ASSESSING CLIMATE CHANGE IMPACTS ON PRODUCTIVITY OF SUGARBEET AND SUGARCANE USING AQUACROP

by

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PREFACE

The research contained in this dissertation/thesis was completed by the candidate while based at the Centre for Water Resources Research, School of Agricultural, Earth and Environmental Sciences, in the College of Agriculture, Engineering and Science, University of KwaZulu-Natal, Pietermaritzburg Campus, South Africa. The research was financially supported by the National Research Foundation and the Water Research Commission (WRC) of South Africa through WRC Project No. K5/1874//4 titled "Water use of cropping systems adapted to bio-climatic regions in South Africa and suitable for bio-fuel production".

The contents of this work have not been submitted in any form to another university and, except where the work of others is acknowledged in the text, the results reported are due to investigations by the candidate.

As the candidate's supervisor I agree to the submission of this dissertation

Signed: RP Kunz

Date: 30 September 2018

As the candidate's co-supervisor I agree to the submission of this dissertation

Co-Supervisor: Dr. Tafadzwanashe Mabhaudhi
Date: 30 September 2018

DECLARATION: PLAGIARISM

I, Ofentse Mokonoto, declare that:

(i) the research reported in this dissertation, except where otherwise indicated or acknowledged, is my original work;

(ii) this dissertation has not been submitted in full or in part for any degree or examination to any other university;

(iii) this dissertation does not contain other persons' data, pictures, graphs or other information, unless specifically acknowledged as being sourced from other persons;

(iv) this dissertation does not contain other persons' writing, unless specifically acknowledged as being sourced from other researchers. Where other written sources have been quoted, then:

a) their words have been re-written but the general information attributed to them has been referenced;

b) where their exact words have been used, their writing has been placed inside quotation marks, and referenced;

(v) where I have used material for which publications followed, I have indicated in detail my role in the work;

(vi) this dissertation is primarily a collection of material, prepared by myself, published as journal articles or in research reports, or presented as a poster and oral presentations at conferences. In some cases, additional material has been included;

(vii) this dissertation does not contain text, graphics or tables copied and pasted from the Internet, unless specifically acknowledged, and the source being detailed in the dissertation and in the References section.

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ABSTRACT

Globally, the use of biofuels has grown over the years and their importance in helping to reduce a) dependency on fossil-based fuels and b) greenhouse emissions has been widely recognised. Various feedstocks are used for biofuels, *viz*. sugar-based crops for bioethanol production and oil from vegetable crops for biodiesel production. The research presented in this study focused on sugar crops such as sugarcane and sugarbeet. The sugarcane industry is widely established in South Africa, whereas sugarbeet is still a new crop and hence, there is little information on its water use efficiency (WUE) and potential yields under South African growing conditions. Overall, there is a need to better understand the agricultural potential and water use requirements of these feedstocks, in order to grow the biofuels industry in South Africa in a sustainable manner. Furthermore, climate change poses a threat to global food security as well as to biofuel feedstock production. There are uncertainties regarding the potential impacts of climate change on the yield and WUE of agricultural crops.

One of the main objectives of this study was to calibrate the AquaCrop crop model for sugarcane and sugarbeet using experimental datasets. This study then followed a modelling approach to estimate dry yields and WUEs of these two sugar feedstocks to add to the existing knowledge base for potential biofuel production in South Africa. Sugarbeet was planted at the Ukulinga research farm and field equipment was used to collect data for the calibration of the crop model to better estimate attainable yield and WUE. Growth and yield datasets were provided by the South African Sugarcane Research Institute to calibrate the model for sugarcane, as well as validate AquaCrop for both feedstocks. The performance of the crop model was tested using various statistical methods. The model's performance was satisfactory after calibrating it for sugarcane. However, the calibration process was compromised by the lack of sufficient leaf area index data. For sugarbeet, AquaCrop simulated the canopy cover, yield and WUE well, but tended to over-estimate observations. For the validation process, simulations closely matched the observed yields for both feedstocks. However, the model's ability to simulate soil water content at Ukulinga was considered unsatisfactory. The calibrated AquaCrop model was used for long term assessments of yield and WUE. Baseline simulations were undertaken using 50 and 30 years of climate data and the results indicated that the 30 years of data could adequately estimate

the long-term attainable productivity of sugarcane and sugarbeet.

