))	Significance	Qmin95	Qmax95	Sen's (Q)
September	1.84	*	-0.002	0.09	0.04
October	1.38		-0.02	0.09	0.04
November	2.92	*	0.02	0.09	0.05
December	2.93	*	0.01	0.06	0.03
January	2.76	*	0.007	0.047	0.03
February	0.18		-0.02	0.02	0
March	2.69	*	0.008	0.05	0.03
April	2.38	*	0.004	0.04	0.02
May	1.64		-0.004	0.03	0.02
June	1.61		-0.003	0.04	0.02
July	2.23	*	0.004	0.05	0.03
August	1.08		-0.02	0.06	0.02
ANNUAL	4.21	*	0.02	0.04	0.03

* Statistically significant at 95 % confidence level

4.4 Discussion

In this chapter long-term historical maximum and minimum temperature together with rainfall were analyzed for trends and variability from 1979 to 2014. The average maximum temperature for the cropping season (October to March) of 1979-2014 was 29.42 °C while the average minimum temperature was 16.70 °C resulting in an average cropping season temperature of 23.07 °C. Mean annual rainfall ranges from about 240 mm to 850 mm but lies below 500 mm 65% of the time. These rainfall amounts indicate that the study area is relatively dry compared to other areas in the southern African region where the values can be as high as 2000 mm. Time series plots indicated that as temperature increased, the rainfall was showing a decreasing trend. In general there is low variability in temperature which is in the range of 5-11 % compared to the high seasonal rainfall variability (>60 %) and the variation in annual rainfall of about 32 %. In general temperature was observed to be increasing while rainfall decreased during the period under study. Overall statistically significant and increasing trends were observed for temperature while the trend in annual rainfall was statistically insignificant for some of the months. According to FAO (2008) the minimum temperature range for sorghum production should be 8 °C -10 °C while the maximum temperature should range between 30 °C and 33 °C with an average of not less than 20

°C. In addition the required optimum temperatures for germination, growth and development and reproductive growth of sorghum are in the respective ranges of 21 °C to 35 °C, 26 °C to 34 °C and 25 °C to 28 °C (DAR 2012). Therefore the historical temperature experienced in the study area was favorable to sorghum production.

Lobell et al. (2011) studied twelve major Californian crops and concluded that rainfall contributed more than 60 % of variability in crop yields that were studied. However Cooper et al. (2008) reported that inter-season and intra-seasonal variability are important to crop yield accumulation. Rainfall is important in recharging the soil profile and making moisture available to crops which usually takes place when there is no crop growth (period between harvesting and planting). Nonetheless it should be noted that the timing and amount of rainfall received during the cropping season is very critical in crop production because rainfall amounts influence crop yields during seed germination and seedling emergence. At the same time too much rainfall with low temperatures usually results in outbreak of seed diseases and hence poor crop stands (Shrivastava, 2015). If there is too much rainfall there is an increased chance of water logging in the soil which will lead to poor soil aeration hence seed germination may be negatively affected. Germination in dry soils on the other hand may result poor seed germination and seedling emergence hence small plants and small plant population. Also during vegetative growth high amounts of rainfall can result in a smaller shoot to root ratio plus shallow roots (Adams and Erickson, 2017) while less rain can also result in reduced photosynthesis due to shortage of moisture especially if it is coupled with high temperature because of evapotranspiration and soil evaporation. Moreover if the soil profile is not sufficiently recharged, there is a likelihood of soil water deficit during the critical growth stages.

CHAPTER 5

AquaCrop model calibration

5.1 Introduction

The AquaCrop model is a water-driven crop model used to simulate yield response of different herbaceous crops to water. It is suitable for use under conditions where water is a key limiting factor in crop production. The model is applicable to a wide range of environmental and climatic conditions since it is location specific. Model input parameters include climate, soil, and crop and field data. This chapter presents the AquaCrop model calibration and validation results for the southern district of Botswana. Once calibrated, the model could be applied to examine different farming strategies for farmers as a way of improving crop yields. The model could also be used to simulate future crop yields if driven by downscaled climate data from global circulation models under different climate scenarios.

5.2 Model parameterization

The model input parameters of daily rainfall, minimum and maximum temperature and reference evapotranspiration (ET_o) and soil physical characteristics and management were obtained from the Goodhope Agricultural Research Experimental station under which the Mosisedi Farms are found. The model was calibrated under conditions that are rainfed, pest controlled and with non-limiting nutrients.

5.2.1 Soil data

Composite soil samples were obtained within the upper three layers of the soil profile at a depth of 0-0.30 meters (DAR Annual Report Hand Book, 1985). The samples were analyzed for soil particle distribution (percent clay, silt and sand), texture, and moisture content and water retention capacity (Table 14).

Table 14: Soil characteristics

Properties	Components	Values
Moisture content (%)		2.31
Water retention capacity (%)		43.8
Particle size distribution (wt %)	Sand	82.25
	Silt	11.99
	clay	5.76
Texture	Sandy loam	

5.2.2 Sorghum Crop input parameters: Conservative parameters

The AquaCrop model requires conservative and non-conservative input parameters. In addition to the non-conservative parameters that are adjusted during calibration to suit the local conditions, the AquaCrop model has a list of conservative parameters that are constant across all locations and remain fixed for each crop type. Table 15 shows the conservative parameters of sorghum production.

Table 15: Conservative parameters (Raes et al., 2012)

Conservative parameter	Value
Base temperature (°C)	8
Upper temperature (°C)	30
Crop coefficient when canopy is complete but prior to senescence	1.07
Water productivity normalized for ETo and CO ₂ (gram m ⁻²)	33.7
Possible increase (%) of HI due to water stress before flowering	0
Coefficient describing negative impact of stomatal closure during yield on HI	3
Allowable maximum increase (%) of specified HI	15
Soil water depletion factor for canopy expansion – Upper threshold	0.14
Soil water depletion factor for canopy expansion – Lower threshold	0.72
Soil water depletion fraction for stomatal control – Upper threshold	0.69
Soil water depletion factor for canopy senescence – Upper threshold	0.69
Minimum growing degrees required for full biomass production (°C-day)	15

5.3 Non-Conservative parameters and Model calibration

In order to calibrate the model non-conservative parameters were adjusted within a reasonable range guided by location specific values and also according to values specified in the Botswana

Field Crop Reference Handbook (1999) where, the length of seedling emergence is within 7 to 15 days, and the time from sowing to reach maturity ranges from 110 days to 140 days. The type of method for sowing sorghum is direct sowing with an expected plant population of 40 000 plants per hectare using an inter-row spacing of 90 cm and intra-row spacing of 30 cm. The depth of sowing usually is dependent on the size of the seed and it is 2-3 times the diameter of the seed while seedling emergency ranges from 7 days to 15 days which is also dependent on the depth of sowing. Crop development is specified in growing degree days (GDD) and the parameters include canopy development, flowering and yield formation, root deepening and temperature requirements. Maximum canopy cover is dependent on plant density and summation of the canopy cover contributed by each seedling while the senescence starting time depends on phenology.

The time for sowing to reach maturity is cultivar specific which ultimately influences flowering stage and duration of flowering. The Harvest Index (HI) is expected to reach its reference value at or shortly before maturity. For root deepening the minimum effective rooting depth refers to the depth from which the germinating seedling can extract water. For the purpose of simulation this study considered a rooting depth of 0.20 m to 0.30 m. The maximum effective rooting depth for medium rooted crops ranges from 0.4 m to 0.99 m. The experimental field data for the non - conservative parameters for sorghum are provided in Table 16.

Table 16: Experimental field data used for calibration; Sourced from Annual Report Hand Book, DAR (1985)

Sorghum Cultivar	Days to flowering	Sowing date	Population (Plants/ha)	Observed yield	Observed biomass
Segaolane	67	10/11/1979	40 000	2.034	5.8
Segaolane	66	15/11/1980	40 000	1.373	5.54
Segaolane	61	10/11/1981	40 000	2.8	5.7
Segaolane	67	17/11/1982	40 000	3.333	5.9

Calibration was done in a one-step manner, where the value of each key parameter was further adjusted until the simulated and observed values are almost the same. The values were based on annual reference handbooks from DAR (2010). Thus, plant population, sowing dates and days to flowering were put as they are based on Table 16 in the model. Calibration was started at minimum values based on Table 17, the values were changed based on range of values for each parameter,

and however one parameter was changed at a time while other parameters were held constant. For example the reference harvest index was modified over a range of values, between 28 % and 34 % while other parameters were at the minimum values. The number of days to reach maturity was also changed in a range of 120 days to 130 days while harvest index was left at 31 % and other parameters left at their minimum values. This was repeated for other parameters, and those initially adjusted were also further adjusted until arriving at final values of calibration presented in Table 18. The final selected value was selected by minimizing difference between the variance in the observed yields and the simulated yields.

Table 17: Range for adjusting the parameters (DAR, 2010)

Parameter	Unit	Minimum values	Maximum values
Number of plants per hectare	Ha-1	40 000	60 000
Time from sowing to emergence	days	7	15
Maximum canopy cover	%	80	90
Time from sowing to start of senescence	days	95	110
Time from sowing to maturity	days	110	140
Time from sowing to 50% flowering	days	60	65
Length of flowering stage	days	65	70
Minimum effective rooting depth	M	0.2	0.3
Maximum effective rooting depth	M	0.4	0.99
Reference Harvest Index	%	28	34

Table 18: Calibrated parameters and default parameters of the model for sorghum

Parameter	Unit	Default parameters	Calibration values
Number of plants per hectare	Ha-1	200 000	40 000
Time from sowing to emergence	days	15	10
Maximum canopy cover	%	90	87
Time from sowing to start of senescence	days	135	105
Time from sowing to maturity	days	147	128
Time from sowing to 50% flowering	days	50	65
Length of flowering stage	days	85	60
Minimum effective rooting depth	M	0.35	0.3
Maximum effective rooting depth	M	0.6	0.7
Reference Harvest Index	%	33.7	33

Although the model output is given in terms of biomass and grain yield, it should be noted that the local farmers are interested in grain yield. Also worth noting is that biomass is always more than

grain yield because plant growth is a process of biomass accumulation which takes place every day (Karamanos and Gimenez, 1991), it is a result of the interaction of internal processes of the plant that include photosynthesis, active transport, osmosis, diffusion and respiration, therefore grain yield is derived as a function of final biomass. Simulated and observed yields for sorghum are presented in Figure 14 while the calibration results for biomass are presented in Figure 15.

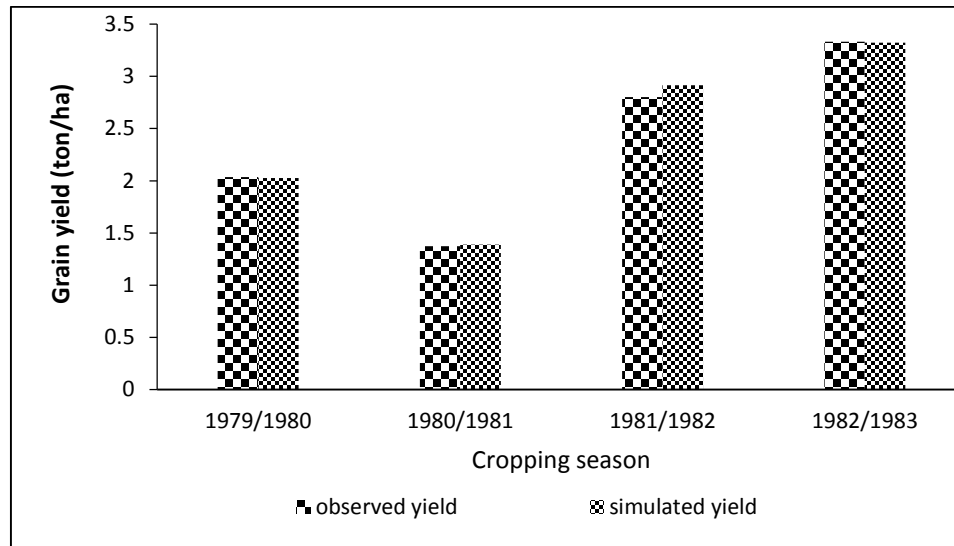


Figure 14: Observed and simulated yield of sorghum for the cropping seasons of 1979-1983