According to the literature, an ensemble approach to climate change modelling reduces uncertainty in long-term assessments. Hence, climate projections from several global climate models (GCMs), that were downscaled using dynamical and statistical approaches, were obtained and used to assess the potential impacts of climate change on yield and WUE of the selected feedstocks. An increase in yield and WUE of both feedstocks is projected in the distant future. The statistically downscaled GCMs projected higher increases compared to the dynamically downscaled GCMs. Increases in future WUE are much higher compared to yields projections. The so-called "CO_2 fertilisation" effect largely benefits C3 crops (sugarbeet) with regards to yield improvements. However, the results also show that C4 crops (sugarcane) also benefit from improved WUE. Both sugarcane and sugarbeet will benefit from the anticipated climate change when planted in February and May, respectively. However, it is recommended that other planting dates should be studied for sugarcane.

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LIST OF ABBREVIATIONS

AWS	Automatic Weather Station
ACCI	African Centre for Crop Improvement
AgMIP	Agricultural Model Intercomparison and Improvement Project
B	Dry biomass (tonne ha^{-1})
CSAG	Climate Systems Analysis Group
CSIR	Council for Scientific and Industrial Research
CC	Canopy Cover
CDC	Canopy decline coefficient
CGC	Canopy growth coefficient
$[CO_2]$	Carbon dioxide concentration in the atmosphere (ppm)
DAFF	Department of Agriculture, Forestry and Fisheries
DAP	Days after planting
DME	Department of Minerals and Energy
DoE	Department of Energy
DWAF	Department of Water Affairs and Forestry
DWS	Department of Water and Sanitation
ET	Evapotranspiration (mm per unit time)
ET_a	Actual evapotranspiration (mm per unit time)
ET_x	Maximum evapotranspiration (mm per unit time)
ET_o	Reference crop evaporation (mm per unit time)
EU	European Union
FACE	Free Air Carbon Enrichment
FAO	Food and Agriculture Organisation
GCM	Global climate model
GDD	Growing degree days (°C day)
HI	Harvest index (percentage)
IoA	Index of Agreement
ICFR	Institute for Commercial Forestry Research
IPCC	Intergovernmental Panel on Climate Change
KZN	KwaZulu-Natal
LAI	Leaf area index (m^2 leaf area per m^2 soil surface)
MAP	Mean annual precipitation (mm)
MAT	Mean annual temperature (ºC)
MOS	Model output statistics
NBIS	National Biofuels Industrial Strategy
PAR	Photosynthetically active radiation
PP	Perfect prognosis
PPA	Petroleum Products Act
RCM	Regional climate model
RMSE	Root mean square error
RUE	Radiation use efficiency (kg of biomass per MJ of intercepted solar radiation)

SASRI	South African Sugarcane Research Institute
SPAC	Soil-plant-atmosphere continuum
SOM	Self-organising map (
TDR	Time domain reflectometry
Tr	Crop transpiration (mm per unit time)
UKZN	University of KwaZulu-Natal
WRC	Water Research Commission
WUE	Water use efficiency (kg m^{-3})
WP	Water productivity (tonne of biomass per ha)
Y	Dry yield (tonne ha^{-1})
Y_a	Actual yield (tonne ha^{-1})
Y_x	Maximum yield (tonne ha^{-1})

1 INTRODUCTION

1.1 Rationale for the Research

Globally, most of the energy used for transportation purposes is derived from non-renewable resources such as fossil fuels (Eltrop *et al*., 2011). Of the 53 nations in Africa, South Africa uses the most energy, of which 99.6% is acquired from fossil fuels (Pradhan and Mbohwa, 2014). This dependency on fossil fuels (i.e. petrol and diesel) has contributed to an increase in greenhouse gas emissions and atmospheric pollution leading to human-induced climate change. However, the use of fossil fuels can be supplemented with biofuels (i.e. bioethanol and biodiesel). The interest in biofuels is due to the renewability of the raw materials and the lower emission of greenhouse gases when combusted (Jewitt *et al*., 2009). Biodiesel is a renewable fuel produced from vegetable oil, animal fat or waste cooking oil. Bioethanol is a renewable fuel produced from the fermentation of sugar- and starch-based crops (Demirbas, 2009; Magana *et al*., 2011). Presently, bioethanol is the most used biofuel globally. The CO_2 emissions generated by the combustion of bioethanol are compensated by the CO_2 absorption during the crop growth phase, avoiding a net emission of this gas (McMillan, 1997). The offset of CO_2 emissions is valid when unexploited or cattle farming lands are used for cultivating biofuels crops. However, if agricultural expansion results in clearing of natural grasslands, indigenous forests or peatlands, the opportunity of reducing CO_2 emissions is lost though poor land use change decisions. According to the National Biofuels Industrial Strategy (NBIS), the plan in South Africa is to grow biofuel feedstock on currently underutilised arable land (DME, 2007a).

Therefore, the main rationale is to reduce dependency on fossil use, which will lower greenhouse gas emissions that contribute to climate change. Compared to other anthropogenic activities, agriculture is highly climate dependent and up to 70% of the sub-Saharan African livelihood is sustained by agriculture (Cooper *et al*., 2008). This highlights the issue of food security which is likely to worsen in the future if no climate change adaptation or mitigation strategies are in place. To avoid such an outcome, there has been an increase in studies related to climate change impacts on crop productivity and water resources (Kang *et al*., 2009). Presently, climate change has already caused substantial impacts on water resources, food security and human health, more so on the African continent, but also across the world (Magadza, 2000). Effects of climate change on crops will be due to changes in CO_2, temperature and rainfall patterns. According to the Intergovernmental Panel on Climate Change (IPCC, 2014a; 2014b), crop yields in 2050 may be halved, particularly in some regions of sub-Saharan Africa. Additionally, extreme events such as droughts, floods and biotic influences such as pests and diseases may contribute to crop yield losses. These factors highlight both the importance and urgency to study (and determine) impacts of climate change on crop production and water resources in order to develop possible adaptation strategies. Future climate scenarios can be simulated with the use of global climate models (GCMs) and regional climate models (RCMs) (downscaling approach). Climate data from these models is then be used as input for crop yield models at local scales. In this study, the AquaCrop model (Hsiao *et al*., 2009; Raes *et al*., 2009 and Steduto *et al*., 2009) developed by the Food and Agriculture Organisation (FAO) was selected for crop yield modelling.

In South Africa, the production and use of biofuels is minimal compared to other countries. The growth of biofuel use will require government policy regulations and incentives (DME, 2007a). The use of biofuels tends to raise concerns over food security and potential environmental impacts, i.e. increased water use (Balat and Balat, 2009). Therefore, research concerned with identifying potential biofuel feedstocks as well as their sustainability and production potential needs is necessary in addressing such concerns. It is important that preferred biofuel feedstocks should have high yields with minimal impact on the environment. This is of importance because the agricultural sector is already the biggest user of water in the world. Additionally, the global rise in biofuel use has led to increased utilisation of water resources and more competition for water amongst users (Gheewala *et al*., 2011). Given that South Africa is a water stressed country, it is preferred that biofuel feedstocks are grown under rainfed conditions (DWS, 2016).

1.2 Problem Statement

The NBIS stated that sugarcane and sugarbeet are the preferred feedstocks for the production of bioethanol (DME, 2007a). Furthermore, a scoping study was undertaken in South Africa to identify potential feedstocks, based on suitable growing conditions, for biofuel production and their associated water use (Jewitt *et al*., 2009). The study identified sugarcane and sugarbeet as two such feedstocks, but noted that there was a need for better understanding of the following:

1) the preferred feedstocks for biofuel production,
2) water use efficiency of each feedstock, and
3) the impact of climate change on feedstock production such as increased water use and shifting cropping patterns.

In addition, the Energy Security Master Plan for Liquid Fuels (DME, 2007b) highlighted that, "in the case of biofuels, the climate change module will allow for modelling of likely climate changes on the production of a particular crop. The module should also allow for the development of adaptation strategies for particular areas". Based on the above, there is a need for improved knowledge regarding the water use efficiency (WUE) of preferred biofuel feedstocks (i.e. sugarbeet and sugarcane) as well as the likely impacts of climate change on crop production.

1.3 Research Questions and Objectives

In light of the above problem statement, the following research questions were addressed:

- What are the attainable yield and WUE of sugarbeet and sugarcane?
- What are the potential impacts of climate change on yield and WUE of these two feedstocks?