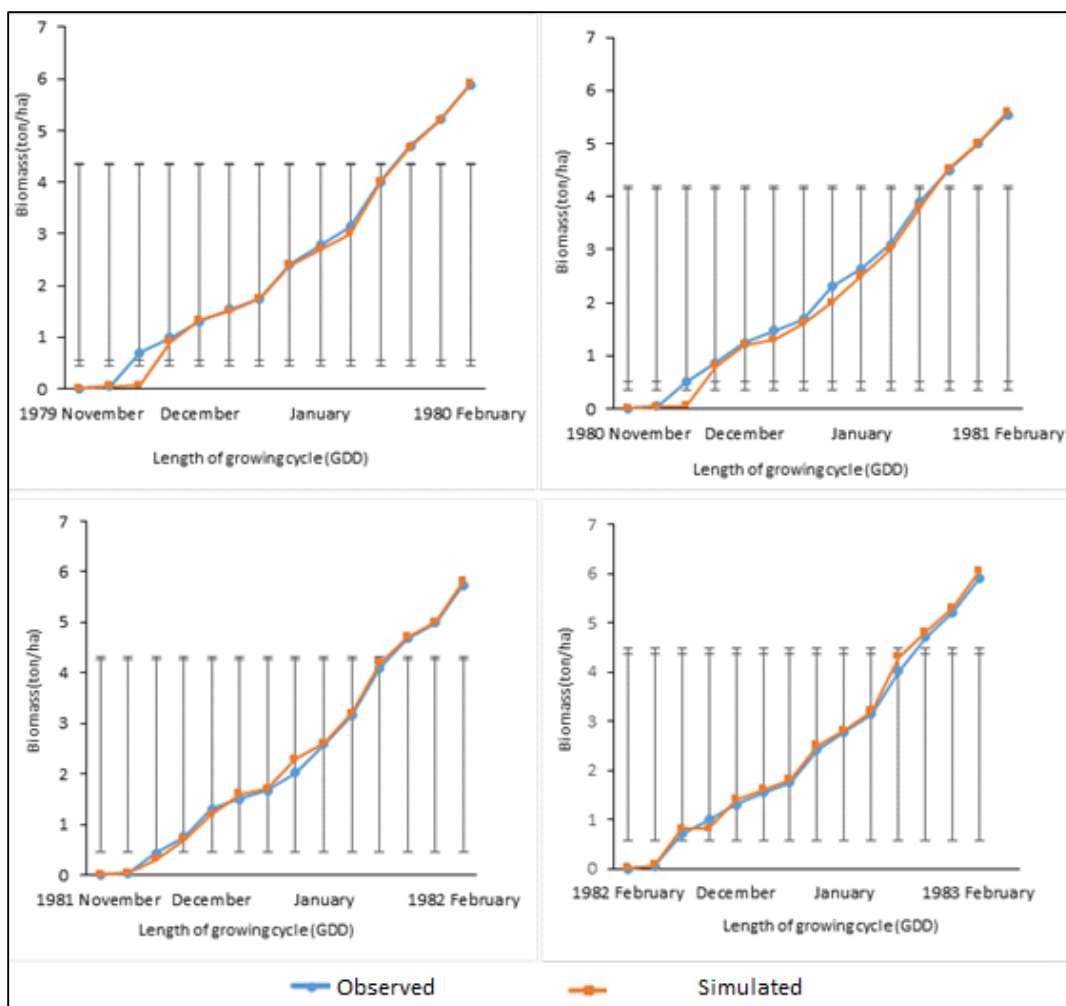


Figure 15: Simulated and observed biomass for the cropping seasons used in calibration

The model calibration process was evaluated using the statistical objective functions of the root mean square error (RMSE), the model coefficient of efficiency (CE) and coefficient of determination (R^2) as shown in Table 20. For all the seasons values ranging from 0.96 to 1.0 were obtained for both R^2 and CE while the RMSE varied between 0.06 and 0.5. Based on the parameter values obtained during calibration, the AquaCrop model is able to adequately simulate sorghum yield and biomass for the Goodhope Sub District.

Table 19: Statistical analysis of AquaCrop model

Year/season	Observed	Simulated	Observed	Simulated	R^2	RMSE	CE
1979/1980	5.8	5.9	2.034	2.026	1	0.06	1
1980/1981	5.54	5.6	1.373	1.39	0.99	0.12	0.99
1981/1982	5.7	5.8	2.8	2.915	0.99	0.41	0.97
1982/1983	5.9	6.03	3.333	3.323	0.99	0.5	0.96

5.4 Model Validation

The calibrated model was validated using historical yield data from Barolong Farms from 1979 to 2012 (Figure 16). The average simulated yield for the whole period is 1.33 ton/ha while for observed is 1.15 ton/ha, however it should be noted that data was not recorded for some cropping seasons. Generally the simulated values were greater than the observed values for the entire period except for the cropping season of 1995/96, 1998/99, 2008/09, 2010/11, 2011/12 and 2012/13. The statistical objective performance functions for the validation process are as follows; R^2 (0.77) RMSE (0.41) and the CE (0.78). The results show that the model can be used to adequately simulate the sorghum grain yield in the district. However, it is observed that in most cases the model is over-simulating; this may be attributed to other external factors that are not explicit in the model.

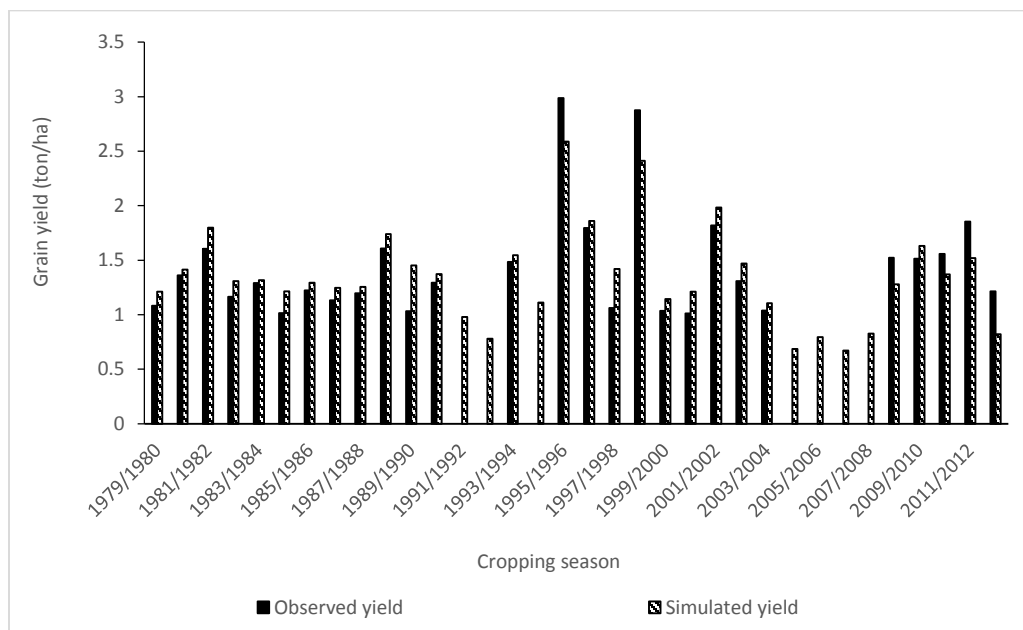


Figure 16: Model yield validation for the cropping seasons of 2011-2014

5.5 Discussion

The AquaCrop model was calibrated using the experimental observed data from Goodhope agricultural experimental station as well as rainfall and temperature data from the Goodhope Meteorological. These stations are the ones that supply data for the Mosisedi Farms. The calibration was based on the local variety of sorghum known as segaolane. Results show that the

AquaCrop model was able to adequately simulate the historical grain yield for Mosisedi and Barolong Farms as indicated by CE values which were greater than 0.5. Therefore it can be concluded that AquaCrop could be used to simulate with some degree of accuracy sorghum production under rainfed conditions in Mosisedi Farms and in the Barolong farms. Based on literature the AquaCrop model has been applied to a wide range of crops under different conditions. For example, Heng et al. (2009) and Hsiao et al. (2009) reported that the model was successfully used to simulate sorghum development and grain yield under non-limiting conditions. Hadebe et al. (2017) conducted a study on calibration and testing of AquaCrop model for selected sorghum genotypes and reported that the model was able to simulate canopy cover, biomass accumulation, harvest index and yield relatively well for all sorghum genotypes. Despite the reasonable simulations, the model overestimated both yield and biomass and this was attributed to the fact that conservative parameters in the default sorghum crop file may not be true representatives of local genotypes (Hadebe et al., 2017). This may also be the case in this study where yield was generally over estimated in some cropping seasons. Therefore overestimation of yield suggests that conservative parameters, such as canopy sensitivity to water stress, water stress coefficient and water productivity (WP) need to be calibrated for local genotypes. Nonetheless, Todorovic et al. (2009) conducted a study to compare the performance of the AquaCrop model with the CropSyst and WOFOST models and reported that in the cases where input data is limited the AquaCrop model should be preferred because it requires less input parameters, hence it was the most applicable crop model in the study area.

CHAPTER 6

Climate and sorghum yield projections under RCP 4.5 climate scenario

6.1 Introduction

Quantifying the effects of climatic change on agriculture is crucial as it will provide information for planning and management of food resources and livelihoods in the future. Through coupling of the calibrated AquaCrop model and the GCM data under the RCP4.5 pathway scenario, this chapter provides an assessment of the impacts of climate change on sorghum production in the Goodhope Sub District of Botswana. Five downscaled GCMs namely; BNU-ESM, CanEsm2, GFDL-ESM2M, MIROC5 and MRI-CGMC were used in this study for the near future period of 2030-2060. It should be noted that this study aims to provide a preliminary and generalized assessment of the likely trends in sorghum productivity under the assumed radiative scenarios, as such it is not meant to provide a comprehensive assessment of climate change in the district.

6.2 Temperature Projection

For all the GCMs the average mean monthly temperatures (2030-2060) are projected to be higher than the historical temperatures (1979 to 2014) indicating a warmer climate under RCP 4.5 moderate emission scenario (Figure 17), however seasonal variability is maintained. During the summer months the temperature is predicted to range from 24.53 °C in October to 25.92 °C in December while the winter temperature is expected to range from 16.40°C in June to 18.07 °C in August across all GCMs. Table 20 specifically shows the expected temperatures during the cropping season.

Table 20: Mean monthly temperature for growing season (historical and projected)

	October	November	December	January	February	March
Historical	21.51	23.03	23.54	24.26	23.67	22.37
BNU-ESM	23.64	25.41	26.27	26.26	25.65	25.45
CanEsm2	26.63	26.84	26.64	26.63	26.43	26.13
GFDL-ESM2M	25.91	25.78	25.36	25.60	25.47	24.06
MIROC 5	23.42	24.76	25.42	25.58	25.41	24.42
MRI-CGMC	23.05	24.76	25.94	25.40	24.84	24.25

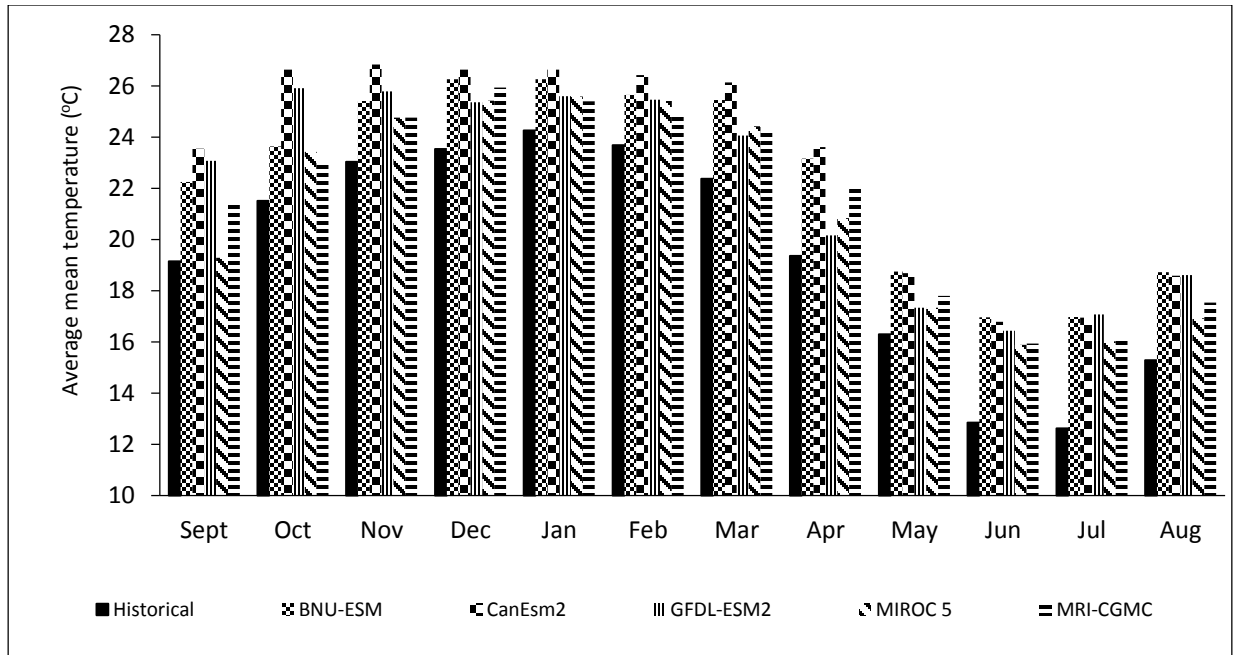


Figure 17: Seasonal distribution of historical (1979 to 2014) and projected mean monthly temperature (2030 to 2060) for Barolong Farms

On an annual basis and focusing on the growing season (Figure 18), all the years are expected to have above average mean temperatures compared to the baseline historical average of 23.07 °C. CanEsm2 predicts the highest average mean temperature for the whole future period at a maximum value of 27.77 °C in 2060/61 and a minimum value of 25.85 °C in 2038/2039 where it is expected to record its lowest temperature, the highest temperature of 27.77°C is expected. The temperature ranges projected by the other models are: BNU-ESM 24.11°C in 2033/34 and 26.42 °C 2058/59; GFDL-ESM 23.56 °C in 2031/32 and 26.77 °C in 2054/55; MIROC5 23.48°C in 2031/32 and 25.80 °C in 2053/54; MRI-CGMC 23.14 °C in 2030/31 and 26.03 °C in 2050/51. Overall an increasing trend in temperature is expected for all the GCMs.