In order to answer the above research questions, there are several objectives that were met in this study, namely:

- Calibration of AquaCrop for sugarcane and sugarbeet;
- Validation of the crop model using independent datasets;
- Test AquaCrop's ability to simulate soil water content;
- Comparison of 30 and 50 years of input climate data for long-term assessment of yield and WUE;
- Comparison of dynamical and statistical downscaled projections against the baseline climate;
- Use of downscaled GCMs to estimate future yield and WUE of sugarcane and sugarbeet under rainfed and/or irrigated conditions; and
- Assessment of climate change impacts (i.e. CO_2; temperature and rainfall) on crop yield and WUE.

1.4 Chapter Overview

This dissertation has been divided into various chapters as follows:

- Literature Review:
  - **Chapter 2** discusses the biofuel feedstocks selected in this study.
  - **Chapter 3** discusses the history of crop modelling, the types of models available and why AquaCrop was selected.
  - In **Chapter 4**, the potential impacts of climate change on crop productivity are discussed as well as the advantages of using AquaCrop in climate change studies.
  - **Chapter 5** discusses the value of different downscaling techniques and the use of multiple GCMs to aid in reducing uncertainty in modelling.
- Material and Methods:
  - **Chapter 6** is broken down into three subsections; 1) field work carried out to obtain model parameters specific to each feedstock, 2) calibration and validation of the AquaCrop model and 3) assessment of climate change including acquisition of climate projections.
- Results, Discussion and Final Thoughts
  - In **Chapter 7**, AquaCrop's performance is assessed using soil water simulations. Secondly, the results that address each research question are presented.
- Conclusion
  - The conclusion of the study is provided in **Chapter 8**.
- References and Appendixes are presented in **Chapters 9** and **10** to **15**, respectively.

2 BIOFUEL FEEDSTOCKS

In this chapter, an overview of the global and local biofuel industry is presented. The rationale behind selecting the two biofuel feedstocks used in this study is discussed. Lastly, a more detailed description of the two feedstocks is given.

2.1 Background

The use of biofuels (i.e. bioethanol and biodiesel) is deemed to decrease the dependency on fossil fuels (Perkins, 2012). In 2001, 20 billion litres of biofuels were produced globally. By 2011, production was at 110 billion litres and it has been projected to double to 221 billion litres in 2021 (Pradhan and Mbohwa, 2014). The move to greener energy at the global scale has resulted in decreases in fossil fuel usage in countries such as Brazil and the United States of America (USA). These two countries are the top producers of bioethanol in the world, followed by the European Union (EU). Brazil uses sugarcane as the primary feedstock for bioethanol production, whilst the USA utilises maize and the EU uses both sugarbeet and cereal crops (Demirbas, 2009).

South Africa has adopted a more conservative approach regarding biofuel production compared to other countries. According to the NBIS, the country intends to achieve a 2% blend of biofuels (equivalent to 400 million litres of biofuel production per year) in the national liquid fuel supply (DME, 2007a). Furthermore, the former Department of Minerals and Energy (DME) proposed blending rates of 2% for biodiesel and 8% for bioethanol. By 2012, the DME revised the rates, as stipulated in the Petroleum Products Act (PPA) of 1977. The PPA states a blend of 5% biodiesel and 2% to 10% ethanol with diesel and petrol respectively (DoE, 2012a). The South African Department of Energy (DoE) announced that the blending of biofuel with fossil-based fuel would commence from October 2015 (DoE, 2013). However, to date, this has not materialised.

2.2 Feedstock Selection

The NBIS (DME, 2007a) proposed sugarcane and sugarbeet for bioethanol production as both crops are suitable for dryland agriculture. Jewitt *et al.* (2009) conducted a scoping study which identified 20 potential biofuel feedstocks (i.e. suitable for South Africa’s climate), but crops such as maize and jatropha have been excluded for reasons of food security and alien invasiveness, respectively. Amongst the potential biofuel feedstocks considered by Jewitt *et al*. (2009), sugarcane and sugarbeet were also identified as possible feedstocks for bioethanol production. In addition, the draft version of the biofuels regulatory framework released by DoE in 2014 noted that the preferred crops for bioethanol production are grain sorghum and sugarcane. DoE (2014) also noted that economically, sugarbeet should be considered based on its sugar content and its pricing would be similar to that of sugarcane. However, the focus of this research is not on financial returns regarding biofuel manufacturing.

Based on the above, sugarcane and sugarbeet were selected for this study. Sugarcane is grown extensively in South Africa. However, there remains a gap in knowledge with regards to the sustainability and production potential of sugarbeet within the context of biofuel production in South Africa. The Water Research Commission (WRC) has played a pivotal role in this regard by funding research on biofuels. To date, 13 (2007-2018) years of research has been conducted (including this work) by various higher learning institutions funded by the WRC. This research attempts to reduce the knowledge gap by estimating feedstock water use to yield using a modelling approach and thus, addressing their biofuel production potential. The two selected feedstocks are described next in more detail.

2.3 Sugarcane

2.3.1 Crop description and distribution

Sugarcane is a C4 carbon-fixing perennial crop and is grown in tropical as well as subtropical regions of the world. It contributes to 70% of the global sugar production and 29% of the total world crop production (Magana *et al*., 2011; Gerbens-Leenes and Hoekstra, 2012; Steduto *et al*., 2012). Unlike sugarbeet, sugarcane is grown in over 100 countries (Steduto *et al*., 2012). It is the main feedstock for bioethanol production in countries such as Brazil and India (Quintero *et al*., 2008). Within South Africa, the sugarcane industry is well established and there are investigations into cane varieties for energy production (Jewitt *et al*., 2009).

Sugarcane is grown in 14 cane-producing areas in South Africa, which extend from the Eastern Cape (Northern Pondoland) through the coastal belt of KwaZulu-Natal and the

Midlands, up into the Mpumalanga Province (DAFF, 2012). However, the main regions for growing sugarcane in South Africa are KwaZulu-Natal (KZN) and Mpumalanga, specifically the Lowveld (Smith, 2006). Of the total sugarcane produced in South Africa, 84.7% is by commercial farmers of which there are 1550 growers. According to DAFF (2011), the remaining production is split between 27580 small-scale farmers on tribal land (8.6%) as well as milling companies who own their own sugarcane estates (6.7%).

Sugarcane planting dates vary in the KZN region. In the Midlands Misbelt of KZN, it is recommended to plant between mid-September to mid-October, whereas planting occurs in early August to end October in the coastal lowlands of KZN. Supplemented with irrigation, planting can take place in any month in Mpumalanga except during the winter months (i.e. June and July), due to low soil temperatures that hinder germination. According to Smith (2006), sugarcane's season length also varies between the different regions, ranging from 12 to 14 months in hotter regions and 14 to 24 in the cooler (i.e. higher altitude) regions.

2.3.2 Growth criteria

Adequate moisture and temperature are the two main ecological requirements for efficient growth of the sugarcane crop (Tarimo and Takamura, 1998). Kunz *et al*. (2015b) produced a summary table (**Table 2-1**) of minimum and maximum limits of temperature and rainfall to ensure optimum sugarcane production.

Table 2-1 Growth criteria for sugarcane derived from values published in the literature (Kunz *et al*., 2015b)

Variable	Abs	Sub	Opt	Opt	Sub	Abs
	Minimum			Maximum		
Seasonal rainfall (mm)	850	1100	1300	1500	1800	2000
Monthly mean temperature (°C): Sep-Apr	15	20	22	30	32	35
Monthly mean temperature (°C): May-Aug	8	10	12	14	20	24
Monthly mean relative humidity (%): Sep-Apr	30	70	80	85	90	95
Monthly mean relative humidity (%): May-Aug	20	35	45	65	75	85
Soil depth (mm)	400	700	1000			

Note: Abs - Absolute; Sub - Sub optimum; Opt - Optimum

The absolute minimum seasonal rainfall of 850 mm is required to ensure the soil is moist enough for sugarcane growth. For optimum growth, 1300 - 1500 mm of rainfall should fall over the growing season (Jewitt *et al*., 2009). A mean monthly temperature of 22 to 30°C will result in optimum stalk growth and 10 to 20°C is essential for ripening (Tammisola, 2010; Jewitt *et al.*, 2009). According to Smith (1998), mean monthly temperatures below 15°C and above 35°C result in minimum growth for sugarcane. Sugarcane prefers soils that are up to 1 m deep, with available soil water content greater than 150 mm (Kunz *et al.*, 2015b).