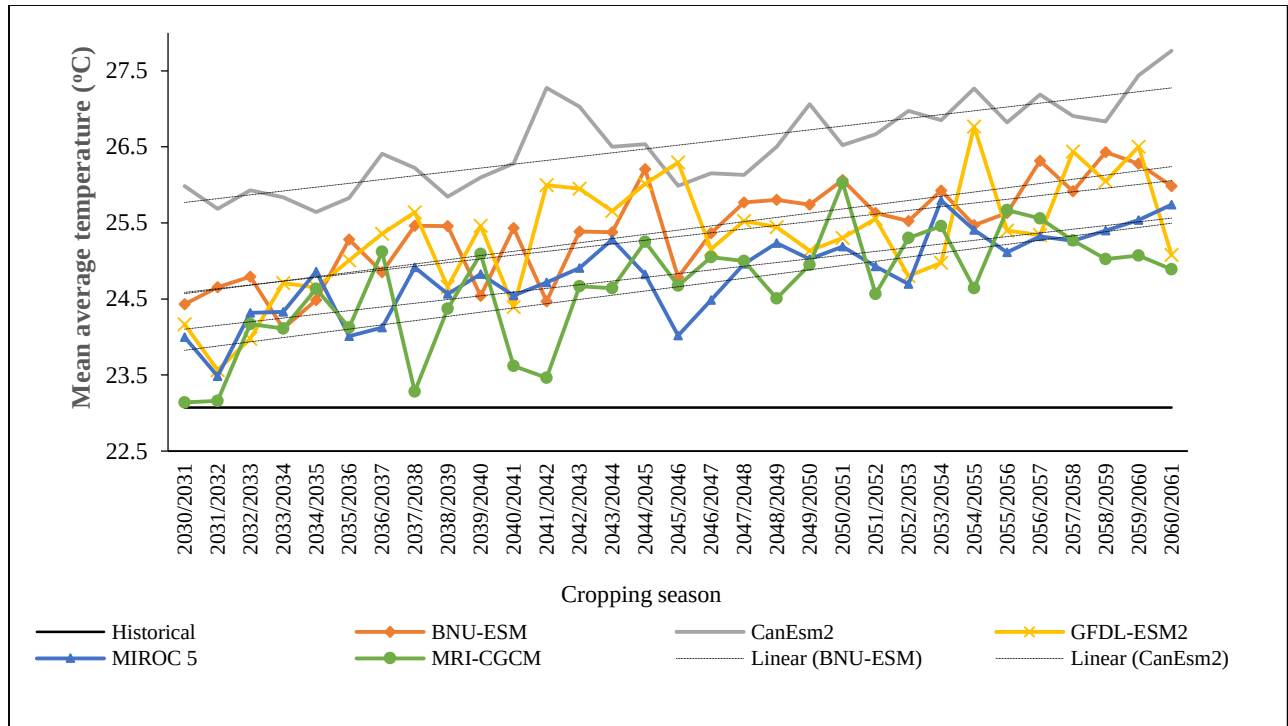


Figure 18: Historical (1979/80 to 2013/14) and future (2030/31 to 2060/61) average seasonal temperature for the cropping season of Barolong Farms

The change in future temperature relative to the historical period is shown in Figure 19. The maximum change in temperature is expected to be 14.56 % in 2058/59 by BNU-ESM, 20.40 % in 2060/61 by CanEsm2, 16.02 % in 2054/55 by GFDL-ESM2, 11.82 % in 2053/54 by MIROC5 and 12.83 % in 2050/51 by MRI-CGMC. The respective minimum changes are 4.51% in 2034/35, 11.19 % in 2034/35, 2.14 % in 2031/32, 1.79 % in 2030/31 and 0.3 % in 2030/31.

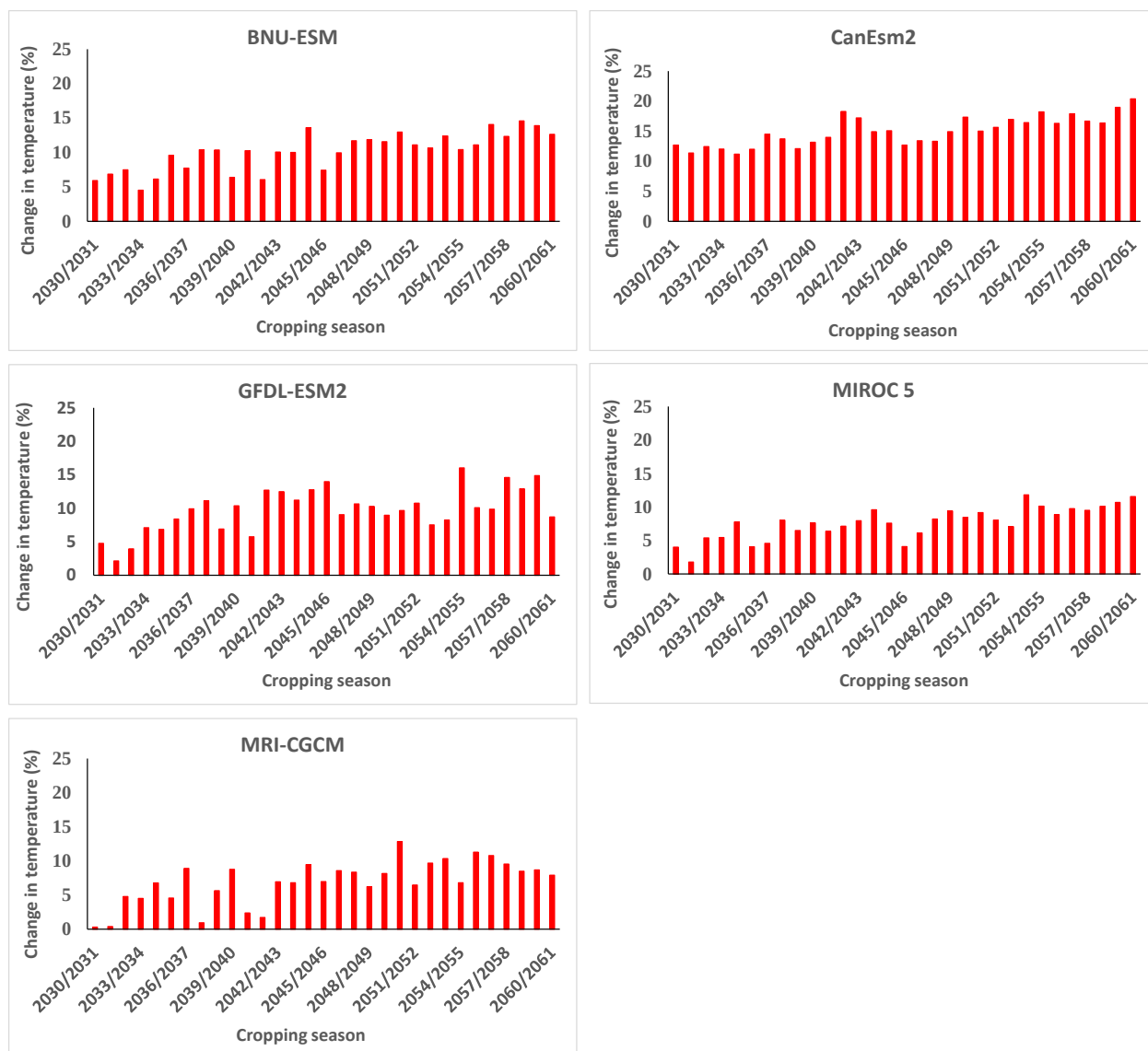


Figure 19: Change in temperature with respect to historical temperature

6.3 Projected Rainfall

The projected monthly rainfall and the historical monthly rainfall are depicted in Figure 20. With the exception of October all the cropping season months (November to March) are expected to receive seasonal rainfall amounts below the long term historical values. However, BNU-ESM2 predicts values above the historical for the months of November, February, March and April. Moreover for the same GCM the rainfall peaks in February suggesting a slight shift in seasonality in the future. For the dry season months all GCMs simulate increased rainfall amounts compared

to the historical. Nonetheless these amounts still remain negligible especially given that the study area is semi-arid.

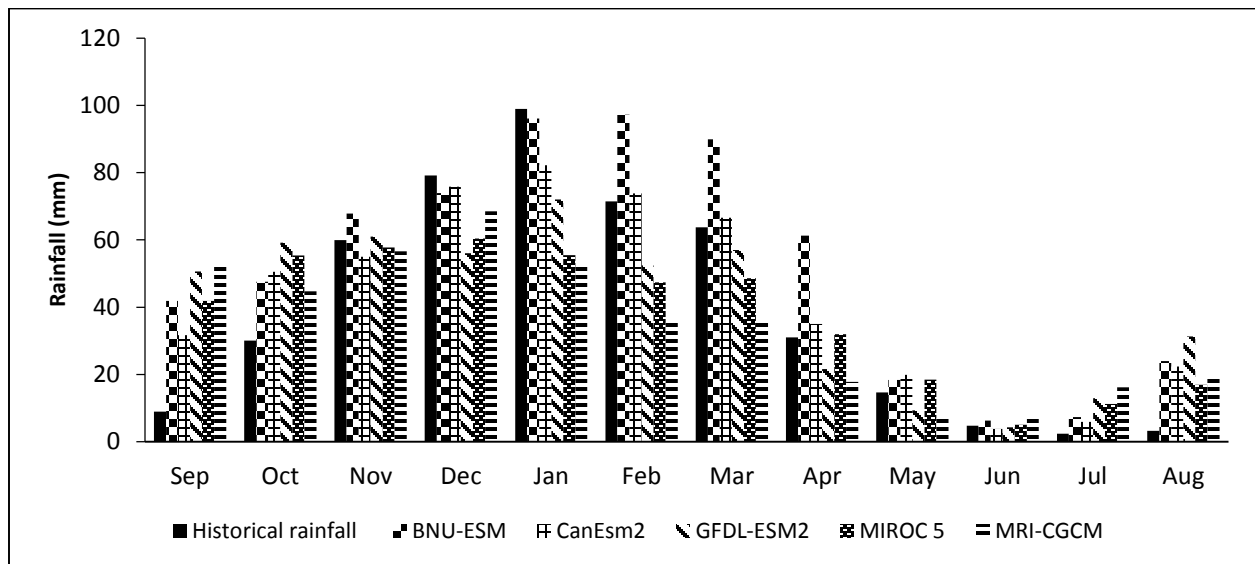


Figure 20: The projected average monthly rainfall generated by different GCMs (2030-2060) and monthly average historical rainfall (1979 to 2014)

The predicted total annual rainfall for the growing season months is shown in Figure 21. Relative to the long term mean annual historical amount of 408.96mm, BNU-ESM2 and CanEsm2 project rainfall amounts that are higher than the historical for most of the years and decreased amounts for the other models. With the exception of BNU-ESM2 the years 2040/2041, 2044/2045, 2053/2054 and 2059/2060 are anticipated to have rainfall amounts below 200 mm per year. Irrespective of the magnitude of change all GCMs project a slightly decreasing trend in rainfall with time. Figure 22 shows that the means generated by different GCMs are significant compared to the historical rainfall amounts and it is therefore anticipated that the study area may experience a general decrease in rainfall under RCP 4.5 emission scenario.

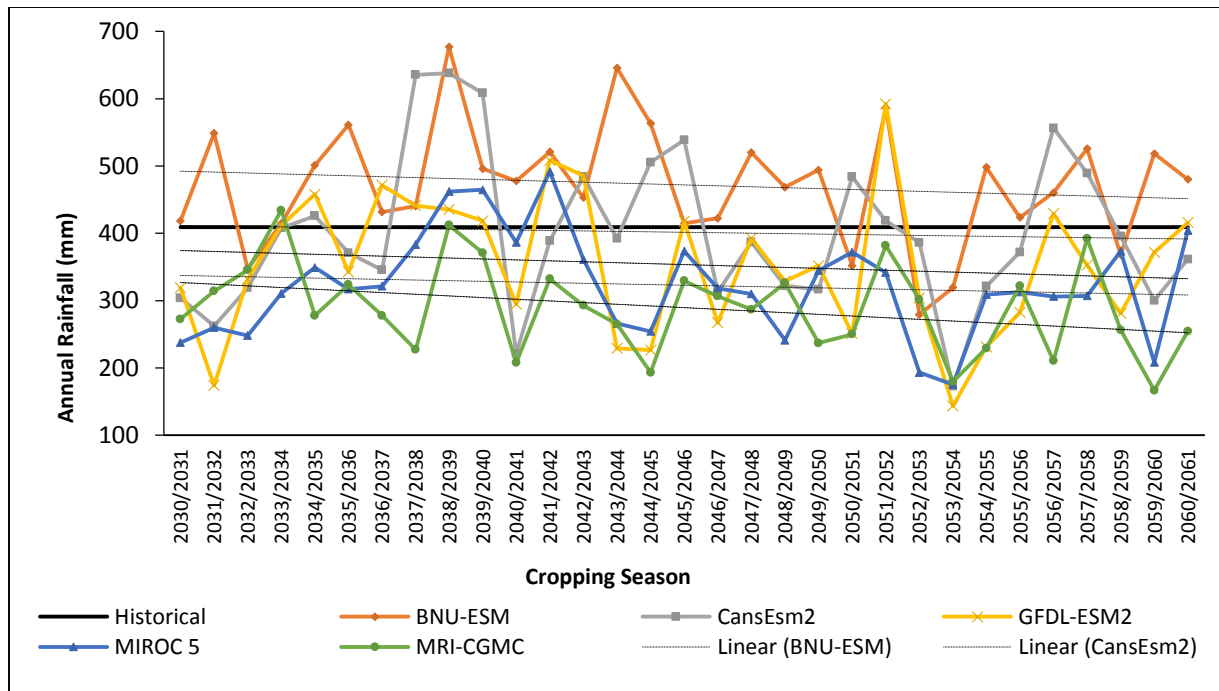


Figure 21: Historical (1979-2014) and projected average annual rainfall (2030-2060) for the cropping season.