2.3.3 Yield and water use

Sugarcane yield is directly proportional to the amount of water used under prevailing climatic conditions (Kunz *et al.*, 2015b). The water productivity of sugarcane ranges between 3.5 kg m^{-3} to 5.5 kg m^{-3} (Steduto *et al.*, 2012). Sugarcane fresh yields range between 80 t ha^{-1} to 150 t ha^{-1} for irrigated conditions (Waclawovsky *et al.*, 2010). However, yields of 120 t ha^{-1} are respectable under full irrigation. Under rainfed conditions, yields vary from 30 to 90 fresh t ha^{-1} across the globe (Steduto *et al.*, 2012). The average cane yield for South Africa is 66.1 t ha^{-1} harvested from an area of 305753 ha (DAFF, 2011). Simulated yields for rainfed conditions range from 15 to 40 dry t ha^{-1} (Kunz *et al.*, 2015b). Therefore, actual yields are dependent on soil and climatic conditions.

Up to 2015, sugarcane yields have been estimated across South Africa using, *inter alia*, using an empirical crop yield model developed by Barry Smith (Smith, 2006). The model predicts fresh yield using mean annual rainfall, mean annual temperature, accumulated heat units, length of growing cycle as well as other factors relating to soil (structure and depth) and land management. However, a disadvantage of the Smith model is that it does not consider the effects of carbon dioxide (CO_2) on plant response. CO_2 is an important variable in crop development and its benefits to crop growth and yield were already understood in the 1930s (Nederhoff, 1994). Physically-based crop models that incorporate CO_2 as an input parameter are widely used in climate change studies (see **section 4.3** for more information on CO_2 effects and crop modelling).

2.3.4 Biofuel production

Brazil depends largely on sugarcane for bioethanol production and is the second largest producer after the USA, who produce bioethanol from maize (RFA, 2015). In 2014 for example, the USA accounted for 60% of the global bioethanol production while Brazil accounted for approximately 25% of the total bioethanol production (RFA, 2015), However, in 2012, Brazil produced the largest volume of bioethanol compared to the USA. This was due to a 1 in 50-year drought experienced in the USA during 2012 and early 2013 which affected maize yields (RFA, 2015). With regards to sugarcane, Brazil is the global leader of sugar production and bioethanol produced from sugarcane. In the 2015/16 season, Brazil produced 30.23 billion litres of bioethanol, the largest in the past 10 years (SugarCane, 2017). Brazil has shown that large-scale bioethanol production from sugarcane is achievable and has replaced around 42% of fossil fuel with bioethanol (SugarCane, 2017).

In South Africa, bioethanol production from sugarcane has potential especially given the industry is well established. The crop is listed as a preferred feedstock for bioethanol production in the national biofuels strategy (DME, 2007a). However, only one licenced processing plant (50 million litres capacity per annum) to be located in Jozini (KwaZulu-Natal) plans to use sugarcane as a feedstock for bioethanol production (DoE, 2014). It is likely that bioethanol production from grain sorghum will meet the 2% (E2 or 240 million litres of bioethanol) blend as proposed by government. The use of sugarcane is necessary to increase the blending ratio above 2% up to 10% (E10) as per the blending legislation (DoE, 2012a). An E10 blend requires an additional production of about 960 million litres of bioethanol. As noted by Kunz *et al*. (2015b), "the biofuels industry can create an alternative market for surplus cane production which will encourage expansion of the industry". With current plantations, South Africa can produce a surplus of sugarcane up to 1 million tonnes, which can satisfy an E5 blend (Naidoo, 2011).

2.4 Sugarbeet

2.4.1 Crop description and distribution

Sugarbeet is a C3 plant with relatively large roots and tubers. The crop is susceptible to diseases and it is generally advised that a three-year crop rotation is practised to minimise root diseases, *Cercospora* leaf spot and herbicide carryover (Steduto *et al*., 2012). Globally, sugarbeet contributes to 30% of all sugar produced and 4% to total crop production (Gerbens-Leenes and Hoekstra, 2012; Magana *et al*., 2011). World sugarbeet production is estimated at 227 million tonnes over 4.2 million hectares (Steduto *et al*., 2012). Countries such France, USA, Germany, Russia, Turkey, Poland, Ukraine, United Kingdom and China grow the crop on a large scale (Steduto *et al*., 2012).