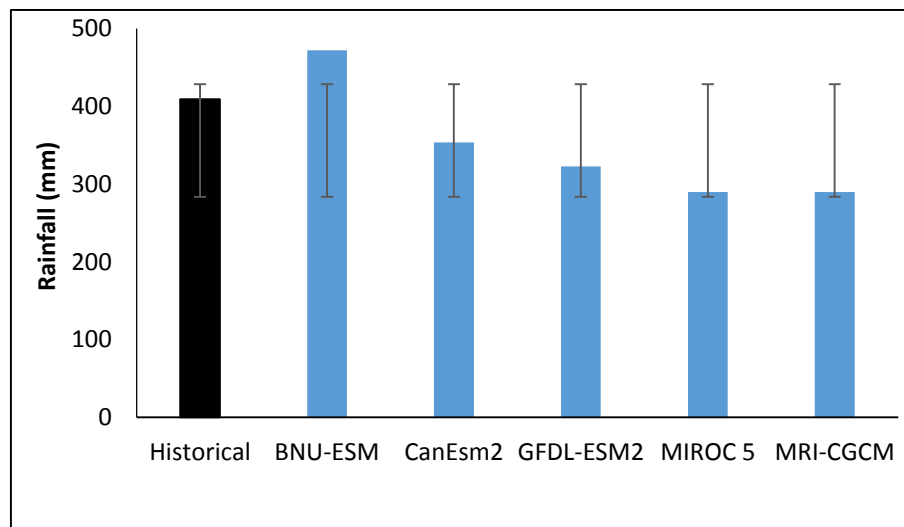


Figure 22: Historical and future average annual rainfall for Barolong Farms

It is clear that the direction and magnitude of change in future rainfall is uncertain across all the GCMs (Figure 23). For example it is expected from BNU-ESM2 that the cropping season rainfall may increase for the entire future period, but with varying amounts and with exceptional decreases of 14.44 %, 13.30 % and 9.33 % respectively in 2032/33, 2050/51 and 2058/59. In general most

of the GCMs predict decreased rainfall in the future. In general an average decrease in mean annual cropping season rainfall of 5 % to 30 % is expected by all the GCMs.

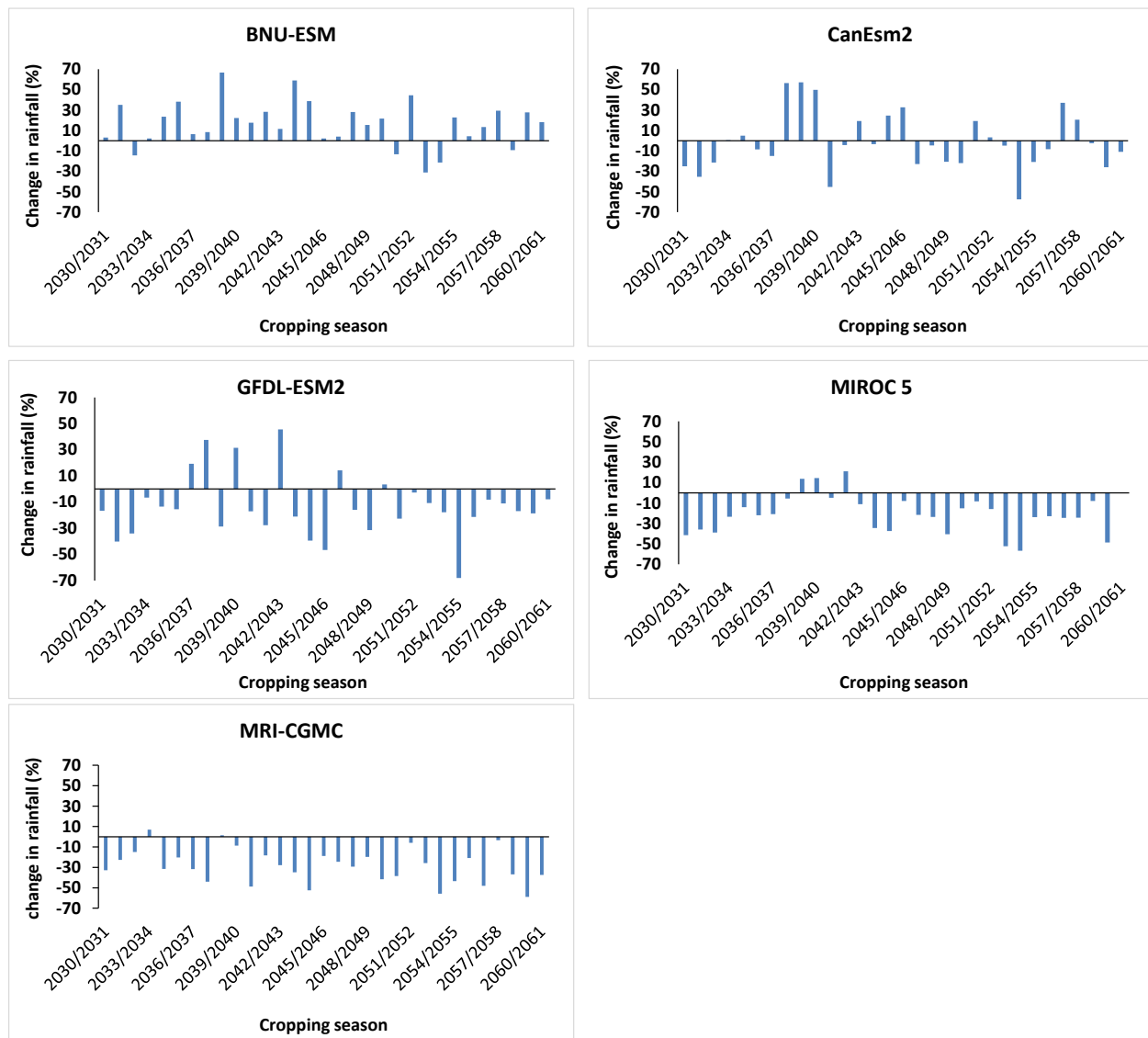


Figure 23: Percentage change in the future cropping season rainfall of Barolong Farms relative to the historical amount

6.4 Projecting sorghum yield for Barolong Farms

The projected rainfall and temperature data from the downscaled GCMs were used to drive the calibrated AquaCrop model in order to predict the future yield of sorghum. Simulations were carried out under rainfed conditions not limited by nutrients, weeds, pest and diseases. Generally all the GCMs projected a low yield of sorghum for the period of 2030 to 2060 relative to the simulated historical sorghum yield of the Barolong Farms (Figure 24). The simulated future yields were compared to the historical average yield of sorghum of 1.33 ton/ha. In general all models simulate yields below the historical average. There are few exceptions where it is speculated that in some years the yield will be above the historical average and these are: BNU-ESM2 at 1.35 ton/ha in 2053/54, followed by 2038/39 at 1.32 ton/ha, GFDL-ESM2 at 1.39 ton/ha in 2051/2052, CanEsm2 at 1.38 ton/ha in 2054/55 and MIROC5 at 1.35 ton/ha in 2055/2056. Out of all the GCMs the MRI-CGMC model simulates the lowest yields at 0.85 ton/ha, 0.92 ton/ha, 0.95 ton/ha, 0.92 ton/ha and 0.91 ton/ha in 2031/32, 2033/2034, 2036/2037, 2041/2042, 2043/2044 respectively. Overall it is difficult to tell the direction and magnitude of change with any degree of certainty.

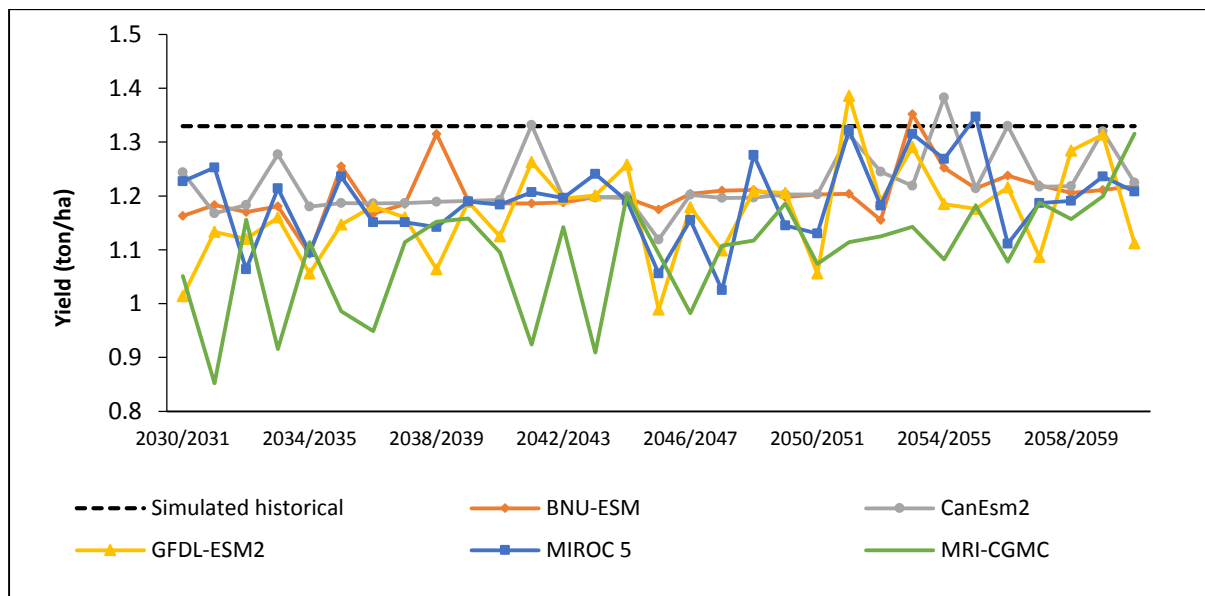


Figure 24: Average sorghum yield for Barolong Farms from 2030 to 2060

The average expected yields for the period of 2030 to 2060 generated by GCMs are as follows; BNU-ESM (1.2 ton/ha), CanEsm (1.22 ton/ha), GFDL-ESM2 (1.17 ton/ha), MIROC5 (1.19 ton/ha) and MRI-CGMC (1.09 ton/ha). These yields fall below the historical yield of 1.33 tons/ha. The change in the mean yields (Figure 25) is significant relative to the simulated historical yield of the Barolong Farms.

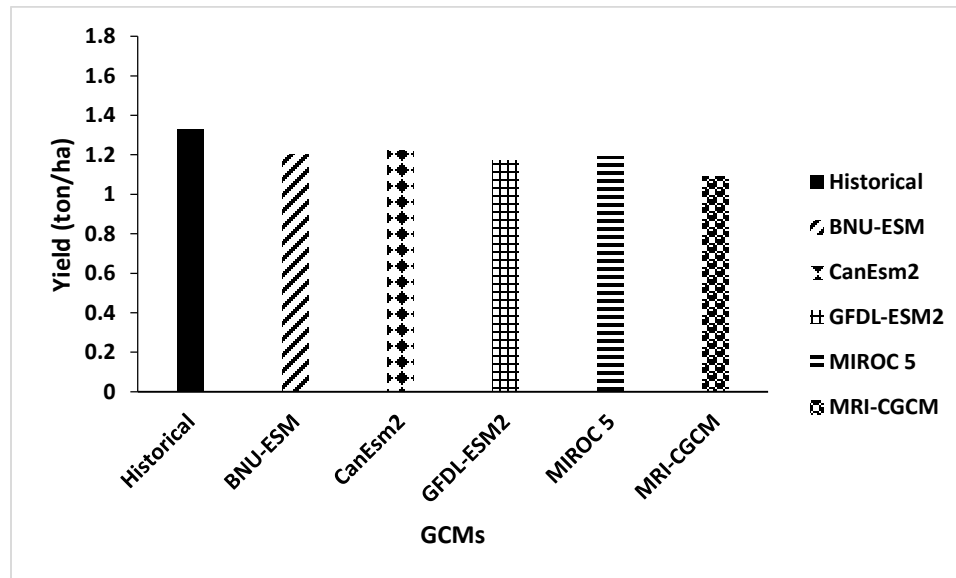


Figure 25: Average simulated sorghum yield (historical and generated by GCMs) for Barolong Farms from 2030 to 2060

The percentage change in the expected yield across all the GCMs is depicted in Figure 26. Generally all the GCMs project a reduced yield of sorghum during the period of 2030 to 2060 relative to the simulated historical yield of 2011 to 2014. MRI-CGMC is expected to experience a decrease across all the cropping seasons with the highest decrease in in 2031/32 of 35.94 %, 31.65 % in 2043/44 and 30.53 % in 2041/42. On average the sorghum yield is expected to decrease by 5 % to 10 % for BNU-ESM and CanEsm2 while a decline of 5-15 % is projected for GFDL-ESM2 and MIROC5 and the largest decrease of 10 % to 25 % is expected by MRI-CGMC. The average percentage decrease in yield of sorghum for the entire future period of 2030-2060 and for each of the GCMs is 8.04 %, 9.47 %, 10.5 %, 12.09 %, and 17.87 % for BNU-ESM, CanEsm2, MIROC5, GFDL-ESM2 and MRI-CGMC respectively.