Sugarbeet is a new crop in South Africa where little is known about its water use or its potential production (DoE, 2012b). The majority of research on sugarbeet has been carried out in other countries, mostly located in the temperate and cool regions of the Northern Hemisphere (Jewitt *et al*., 2009). Sugarbeet can also be grown as a winter or summer crop in Mediterranean regions and some arid environments (Campbell, 2002). In South Africa, sugarbeet has been grown across three regions, *viz*. at Cradock in the Eastern Cape (Dugmore, 2010); on a commercial farm in Lichtenburg of the North-West Province (Dugmore, 2011); the Ukulinga research farm at the University of KwaZulu-Natal (UKZN) (Kunz *et al*., 2015b).

2.4.2 Growth criteria

The climate and type of soils are two major determinants in the production success of the crop (Draycott, 2006). Depending on the region in which sugarbeet is grown and the sowing period, it can reach maturity between 120 and 250 days after planting (Steduto *et al*., 2012). According to Steduto *et al*. (2012), sugarbeet requires about 500 mm to 800 mm of water during the growing season. Kunz *et al*. (2015b) also produced a summary table (see **Table 2-2**) for sugarbeet showing the minimum and maximum limits of temperature and rainfall to ensure optimum sugarbeet production. In the table, the optimal rainfall over the growing season is similar to that published in the FAO's Irrigation and Drainage Paper No. 66 (Steduto *et al*., 2012).

Table 2-2 Growth criteria for sugarbeet derived from values published in the literature (Kunz *et al*., 2015b)

Variable	Abs	Sub	Opt	Opt	Sub	Abs
	Minimum			Maximum		
Summer seasonal rainfall (mm)	400	500	600	800	900	1000
Winter seasonal rainfall (mm)	350	450	550	750	850	950
Monthly mean temperature (°C)	5	10	15	20	25	30
Monthly maximum relative humidity (%)				60	70	80
Soil depth (mm)	500	700	900			

Note: Abs - Absolute; Sub - Sub optimum; Opt - Optimum

A minimum soil temperature of 4-5°C is required for germination (Steduto *et al*., 2012). For maximum productivity, the optimum mean monthly temperature range is approximately 15°C to 25°C (Petkeviciene, 2009; Wahab and Salih 2012). Sugarbeet requires a minimum soil depth of 500 mm and 900 mm for optimum growth. In deep soils, the crop can develop a deep tap root system. Water extraction down to 3 m has been reported for deficit-irrigated sugarbeet in very deep soils (Steduto *et al*., 2012). The crop should not be planted in clayey soils which are characterised by water logging. Such conditions aggravate root rot (Johl, 1980). In high rainfall and humid areas, sugarbeet is highly susceptible to both above-ground (i.e. leaf spot) and below-ground (i.e. root rot) diseases (Kunz *et al*., 2015b).

2.4.3 Yield and water use

A fresh yield of 40 to 60 t ha^{-1} of sugarbeet is considered good for commercial purposes (Steduto *et al*., 2012). The water productivity of sugarbeet is reported to range between 2.1 and 6.8 kg m^{-3} (Dunham, 1993). However, these water productivity values are representative of sugarbeet studied in Northern Europe and America. A study in South Africa was undertaken over two seasons by Kunz *et al*. (2015a). The study indicated that sugarbeet used 562 mm of water in the 2010/11 season and 556 mm the following season. A fresh yield of 53.1 t ha^{-1} (2010/11) and 21.7 t ha^{-1} (2011/12) was measured, which gives a water productivity of 9.44 kg m^{-3} (2010/11) and 3.91 kg m^{-3} (2011/12). The vast difference in yields between the two seasons were due to root rot from over-irrigation and weeds, which affected the development of the crop in the 2011/12 season (Kunz *et al*., 2015a).

2.4.4 Biofuel production

Although sugarbeet has a high bioethanol yield per hectare (Gerbens-Leenes and Hoekstra, 2012), its use for bioethanol is limited compared to sugarcane (Brandling, 2010). However, sugarbeet requires 35% to 40% less water and fertilisers compared to sugarcane (Kumar *et al*., 2006). In addition, sugarbeet can accumulate a large quantity of sugar in its storage root, as much as 16-20% of fresh weight (Kunz *et al*., 2015b). According to Draycott (2006), sugar content decreases in the upper parts of the crop (7-9% sugar). After harvest, the sugar concentration in the sugarbeet deteriorates quickly, which is common in sugar crops (Kunz *et al*., 2015b). Therefore, sugarbeet must be grown and harvested within a 70 to 100 km radius of the bioethanol plant (Maclachlan, 2012).