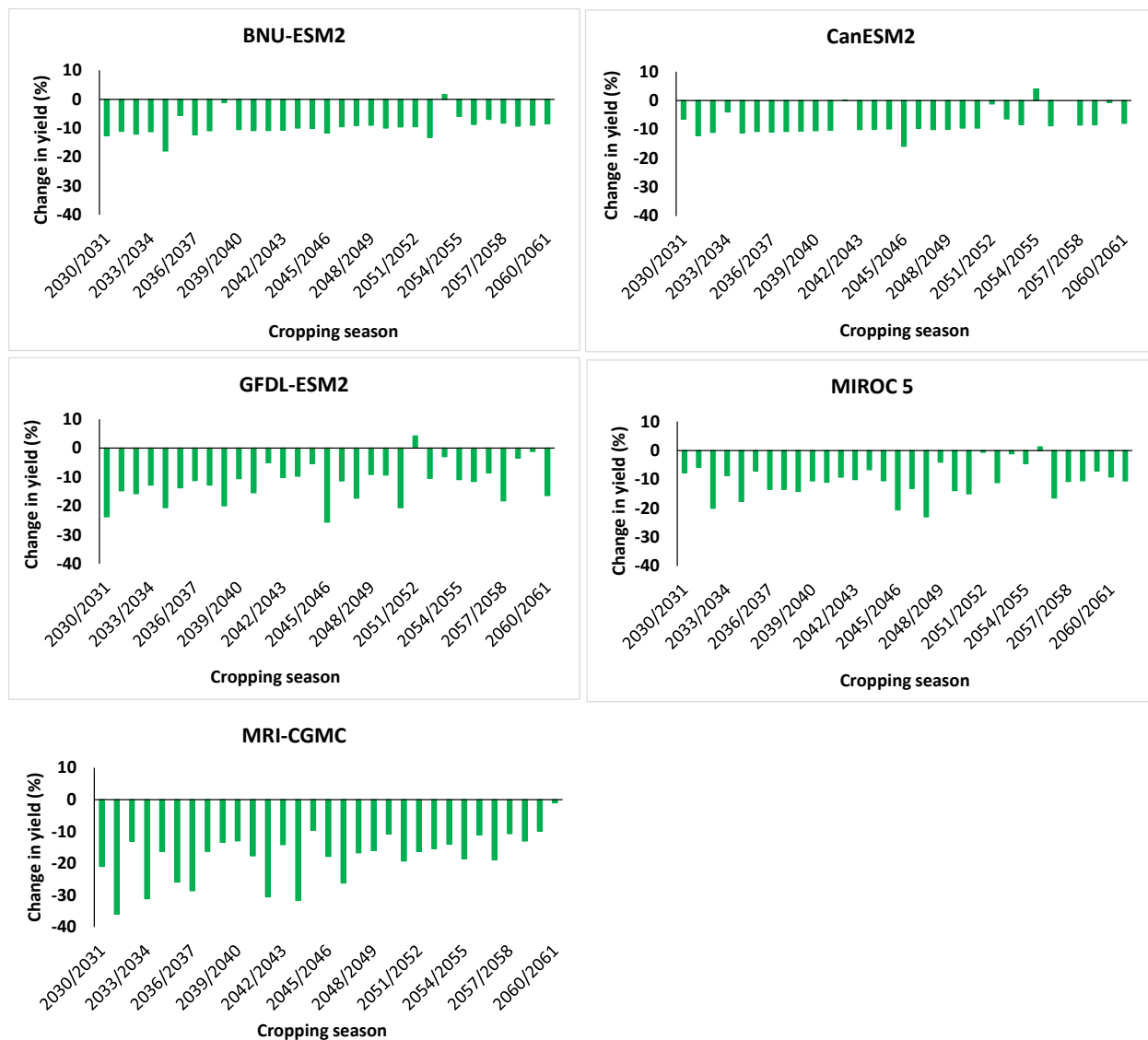


Figure 26: Average percentage change of yield generated by each GCM for Barolong Farms from 2030/31 to 2060/61

The most important climatic factors that influence growth, development and yield of crops are temperature and rainfall. Figure 27 shows average percentage change in rainfall, temperature and sorghum yield for the Barolong Farms. Based on BNU-ESM2 the study area is likely to experience an increase in both temperature and rainfall by an average of 10.12 % and 16.21 % respectively while yield is anticipated to decline by 9.47 %. For CanEsm2 temperature is expected to increase by an average of 15 % while both rainfall and yield are expected to decrease by an average of 1.13 % and 8.04 % respectively. GFDL-ESM2 projected decreases of 13.21 % in rainfall, 3 % in

temperature and 12.09 % in yield. MIROC5 is likely to have an average temperature increase of 7.64 % and decreases in rainfall and yield of 20.51 % and 10.51 % respectively. MRI-CGMC estimated to experience a temperature increase of 6.90 % and a decrease in both rainfall and yield by 28.67 % and 17.87 % respectively. From the results it can be inferred that sorghum yield is more sensitive to temperature increase compare to a decline in rainfall. For example the average rainfall is expected to increase considerably in BNU-ESM yet the yield is speculated to decrease. For Can Esm2, although the rainfall amount is projected to remain near normal to the historical amount the yield may decrease in the future and this can be attributed to an increase in the projected temperature.

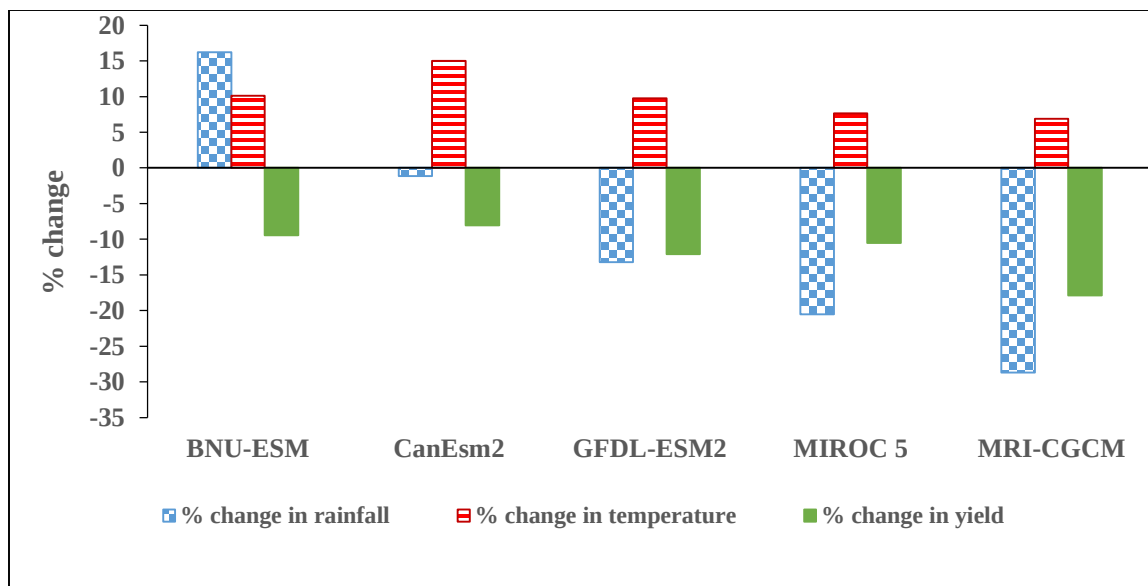


Figure 27: Average percentage change in yield, rainfall and temperature at Barolong Farms for the future (2030 to 2060).

6.5 Discussion

Based on the results all the GCMs agree on the direction of change of temperature and sorghum yield but there is no agreement in the direction of change and magnitude of rainfall. Temperature is expected to increase by between +5 % and +15 % across all GCMs while rainfall may change within a range of +5 % to -25 % and the yield is expected to change within -5 % and -15 %. Although the average mean temperature is expected to increase, it is still within the range needed for crop production in all the GCMs but implicating reduction in sorghum yield. This is because

increase in the mean seasonal temperature can possibly shorten the growth cycle of sorghum and reduces the amount of water available to crops; hence it leads to low yield. In addition, increase in temperature accelerates plant phenology reducing dry matter accumulation and crop yields by 10 % -40 % (Tubiello et al., 2006).

Rainfall on the other hand is generally expected to decrease across all the GCMs except BNU-ESM2, this is likely to contribute to low yield because of limited soil recharge. Nonetheless, it seems that the effects of increased temperature outweigh those imposed by low or decreased rainfall amounts. This can be attributed to the fact that sorghum is a drought resistant crop. Limited rainfall and increased temperature may also have a negative effect on yield due to increased rates of soil evaporation in an area which is already limited in soil moisture by virtue of a semi-arid environment. For BNU-ESM2 increased rainfall leads to reduction in yield as there is a possibility that rainfall may not be received at the right time since the results show a change in seasonality where the rainfall peaks in February rather than January. Also different stages of development of a plant need different amount of moisture, so if the rainfall increases it is not obvious that yield will increase rather it depends on the stage of crop development and the timing of the rainfall.

Finally the results show the same patterns of variability in future climate compared to the historical climate where rainfall is expected to decrease linearly while the temperature is expected to increase with time in the future.

CHAPTER 7

CONCLUSION AND RECOMMENDATIONS

7.1 Introduction

In view of the impending threats of climate change on water resources and agriculture and due to the fact that rainfed agriculture is the most common farming practice in the country, this study aimed to assess the impacts of climate variability and future climate change on sorghum yield in the Goodhope Sub District. This study concludes that the historical pattern of variability in rainfall and temperature will persist into the future while at the same time it is expected that climate change may occur in the near future of 2030-2060. Climate change is expected to have negative impacts on sorghum yield in the study area and consequently on the whole district. In order to safeguard the food security in the face of climate change it is important to have knowledge of the historical patterns of variability as well understanding and quantifying the relationships between crop productivity and climate change. Effective adaptation strategies require relevant and reliable predictions that are based on the availability of decision support tools that can adequately estimate the amount of water and grain yield in the future. This chapter presents an interpretation and implication of the results in light of the stated study objectives.

7.2 Climate variability and trends in rainfall and temperature for the Barolong farms

Understanding the historical patterns of variability is important as it can be used to make future plans in the management of water resources and in agricultural planning. It also acts as a baseline to be able tell whether there has been a change or not in the future climate. The observed trend of decreasing rainfall agrees with Batisani and Yarnal (2010) who reported that there was a trend towards decreased rainfall throughout Botswana which is linked to the decrease in the number of rainy days. If variability continues into the future then food security will continue to be under threats of a variable climate. Msongaleli et al. (2017) state that rainfall variability contributes significantly on crop production, with a possibility of crop failure in semiarid regions. However sustainable agriculture can be achieved with continuous monitoring and prediction of the rainfall and temperature patterns in the study area.

The observed rate of increase in temperature is in agreement with Knowles et al. (2006) who concluded that minimum temperatures are anticipated to increase in the future and maximum temperatures would increase at a slower rate than the minimum temperature (Hatfield and Prueger, 2015). This was attributed to the fact maximum temperatures are affected by local conditions, including soil water content and soil evaporation due to heat while minimum temperatures on the other hand are affected by changes in atmospheric water vapor content. According to Alfaro et al. (2006) temperature increase may severely affect the yield of sorghum although the impact on the yield depends on the stage of crop development (Gornall et al., 2010). Moreover (FAO 2009) state that, the optimum temperature for sorghum growth should range between 33 °C and 38 °C while the average temperature should fall within 20 °C to 25 °C. It can therefore be said that the historical temperatures were conducive to sorghum growth. Varying rainfall patterns also have a significant impact on crop production but the changes in seasonal rainfall are more important to crop production than changes in annual rainfall (Gornall et al., 2010). The observed trend of decreasing rainfall might have negative impacts on the yield of sorghum by limiting soil moisture. Lobell and Burke (2008) concluded that changes in rainfall amounts by one standard deviation during the growing season can be associated with as much as a 10 % change in crop production.

7.3 AquaCrop model calibration and sorghum yield simulation under projected climate change

The AquaCrop model was calibrated using the Goodhope Agricultural Research experimental station and validated using Barolong Farms yield data, and the model performed well. AquaCrop model has already been parameterized and tested for different crops (Hsiao et al., 2009; Steduto et al., 2009) under varying conditions of the environment, thus demonstrating that the model can be used to accurately simulate yield in response to water. It should be noted, however, that the limitation of the model includes the absence of the impact of solar radiation on crop production in terms of radiation level (Vanuytrecht, 2013). Another restriction is that the model is available for use as an assembled software package (Raes et al., 2016) which limits the applicability for users who want to relate the AquaCrop model with other crop models.

In predicting future climate change from the five downscaled GCMs, it was revealed that temperature was likely to increase while rainfall was expected to decrease in the near future period of 2030-2060. Temperature plays a significant role in the growth and yield of sorghum since optimum growth is achieved when temperatures are favorable. Both high and low temperature can cause significant decreases in sorghum grain yields by delaying seed germination and decreasing seed filling duration resulting in smaller seed size respectively. Generally the GCMs are in good agreement about warming in the future but they agree less on how climate change will impact rainfall. Unlike temperature the results showed that the direction and magnitude of change of rainfall were uncertain over all the cropping seasons across all the GCMs. These uncertainties may be attributed to model structure, parameterization and the manner in which the GCMs are conceptualized. It should be noted that an increase in precipitation does not necessarily mean that yields will increase. This is because the distribution of water during the growing season is the most important factor in accumulation of yield. High rainfall can bring outbreak of pests and diseases, flooding, water logging and falling over of plants which results in poor yields. The distribution of rainfall is what matters for crop yields. Distribution takes into consideration the requirements of water by crops during the cropping season as well as during different periods of growth and development and how far these needs are met by rainfall.

Generally the AquaCrop model, driven by all the five GCMs project that the future sorghum grain yield may decrease through a range of 5 % to 20 % but not exceeding 20 %. It can be inferred from the results of the study that the decline in yield would most likely be due to increased temperatures with minimal effects from reduced rainfall. This may be attributed to the fact that sorghum is a drought resistant crop and may not be very sensitive to changes in rainfall amounts but rather to the timing of the rainfall. Hatfield et al. (2011) also concur that increased temperatures are expected to reduce (-2.5 % to -10 %) the yield of a wide number of field crops throughout the 21st century. Furthermore plants grow only within certain limits of temperature at different growth stages and functions, and this also requires different levels of moisture. According to Erda et al. (2006) high temperatures result in increased levels of carbon dioxide, while increased levels of carbon dioxide also lead to increased temperatures. In general high CO₂ in the atmosphere increases the photosynthetic activity and therefore promotes growth, development and yield of

crop (Fuhrer, 2003).). Nonetheless, if temperatures increase further than a certain point, they may negatively affect pollination, the reproductive processes and plant growth and ultimately the yield, (Sacks and Kucharik, 2011). Also changes in temperature together with unreliable rainfall patterns have a negative impact on crops because high temperatures may increase soil evaporation hence reducing the amount of moisture available to crops (Poudel and Shaw, 2016). This situation will impose more drastic impacts on crop productivity especially under semi-arid and rainfed conditions like those at the Barolong Farms, where water is already scarce.

In conclusion this study demonstrated that climate change is likely to have negative impacts on agricultural productivity and this has important implications on food security especially given that most livelihoods in Botswana depend on rainfed agriculture for sustenance. It should be noted that the results of this study are preliminary findings and do not necessarily provide a comprehensive assessment of the impacts of climate change in Botswana. Based on the fact that there are indications that the climate is changing there is need for the country to come up with climate-smart strategies that will safeguard food security and inform better adaptive approaches to climate change. It should be noted, however, that risk assessments will be inaccurate if they do not account for the autonomous adaptation that occurs in changing climates (Challinor, et al., 2018). Therefore the results of this study can contribute to the development and improvement of long-term strategies in managing the risk and adaptation in a changing climate.

7.4 Recommendations

Since the model was able to adequately simulate the future sorghum yield for Barolong Farms, it is recommended that its use be extended to other areas in the country. However, since parameters such as temperature, rainfall, soil characteristics are location specific and sometimes the cultivar of the crop may be different, it is always necessary to recalibrate the model if such parameters change. Climate change poses serious implications on policy and decision making for food security especially because most of the local farmers are traditional farmers as a result climate change education is required and it is recommended for the government to come up with strategies and policies which can help the dryland farmers adapt to climate change. Some of the strategies may

include changes in planting date, irrigation, crop variety and fertilizer application (Challinor et al., 2018).

REFERENCES

- Abedinpour, M., Sarangi, A., Rajput, T. B. S., Singh, M., Pathak, H., and Ahmad, T. (2012). Performance evaluation of AquaCrop model for maize crop in a semi-arid environment. *Agricultural Water Management*, 110, 55-66.
- Adams, C. B., and Erickson, J. E. (2017). Yield enhancement by short-term imposition of severe water deficit in the vegetative growth stage of grain sorghum. *Journal of Agronomy and Crop Science*, 203(4), 309-314.
- Adelabu, S., Areola, O., and Sebego, R. J. (2010). Assessing growing season changes in southern Botswana. *Afr. J. Plant Sci. Biotechnol*, 5(1), 81-88.
- Adhikari, U., Nejadhashemi, A. P., and Woznicki, S. A. (2015). Climate change and eastern Africa: a review of impact on major crops. *Food and Energy Security*, 4(2), 110-132.
- Alexander, L. V., Zhang, X., Peterson, T. C., Caesar, J., Gleason, B., Klein Tank, A. M. G., and Tagipour, A. (2006). Global observed changes in daily climate extremes of temperature and precipitation. *Journal of Geophysical Research: Atmospheres*, 111(D5).
- Alfaro, E.J., Gershunov, A., and Cayan, D., (2006). Prediction of summer maximum and minimum temperature over the central and western United States: the roles of soil moisture and sea surface temperature. *J. Clim.* 19, 1407–1421.
- Altieri, M. A., and Nicholls, C. I. (2017). The adaptation and mitigation potential of traditional agriculture in a changing climate. *Climatic Change*, 140(1), 33-45.
- Amekudzi, L. K., Yamba, E. I., Preko, K., Asare, E. O., Aryee, J., Baidu, M., and Codjoe, S. N. (2015). Variabilities in rainfall onset, cessation and length of rainy season for the various agro-ecological zones of Ghana. *Climate*, 3(2), 416-434.
- Antle, J. M., and Stöckle, C. O. (2017). Climate impacts on agriculture: insights from agronomic-economic analysis. *Review of Environmental Economics and Policy*, 11(2), 299-318.
- Araya, A., Habtu, S., Hadgu, K. M., Kebede, A., and Dejene, T. (2010). Test of AquaCrop model in simulating biomass and yield of water deficient and irrigated barley (*Hordeum vulgare*). *Agricultural Water Management*, 97(11), 1838-1846.
- Asseng, S., Ewert, F., Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., and Brisson, N. (2013). Uncertainty in simulating wheat yields under climate change. *Nature Climate Change*, 3(9), 827.
- Asseng, S., Foster, I. A. N., and Turner, N. C. (2011). The impact of temperature variability on wheat yields. *Global Change Biology*, 17(2), 997-1012.
- Barlow, K. M., Christy, B. P., O’leary, G. J., Riffkin, P. A., and Nuttall, J. G. (2015). Simulating the impact of extreme heat and frost events on wheat crop production: a review. *Field Crops Research*, 171, 109-119.

- Batisani, N., and Yarnal, B. (2010). Rainfall variability and trends in semi-arid Botswana: implications for climate change adaptation policy. *Applied Geography*, 30(4), 483-489.
- Belay, A., Recha, J. W., Woldeamanuel, T., and Morton, J. F. (2017). Smallholder farmers' adaptation to climate change and determinants of their adaptation decisions in the Central Rift Valley of Ethiopia. *Agriculture and Food Security*, 6(1), 24.
- Bitu, C., and Gerats, T. (2013). Plant tolerance to high temperature in a changing environment: scientific fundamentals and production of heat stress-tolerant crops. *Frontiers in plant science*, 4, 273.
- Bremer, S., and Meisch, S. (2017). Co-production in climate change research: reviewing different perspectives. *Wiley Interdisciplinary Reviews: Climate Change*, 8(6).
- Brugnach, M., Craps, M., and Dewulf, A. R. P. J. (2017). Including indigenous peoples in climate change mitigation: addressing issues of scale, knowledge and power. *Climatic change*, 140(1), 19-32.
- Bruinsma, J. (2017). *World agriculture: towards 2015/2030: an FAO study*. Routledge.
- Burns, D. A., Klaus, J., and McHale, M. R. (2007). Recent climate trends and implications for water resources in the Catskill Mountain region, New York, USA. *Journal of Hydrology*, 336(1-2), 155-170.
- Byakatonda, J., Parida, B. P., Kenabatho, P. K., and Moalafhi, D. B. (2018). Influence of climate variability and length of rainy season on crop yields in semiarid Botswana. *Agricultural and Forest Meteorology*, 248, 130-144.
- Cairns, J. E., Sonder, K., Zaidi, P. H., Verhulst, N., Mahuku, G., Babu, R., and Rashid, Z. (2012). Maize production in a changing climate: impacts, adaptation, and mitigation strategies. In *Advances in agronomy* (Vol. 114, pp. 1-58). Academic Press.
- Carter, T. R., Parry, M. L., Harasawa, H. and Nishioka S. (1994). IPCC technical guidelines for assessing climate change impacts and adaptations, IPCC Special Report to Working Group II of IPCC, London, 72pp.
- Ceglar, A., Toreti, A., Lecerf, R., Van der Velde, M., and Dentener, F. (2016). Impact of meteorological drivers on regional inter-annual crop yield variability in France. *Agricultural and forest meteorology*, 216, 58-67.
- Challinor, A. J., Ewert, F., Arnold, S., Simelton, E., and Fraser, E. (2009). Crops and climate change: progress, trends, and challenges in simulating impacts and informing adaptation. *Journal of experimental botany*, 60(10), 2775-2789.
- Challinor, A. J., Müller, C., Asseng, S., Deva, C., Nicklin, K. J., Wallach, D., and Koehler, A. K. (2018). Improving the use of crop models for risk assessment and climate change adaptation. *Agricultural systems*, 159, 296-306.

- Challinor, A. J., Watson, J., Lobell, D. B., Howden, S. M., Smith, D. R., and Chhetri, N. (2014). A meta-analysis of crop yield under climate change and adaptation. *Nature Climate Change*, 4(4), 287.
- Challinor, A. J., Wheeler, T. R., Craufurd, P. Q., Slingo, J. M., and Grimes, D. I. F. (2004). Design and optimisation of a large-area process-based model for annual crops. *Agricultural and forest meteorology*, 124.
- Challinor, A., Allison, R., Carron, J., Errard, J., Feeney, S., Kitching, T., and Ade, P. (2018). Exploring cosmic origins with CORE: Gravitational lensing of the CMB. *Journal of Cosmology and Astroparticle Physics*, 2018(04), 018.
- Chandra, Alvin, Karen E. McNamara, Paul Dargusch, Ana Maria Caspe, and Dante Dalabajan. (2017) "Gendered vulnerabilities of smallholder farmers to climate change in conflict-prone areas: A case study from Mindanao, Philippines." *Journal of rural studies* 50: 45-59.
- Chiew, F. H. S., Teng, J., Vaze, J., Post, D. A., Perraud, J. M., Kirono, D. G. C., and Viney, N. R. (2009). Estimating climate change impact on runoff across southeast Australia: Method, results, and implications of the modelling method. *Water Resources Research*, 45(10).
- Chipanshi, A. C., Chanda, R., and Totolo, O. (2003). Vulnerability assessment of the maize and sorghum crops to climate change in Botswana. *Climatic change*, 61(3), 339-360.
- Clarke L., Edmonds J., Krey V., Richels R., Rose S., and Tavoni M., (2010). International climate policy architectures: overview of the EMF 22 international scenarios. *Energ Econ* 31,suppl 2, S64–S81.
- Confalonieri, R., Acutis, M., Bellocchi, G., and Donatelli, M. (2009). Multi-metric evaluation of the models WARM, CropSyst, and WOFOST for rice. *Ecological Modelling*, 220(11), 1395-1410.
- Conway, D., Van Garderen, E. A., Deryng, D., Dorling, S., Krueger, T., Landman, W., and Thurlow, J. (2015). Climate and southern Africa's water–energy–food nexus. *Nature Climate Change*, 5(9), 837.
- Cooper, P. J. M. (2008) Coping better with current climatic variability in the rain-fed farming systems of Sub-Saharan Africa: An essential first step in adapting to future climate change." *Agriculture, Ecosystems & Environment* 126.1: 24-35.
- Davis, C. L., and Vincent, K. (2017). *Climate risk and vulnerability: A handbook for Southern Africa*.
- De Trincheria, J., Craufurd, P., Harris, D., Mannke, F., Nyamangara, J., Rao, K. P. C., and Leal Filho, W. (2015). Adapting agriculture to climate change by developing promising strategies using analogue locations in eastern and southern Africa: a systematic approach to develop practical solutions. In *Adapting African Agriculture to Climate Change* (pp. 1-23). Springer, Cham.
- Department of Agricultural Research. (DAR), (1977-2000) Annual reports for the Crop Research Division, Ministry of Agriculture, Gaborone, Botswana.

Department of Agricultural Research. (DAR), (1999-2012) Field Crops Reference Handbook in Botswana, Division of Arable Research, Ministry of Agriculture, Gaborone, Botswana.

Department of Meteorological Services. (2014 Goodhope, Botswana

Deryng, D., Conway, D., Ramankutty, N., Price, J., and Warren, R. (2014). Global crop yield response to extreme heat stress under multiple climate change futures. *Environmental Research Letters*, 9(3), 034011.

Doorenbos, J., Kassam, A.H., (1979). Yield Response to Water. FAO Irrig. Drain. Paper 33. FAO, Rome, Italy (193 pp.).

Dossou-Aminon, I., Dansi, A., Ahissou, H., Cissé, N., Vodouhè, R., and Sanni, A. (2016). Climate variability and status of the production and diversity of sorghum (*Sorghum bicolor* (L.) Moench) in the arid zone of northwest Benin. *Genetic resources and crop evolution*, 63(7), 1181-1201.

Dwivedi, A., Dev, I., Kumar, V., Yadav, R. S., Yadav, M., Gupta, D., and Tomar, S. S. (2015). Potential role of maize-legume intercropping systems to improve soil fertility status under smallholder farming systems for sustainable agriculture in India. *International Journal of Life Sciences Biotechnology and Pharma Research*, 4(3), 145.

Easterling, D. R., Meehl, G. A., Parmesan, C., Changnon, S. A., Karl, T. R., and Mearns, L. O. (2000). Climate extremes: observations, modelling, and impacts. *Science*, 289(5487), 2068-2074.

Ehret, U., Zehe, E., Wulfmeyer, V., Warrach-Sagi, K., and Liebert, J. (2012). HESS Opinions" Should we apply bias correction to global and regional climate model data. *Hydrology and Earth System Sciences*, 16(9), 3391-3404.

Elias, E., Marklein, A., Abatzoglou, J. T., Dialesandro, J., Brown, J., Steele, C., and Steenwerth, K. (2017). Vulnerability of field crops to midcentury temperature changes and yield effects in the Southwestern USA. *Climatic Change*, 1-15.

Evet, S. R., and Tolk, J. A. (2009). Introduction: Can Water Use Efficiency Be Modeled Well Enough to Impact Crop Management? All rights reserved. No part of this periodical may be reproduced or transmitted in any form or by any means, electronic or mechanical, including photocopying, recording, or any information storage and retrieval system, without permission in writing from the publisher. *Agronomy Journal*, 101(3), 423-425.

Ewert, F., Rötter, R. P., Bindi, M., Webber, H., Trnka, M., Kersebaum, K. C., and Semenov, M. A. (2015). Crop modelling for integrated assessment of risk to food production from climate change. *Environmental Modelling & Software*, 72, 287-303.

FAO (2008). Unlocking the water potential of agriculture. Food and Agriculture Organisation of the United Nations, Rome Italy.

FAO (2016) The state of food and agriculture - climate change, agriculture and food security. Rome Italy.

FAO (Food and Agriculture Organization of the United Nations) (2009) .The state of food and agriculture. Biofuels: prospects, risks and opportunities. FAO, Rome.

FAO (Food and Agriculture Organization of the United Nations) (2012).Reference Manual, Annex I – AquaCrop, Version 4.0. FAO, Rome.

FAO, I. (2016). WFP (2015). The State of Food Insecurity in the World 2015. Meeting the 2015 international hunger targets: taking stock of uneven progress. Food and Agriculture Organization Publications, Rome.

Farahani Hj, Izzi G and Oweis T.Y., (2009) Parameterization and evaluation of the AquaCrop model for full and deficit

Farshad, A., and Zinck, J. A. (1993). Seeking agricultural sustainability. Agriculture, ecosystems and environment, 47(1), 1-12.

Fatichi, S., Ivanov, V. Y., and Caporali, E. (2011). Simulation of future climate scenarios with a weather generator. Advances in Water Resources 34, 448-467.

Frank, D., Reichstein, M., Bahn, M., Thonicke, K., Frank, D., Mahecha, M. D., and Beer, C. (2015). Effects of climate extremes on the terrestrial carbon cycle: concepts, processes and potential future impacts. Global Change Biology, 21(8), 2861-2880.

Fuhrer, J. (2003). Agroecosystem responses to combinations of elevated CO₂, ozone, and global climate change. Agriculture, Ecosystems and Environment, 97(1-3), 1-20.

Gebrekiros, G., Araya, A., and Yemane, T. (2016). Modeling impact of climate change and variability on sorghum production in Southern Zone of Tigray, Ethiopia. Journal of Earth Science and Climate Change, 7(1), 1-10.

Giorgi, F., and Francisco, R. (2000). Evaluating uncertainties in the prediction of regional climate change. Geophysical Research Letters, 27(9), 1295-1298.

Giorgi, G. (2005). The new deal for young people five years on. Fiscal Studies, 26(3), 371-383.

Glaser, J., Lemery, J., Rajagopalan, B., Diaz, H. F., García-Trabanino, R., Taduri, G., and Jha, V. (2016). Climate change and the emergent epidemic of CKD from heat stress in rural communities: the case for heat stress nephropathy. Clinical Journal of the American Society of Nephrology, 11(8), 1472-1483.

Gleick, P.H. (1989). Climate Change, Hydrology and Water Resources. Reviews of Geophysics, 27(3), 329–344.

Godfray, H. C. J., Beddington, J. R., Crute, I. R., Haddad, L., Lawrence, D., Muir, J. F., and Toulmin, C. (2010). Food security: the challenge of feeding 9 billion people. Science, 327(5967), 812-818.

Gornall, J., Betts, R., Burke, E., Clark, R., Camp, J., Willett, K., and Wiltshire, A. (2010). Implications of climate change for agricultural productivity in the early twenty-first

century. *Philosophical Transactions of the Royal Society of London B: Biological Sciences*, 365(1554), 2973-2989.

Gray, S. B., and Brady, S. M. (2016). Plant developmental responses to climate change. *Developmental biology*, 419(1), 64-77.

Hadebe, S. T., Modi, A. T., and Mabhaudhi, T. (2017). Calibration and testing of AquaCrop for selected sorghum genotypes. *Water SA*, 43(2), 209-221.

Hatfield, J. L., and Prueger, J. H. (2015). Temperature extremes: effect on plant growth and development. *Weather and Climate Extremes*, 10, 4-10.

Hatfield, J. L., Boote, K. J., Kimball, B. A., Ziska, L. H., Izaurralde, R. C., Ort, D., and Wolfe, D. (2011). Climate impacts on agriculture: implications for crop production. *Agronomy journal*, 103(2), 351-370.

Heng, L.K., Hsiao, T.C., Evett, S., Howell, T., and Steduto, P. (2009). Validating the FAO AquaCrop Model for Irrigated and Water Deficient Field Maize. *Agron. J.* 101, 488-498.

Hertel, T. W., and Lobell, D. B. (2014). Agricultural adaptation to climate change in rich and poor countries: Current modelling practice and potential for empirical contributions. *Energy Economics*, 46, 562-575.

Hertel, T. W., and Rosch, S. D. (2010). Climate change, agriculture, and poverty. *Applied Economic Perspectives and Policy*, 32(3), 355-385.

Hewitson, B. C. and Crane, R. G. (1996). Climate downscaling: Techniques and applications. *Clim. Res.* (7), 85–95.

Hsiao, T. C., Heng, L., Steduto, P., Rojas-Lara, B., Raes, D., and Fereres, E. (2009). AquaCrop-The FAO Crop Model to Simulate Yield Response to Water: III. Parameterization and Testing for Maize. *Agronomy Journal* 101, 448-459.

Hsiao, T. C., Heng, L., Steduto, P., Rojas-Lara, B., Raes, D., and Ince, D.C., Hatton, L., Graham-Cumming, J., (2012). The case for open computing, programs. *Nature* 482, 485–488.

Iizumi, T., and Ramankutty, N. (2015). How do weather and climate influence cropping area and intensity. *Global Food Security*, 4, 46-50.

IPCC (2014) *Climate change 2014: Impacts adaptation and vulnerability. Part B: Regional aspects. Contribution of working group II to the fifth assessment report of Intergovernmental Panel on Climate Change* [Barros VR, Field CB, Dokken DJ, Mastrandrea MD, Mach KJ, Bilir TE, Chatterjee M, Ebi KL, Estrada YO, Genova RC, Girma B, Kissel ES, Levy AN, MacCracken S, Mastrandrea PR, and White LL. (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 688.

IPCC (2014a). *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, eds C. B. Field, V.R. Barros, D. J. Dokken, K. J.

Mach, M. D. Mastrandrea, T. E. Bilir, M. Chatterjee, K. L. Ebi, Y. O. Estrada, R. C. Genova, B. Girma, E. S. Kissel, A. N. Levy, S. MacCracken, P. R. Mastrandrea, and L. L. White. Cambridge; New York, NY: Cambridge University Press.

IPCC (2014b). Climate Change 2014: Synthesis Report. Contribution of Working Groups, I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, eds Core Writing Team, R. K. Pachauri, and L. A. Meyer. Geneva: IPCC.

Jacob, D., and Van den Hurk, B. (2012). Climate change scenarios at the global and local scales. In *Climate change adaptation in the water sector* (pp. 45-56). Routledge.

Jevrejeva, S., Moore, J. C., and Grinsted, A. (2012). Sea level projections to AD2500 with a new generation of climate change scenarios. *Global and Planetary Change*, 80, 14-20.

Jones, C. A., Kiniry, J. R., and Dyke, P. T. (1986). *CERES-Maize: A simulation model of maize growth and development*. Texas University Press.

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

Karamanos, A. J. and Gimenez. C. (1991) Physiological factors limiting growth and yield of Faba beans. *Options Méditerranéennes - Série Séminaires - n.O 10 - 1991: 79-90.*

Kaur, A., Sraw, P. K., and Kukal, S. S. (2017). Climatic Variability Impact on Wheat-Based Cropping Systems of South Asia: Adaptation and Mitigation. In *Quantification of Climate Variability, Adaptation and Mitigation for Agricultural Sustainability* (pp. 353-370). Springer, Cham.

Kenabatho, P. K., and Parida, B. P. (2018). Challenges for sustainable water resources management in Botswana: The case of data and associated uncertainty. In *Handbook of Research on Geospatial Science and Technologies* (pp. 115-127). IGI Global.

Kenabatho, P. K., Parida, B. P., and Moalafhi, D. B. (2012). The value of large-scale climate variables in climate change assessment: The case of Botswana's rainfall. *Physics and Chemistry of the Earth, Parts A/B/C*, 50, 64-71.

Kendall, M.G. (1975). *Rank Correlation Methods*. 4th Edition, Charles Griffin, London. 202pp
Kirtman, B., Power, S. B., Adedoyin, A. J., Boer, G. J., Bojariu, R., Camilloni, I., and Prather, M. (2013). Near-term climate change: projections and predictability.

Klove, B., Ala-Aho, P., Bertrand, G., Gurdak, J. J., Kupfersberger, H., Kværner, J., and Uvo, C. B. (2014). Climate change impacts on groundwater and dependent ecosystems. *Journal of Hydrology*, 518, 250-266.

Knowles, N., Dettinger, M. D., and Cayan, D. R. (2006). Trends in snowfall versus rainfall in the western United States. *Journal of Climate*, 19(18), 4545-4559.

Knutti, R., Furrer, R., Tebaldi, C., Cermak, J., and Meehl, G. A. (2010). Challenges in combining projections from multiple climate models. *Journal of Climate*, 23(10), 2739-2758.

- Kpongpor, D. (2007). Spatially explicit modelling of sorghum (*Sorghum bicolor* L) production on complex terrain of a semi-arid region of Ghana using APSIM (Doctoral dissertation, PhD thesis. University of Bonn, Germany.
- Kundzewicz, Z. W., Hirabayashi, Y., and Kanae, S. (2010). River floods in the changing climate—observations and projections. *Water Resources Management*, 24(11), 2633-2646.
- Kurukulasuriya, P., and Rosenthal, S. (2003). Climate change and agriculture: A review of impacts and adaptations World Bank climate change series paper no. 91. Paper prepared and published for the Rural Development Group and Environment Department of the World Bank, 106.
- Laura Uusitalo L., Lehtikoinen A., Helle I. and Myrberg K. (2015). An overview of methods to evaluate uncertainty of deterministic models in decision support. *Environmental Modelling & Software*, 63, 24-31.
- Lawal, J. O., and Omonona, B. T. (2014). The effects of rainfall and other weather parameters on cocoa production in Nigeria. *Communicata Scientiae*, 5(4), 518-523.
- Lobell, D. B., and Burke, M. B. (2010). Why are agricultural impacts of climate change so uncertain. The importance of temperature relative to precipitation. *Environmental Research Letters*, 3(3), 034007.
- Lobell, D. B., Burke, M. B., Tebaldi, C., Mastrandrea, M. D., Falcon, W. P., and Naylor, R. L. (2008). Prioritizing climate change adaptation needs for food security in 2030. *Science*, 319(5863), 607-610.
- Lobell, D. B., Hammer, G. L., Chenu, K., Zheng, B., McLean, G., and Chapman, S. C. (2015). The shifting influence of drought and heat stress for crops in northeast Australia. *Global change biology*, 21(11), 4115-4127.
- Lobell, D. B., Schlenker, W., and Costa-Roberts, J. (2011). Climate trends and global crop production since 1980. *Science*, 333(6042), 616-620.
- Mahmoudi, H., and Knierim, A. (2015). Risk Communication for Farmers' Adaptation to Climate Change: A New Task for Agricultural Advisory Services. *International Journal of Performability Engineering*, 11(6).
- Mainali, K. P., Warren, D. L., Dhileepan, K., McConnachie, A., Strathie, L., Hassan, G., and Parmesan, C. (2015). Projecting future expansion of invasive species: comparing and improving methodologies for species distribution modelling. *Global change biology*, 21(12), 4464-4480.
- Maiorano, A., Martre, P., Asseng, S., Ewert, F., Müller, C., Rötter, R. P., and Alderman, P. D. (2017). Crop model improvement reduces the uncertainty of the response to temperature of multi-model ensembles. *Field crops research*, 202, 5-20.
- Martre, P., Wallach, D., Asseng, S., Ewert, F., Jones, J. W., Rötter, R. P., and Hatfield, J. L. (2015). Multimodel ensembles of wheat growth: many models are better than one. *Global change biology*, 21(2), 911-925.

Martre, P., Wallach, D., Asseng, S., Ewert, F., Jones, J.W., Rotter, R.P., Boote, K.J., Ruane, A.C., Thorburn, P.J., Cammarano, D., Hatfield, J.L., Rosenzweig, C., Aggarwal, P.K., Angulo, C., Basso, B., Bertuzzi, P., Biernath, C., Brisson, N., Challinor, A.J., Doltra, J., Gayler, S., Goldberg, R., Grant, R.F., Heng, L., Hooker, J., Hunt, L.A., Ingwersen, J., Izaurralde, R.C., Kersebaum, K.C., Muller, C., Kumar, S.N., Nendel, C., O'Leary, G., Olsen, J.E., Osborne, T.M., Palosuo, T., Priesack, E., Ripoche, D., Semenov, M.A., Shcherbak, I., Steduto, P., Stockel, C.O., Stratonovitch, P., Streck, T., Supit, I., Tao, F., Travasso, M., Waha, K., White, J.W., Wolf, J., 2014. Mutlimodel ensembles of wheat growth: many models are better than one. *Glob. Chang. Biol.* <http://dx.doi.org/10.1111/gcb.12768>.

Masson-Delmotte, V., Schulz, M., Abe-Ouchi, A., Beer, J., Ganopolski, A., González Rouco, J. F., and Osborn, T. (2013). Information from paleoclimate archives. *Climate change*, 383464, 2013.

Mathobo, R., Marais, D., and Steyn, J. M. (2017). The effect of drought stress on yield, leaf gaseous exchange and chlorophyll fluorescence of dry beans (*Phaseolus vulgaris* L.). *Agricultural Water Management*, 180, 118-125.

Maurer, E. P., and Hidalgo, H. G. (2008). Utility of daily vs. monthly large-scale climate data: an intercomparison of two statistical downscaling methods.

Mizukami, N., Clark, M. P., Gutmann, E. D., Mendoza, P. A., Newman, A. J., Nijssen, B., and Brekke, L. D. (2016). Implications of the methodological choices for hydrologic portrayals of climate change over the contiguous United States: statistically downscaled forcing data and hydrologic models. *Journal of Hydrometeorology*, 17(1), 73-98.

Moss, R. H., Edmonds, J. A., Hibbard, K. A., Manning, M. R., Rose, S. K., Van Vuuren, D. P., and Meehl, G. A. (2010). The next generation of scenarios for climate change research and assessment. *Nature*, 463(7282), 747.

Msongaleli, B. M., Rwehumbiza, F., Tumbo, S. D., and Kihupi, N. (2015). Impacts of climate variability and change on rainfed sorghum and maize: implications for food security policy in Tanzania.

Msongaleli, B. M., Tumbo, S. D., Kihupi, N. I., and Rwehumbiza, F. B. (2017). Performance of Sorghum Varieties under Variable Rainfall in Central Tanzania. *International scholarly research notices*, 2017.

Murphy, C., Tembo, M., Phiri, A., Yerokun, O., and Grummell, B. (2016). Adapting to climate change in shifting landscapes of belief. *Climatic change*, 134(1-2), 101-114.

Nakicenovic, N., Alcamo, J., Grubler, A., Riahi, K., Roehrl, R. A., Rogner, H. H., and Victor, N. (2000). Special report on emissions scenarios (SRES), a special report of Working Group III of the intergovernmental panel on climate change. Cambridge University Press.

New, M., Hulme, M., and Jones, P. (2000). Representing twentieth-century space–time climate variability. Part II: Development of 1901–96 monthly grids of terrestrial surface climate. *Journal of climate*, 13(13), 2217-2238.

Ochieng, D. O., Veetil, P. C., and Qaim, M. (2017). Farmers' preferences for supermarket contracts in Kenya. *Food Policy*, 68, 100-111.

- Ottman, M. J., Kimball, B. A., White, J. W., and Wall, G. W. (2012). Wheat growth response to increased temperature from varied planting dates and supplemental infrared heating. *Agronomy Journal*, 104(1), 7-16.
- Pachauri, R. K., Allen, M. R., Barros, V. R., Broome, J., Cramer, W., Christ, R., and Dubash, N. K. (2014). Climate change 2014: synthesis report. Contribution of Working Groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change (p. 151). IPCC.
- Pohlert, T. (2004). Use of empirical global radiation models for maize growth simulation. *Agricultural and forest meteorology*, 126(1-2), 47-58.
- Porter, J. R., Xie, L., Challinor, A. J., Cochrane, K., Howden, S. M., Iqbal, M. M., and Ingram, J. (2014). Food security and food production systems.
- Porter, J.R. (2014). Chapter 7: Food security and food production systems in IPCC AR5 WG2 A 2014, pp. 488–489.
- Poudel, S., and Shaw, R. (2016). The relationships between climate variability and crop yield in a mountainous environment: a case study in Lamjung District, Nepal. *Climate*, 4(1), 13.
- Raes, D., Steduto, P., Hsiao, T. C., and Fereres, E. (2009). AquaCrop-The FAO Crop Model to Simulate Yield Response to Water: II. Main Algorithms and Software Description. *Agronomy Journal* 101, 438-447.
- Raes, D., Steduto, P., Hsiao, T.C., and Fereres, E. (2016). AquaCrop Version 5.0 Reference, Manual. Food and Agriculture Organization of the United Nations, Rome, Italy.
- Rajewski, D. A., Takle, E. S., Lundquist, J. K., Prueger, J. H., Pfeiffer, R. L., Hatfield, J. L., and Doorenbos, R. K. (2014). Changes in fluxes of heat, H₂O, and CO₂ caused by a large wind farm. *Agricultural and forest meteorology*, 194, 175-187.
- Rao, C. S., Chary, G. R., Rani, N., and Baviskar, V. S. (2016). Real time implementation of agricultural contingency plans to cope with weather aberrations in Indian agriculture. *Mausam*, 67(1), 183-194.
- Reynolds, M. P., Quilligan, E., Aggarwal, P. K., Bansal, K. C., Cavalieri, A. J., Chapman, S. C., and Jagadish, K. S. (2016). An integrated approach to maintaining cereal productivity under climate change. *Global Food Security*, 8, 9-18.
- Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A. C., Müller, C., Arneth, A., and Neumann, K. (2014). Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. *Proceedings of the National Academy of Sciences*, 111(9), 3268-3273.
- Rounsevell, M. D. A., Reginster, I., Araújo, M. B., Carter, T. R., Dendoncker, N., Ewert, F., and Schmit, C. (2006). A coherent set of future land use change scenarios for Europe. *Agriculture, Ecosystems & Environment*, 114(1), 57-68.

Sacks, W. J., and Kucharik, C. J. (2011). Crop management and phenology trends in the US Corn Belt: Impacts on yields, evapotranspiration and energy balance. *Agricultural and Forest Meteorology*, 151(7), 882-894.

Saltelli, A., Tarantola, S., Campolongo, F., Ratto, M., 2004. *Sensitivity Analysis in Practice: A Guide to Assessing Scientific Models*. Wiley, Hoboken, NJ.

Schinko, T., Mechler, R., and Hochrainer-Stigler, S. (2017). A methodological framework to operationalize climate risk management: managing sovereign climate-related extreme event risk in Austria. *Mitigation and Adaptation Strategies for Global Change*, 22(7), 1063-1086.

Schmidhuber, J., and Tubiello, F. N. (2007). Global food security under climate change. *Proceedings of the National Academy of Sciences*, 104(50), 19703-19708.

Schmidli, J., Goodess, C. M., Frei, C., Haylock, M. R., Hurrell, J. W., Ribalaygua, J., and Schmith, T. (2007). Statistical and dynamical downscaling of precipitation: An evaluation and comparison of scenarios for the European Alps. *Journal of Geophysical Research: Atmospheres*, 112(D4).

Seaby, L. P., Refsgaard, J. C., Sonnenborg, T. O., Stisen, S., Christensen, J. H., and Jensen, K. H. (2013). Assessment of robustness and significance of climate change signals for an ensemble of distribution-based scaled climate projections. *Journal of hydrology*, 486, 479-493.

Sen, P. K. (1968). Estimates of the regression coefficient based on Kendall's tau. *Journal of the American Statistical Association*, 63(324), 1379-1389.

Serdeczny, O., Adams, S., Baarsch, F., Coumou, D., Robinson, A., Hare, W., and Reinhardt, J. (2017). Climate change impacts in Sub-Saharan Africa: from physical changes to their social repercussions. *Regional Environmental Change*, 17(6), 1585-1600.

Shim, D., Lee, K. J., and Lee, B. W. (2017). Response of phenology-and yield-related traits of maize to elevated temperature in a temperate region. *The Crop Journal*, 5(4), 305-316.

Shrivastava, P., and Kumar, R. (2015). Soil salinity: a serious environmental issue and plant growth promoting bacteria as one of the tools for its alleviation. *Saudi journal of biological sciences*, 22(2), 123-131.

Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K. B., and Miller, H. L. (2007). Contribution of working group I to the fourth assessment report of the intergovernmental panel on climate change, 2007.

Some'e, B. S., Ezani, A., and Tabari, H. (2013). Spatiotemporal trends of aridity index in arid and semi-arid regions of Iran. *Theoretical and applied climatology*, 111(1-2), 149-160.

Statistics Botswana. (2012). *Annual agricultural survey report*. Gaborone, Botswana: Statistics Botswana.

Statistics Botswana. (2014). *Annual agricultural survey report*. Gaborone, Botswana: Statistics Botswana.

Steduto, P., Hsiao, T. C., Fereres, E., and Raes, D. (2012). Crop yield response to water (Vol. 1028). Rome: FAO.

Steduto, P., Hsiao, T. C., Raes, D., and Fereres, E. (2009). AquaCrop-The FAO Crop Model to Simulate Yield Response to Water: I. Concepts and Underlying Principles. *Agronomy Journal* 101, 426-437.

Stockle, C. O., and Donatelli, M. (1997). The CropSyst model: a brief description. In *Rotation models for ecological farming. CAMASE/PE workshop report. Quantitative Approaches in Systems Analysis No. X. AB-DLO, Wageningen, Netherlands* (pp. 35-43).

Stöckle, C. O., Donatelli, M., and Nelson, R. (2003). CropSyst, a cropping systems simulation model. *European journal of agronomy*, 18(3-4), 289-307.

Stöckle, C. O., Nelson, R. L., Higgins, S., Brunner, J., Grove, G., Boydston, R., and Kruger, C. (2010). Assessment of climate change impact on Eastern Washington agriculture. *Climatic change*, 102(1-2), 77-102.

Stricevic, R., Cosic, M., Djurovic, N., Pejic, B., and Maksimovic, L. (2011). Assessment of the FAO AquaCrop model in the simulation of rainfed and supplementally irrigated maize, sugar beet and sunflower. *Agricultural Water Management*, 98(10), 1615-1621.

Suppiah, V., and Singh Sandhu, M. (2011). Organisational culture's influence on tacit knowledge-sharing behaviour. *Journal of knowledge management*, 15(3), 462-477.

Tardieu, F., Simonneau, T., and Muller, B. (2018). The Physiological Basis of Drought Tolerance in Crop Plants: A Scenario-Dependent Probabilistic Approach. *Annual review of plant biology*, (0).

Taylor, K.E., Stouffer, R.J., Meehl, G.A., 2012. An overview of CMIP5 and the experiment design. *Bull. Am. Meteorol. Soc.* 93 (4), 485–498.

Team, R. C. (2017). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. 2016.

Thornton, P. K., Ericksen, P. J., Herrero, M., and Challinor, A. J. (2014). Climate variability and vulnerability to climate change: a review. *Global change biology*, 20(11), 3313-3328.

Thuiller, W. (2014). Editorial commentary on ‘Patterns and uncertainties of species’ range shifts under climate change’. *Global change biology*, 20(12), 3593-3594.

Timm, O., and Diaz, H. F. (2009). Synoptic-statistical approach to regional downscaling of IPCC twenty-first-century climate projections: seasonal rainfall over the Hawaiian Islands. *Journal of Climate*, 22(16), 4261-4280.

Todoovovic Emumejaye, K. (2009)Activity Concentration in Cassava Tubers Grown In Ebedei Community, an Oil Producing Area of Delta State, Nigeria.

- Tripathi, A., Tripathi, D. K., Chauhan, D. K., Kumar, N., and Singh, G. S. (2016). Paradigms of climate change impacts on some major food sources of the world: A review on current knowledge and future prospects. *Agriculture, Ecosystems & Environment*, 216, 356-373.
- Trnka, M., Rötter, R. P., Ruiz-Ramos, M., Kersebaum, K. C., Olesen, J. E., Žalud, Z., and Semenov, M. A. (2014). Adverse weather conditions for European wheat production will become more frequent with climate change. *Nature Climate Change*, 4(7), 637.
- Trzaska, S., and Schnarr, E. (2014). A review of downscaling methods for climate change projections. United States Agency for International Development by Tetra Tech ARD, 1-42.
- Tubiello, F. N., and Ewert, F. (2006). Simulating the effects of elevated CO₂ on crops: approaches and applications for climate change. *European Journal of Agronomy* 18, 57-74.
- Tumushabe, J. T. (2018). Climate Change, Food Security and Sustainable Development in Africa. In *The Palgrave Handbook of African Politics, Governance and Development* (pp. 853-868). Palgrave Macmillan, New York.
- Twomlow, S., Mugabe, F. T., Mwale, M., Delve, R., Nanja, D., Carberry, P., and Howden, M. (2008). Building adaptive capacity to cope with increasing vulnerability due to climatic change in Africa—A new approach. *Physics and Chemistry of the Earth, Parts A/B/C*, 33(8-13), 780-787.
- van Ittersum, M. K., Leffelaar, P. A., Van Keulen, H., Kropff, M. J., Bastiaans, L., and Goudriaan, J. (2003). On approaches and applications of the Wageningen crop models. *European journal of agronomy*, 18(3), 201-234.
- van Vuuren D.P., Edmonds J., Kainuma M., Riahi K., Thomson A., Hibbard K., Hurtt G.C., Kram T., Krey V., Lamarque J-C., Masui T., Meinshausen M., Nakicenovic N., Steven J. Smith S.j. and & Steven K. Rose S.K. (2011). The representative concentration pathways: an overview *Climatic Change*, 109, 5–31. DOI 10.1007/s10584-011-0148-z.
- Vanuytrecht, E. (2013). *Crop Responses to Climate Change: Impact on agricultural production and the soil water balance in the Flemish Region of Belgium*, Leuven University, Leuven.
- Von Schuckmann, K., Palmer, M. D., Trenberth, K. E., Cazenave, A., Chambers, D., Champollion, N., and Meyssignac, B. (2016). An imperative to monitor Earth's energy imbalance. *Nature Climate Change*, 6(2), 138.
- Walthall, C. L., Anderson, C. J., Baumgard, L. H., Takle, E., and Wright-Morton, L. (2013). *Climate change and agriculture in the United States: Effects and adaptation*.
- Wheeler, T., and Von Braun, J. (2013). Climate change impacts on global food security. *Science*, 341(6145), 508-513.
- Wilby, R. L., Charles, S. P., Zorita, E., Timbal, B., Whetton, P., and Mearns, L. O. (2004). Guidelines for use of climate scenarios developed from statistical downscaling methods. Supporting material of the Intergovernmental Panel on Climate Change, available from the DDC of IPCC TGCIA, 27.

- Wilby, R. L., Dawson, C. W., and Barrow, E. M. (2002). SDSM—a decision support tool for the assessment of regional climate change impacts. *Environmental Modelling & Software*, 17(2), 145-157.
- Wu, X., Lu, Y., Zhou, S., Chen, L., and Xu, B. (2016). Impact of climate change on human infectious diseases: Empirical evidence and human adaptation. *Environment international*, 86, 14-23.
- Yang, H. S., Dobermann, A., Lindquist, J. L., Walters, D. T., Arkebauer, T. J., and Cassman, K. G. (2004). Hybrid-maize—a maize simulation model that combines two crop modelling approaches. *Field Crops Research*, 87(2-3), 131-154.
- Zandalinas, S. I., Mittler, R., Balfagón, D., Arbona, V., and Gómez-Cadenas, A. (2018). Plant adaptations to the combination of drought and high temperatures. *Physiologia plantarum*, 162(1), 2-12.
- Zhao, G., Hoffmann, H., van Bussel, L. G., Enders, A., Specka, X., Sosa, C., and Teixeira, E. (2015). Effect of weather data aggregation on regional crop simulation for different crops, production conditions, and response variables. *Climate Research*, 65, 141-157.
- Zhuo, L., Mekonnen, M. M., and Hoekstra, A. Y. (2016). The effect of inter-annual variability of consumption, production, trade and climate on crop-related green and blue water footprints and inter-regional virtual water trade: A study for China (1978–2008). *Water research*, 94, 73-85.
- Zinyengere, N., and Crespo, O. (2017). Assessing Local Impacts of Climate Change on Crop Production in Southern Africa: Critiquing an Approach. In *Beyond Agricultural Impacts* (pp. 13-37).
- Zorita, E., and Von Storch, H. (1999). The analog method as a simple statistical downscaling technique: comparison with more complicated methods. *Journal of climate*, 12(8), 2474-2489.