2.5 Dryland vs irrigation production

The initial conservative approach to biofuel production in South Africa is due to various factors including government policies, food security issues and environmental concerns such as limited water resources. Regarding biofuel production, feedstocks that produce a high yield using minimal water are more preferred, especially in water-stressed regions such as South Africa. South Africa has catchments that are already water stressed, with irrigated agriculture utilising 60% of the available water resources (DME, 2007a). Hence, allocating additional irrigation water for biofuel production could add to the water scarcity experienced in South Africa. However, biofuel feedstocks should preferably not be irrigated, according to a recent policy position paper published by the Department of Water and Sanitation (DWS, 2016).

2.6 Summary

Biofuels can both compliment and serve as an alternative source of liquid transport fuel. Globally, the use of biofuels is growing rapidly and the South African government has followed suit by planning to introduce it into the country's fuel supply. Studies on crops which have the potential for utilisation as biofuel feedstocks in South Africa have been undertaken and in this study, two crops were investigated.

Globally, sugarcane and sugarbeet are major crops for both bioethanol and sugar production. Sugarbeet is still a relatively new crop in South Africa compared to sugarcane. Nonetheless, sugarbeet is the preferred feedstock together with sugarcane for bioethanol production in South Africa. Additionally, the sugarbeet pricing will be similar to sugarcane. Lastly, both crops are viable for dryland agriculture especially given the unlikelihood of the application of irrigation.

One of the aims of this study was to determine the biofuel yield potential of two feedstocks under rainfed and/or irrigated conditions using a deterministic model. As noted in **section 2.3**, previous studies have used empirical models for sugarcane yield simulations and given that sugarbeet is a new crop in South Africa, there is limited knowledge regarding the water use and yield of this crop. Therefore, the results in this study will contribute to this knowledge gap. The following chapter discusses the types of deterministic models available to estimate crop yield and introduces the crop yield model employed in this study.

3 CROP MODELLING

This chapter gives a background on the history of crop modelling. It further discusses the different type of models available and presents the benefits of selecting the AquaCrop model for this study.

3.1 Background

Crop modelling began as early as the 1960s. Various physiological processes related to plant growth were expressed as mathematical equations and these were then integrated into simulation models (Bouman *et al*., 1996). The first crop models were mostly explanatory in their approach, but with time, models with an application approach (e.g. could make predictions) were developed. The successful implementation of crop growth modelling is attributed to C.T de Wit and these models are often referred to as the "School of de Wit or Wageningen models" (Bouman *et al*., 1996). Today, there are a variety of crop models that have been developed and crop modelling has now become an integral part of agricultural research.

3.2 Functional vs Mechanistic models

A model is a simple representation of a system and the system is a smaller part of reality that contains interrelated elements (Bouman *et al*., 1996). An example of such a system is the soil-plant-atmosphere continuum (or SPAC) which is evident in most crop models. There are functional (or empirical models) and mechanistic (or process-based models) approaches to modelling, but some crop models tend to use both approaches (Singels *et al*., 2010). However, this review focuses on the process-based modelling approach.

A functional model simplifies complex processes with its core focus being on macro-growth processes (Vanuytrecht *et al*., 2012). Benbi and Nieder (2003) stated that functional models are preferable when information about yield production is required at field and macro-scales. A mechanistic approach to modelling is more scientific and aims to improve understanding of a system and hence involves complex physiological processes (Singels *et al*., 2010; Vanuytrecht *et al*., 2012). Examples of crop growth models that are mechanistic in nature are those that are based on the physiological aspects of a plant (Geerts *et al*., 2009).

Mechanistic crop growth models are computer programs (i.e. software-based) that attempt to mimic real plant processes in response to environmental conditions (Jones, 2013). Such models can forecast expected yields from crops by simulating plant physiological processes, plant growth and development. Acquiring such knowledge and information helps in decision making regarding management and planning in agriculture as well as crop science, both in the short and long term (Singels *et al*., 2010). There are many different types of crop growth models that exist and each is unique, due to its complexity and the way in which its addresses the SPAC. Therefore, the main similarity that crop models share is they all have soil, plant and atmospheric components. The difference is often in the level of detail within the individual elements of the SPAC representation.

3.3 Types of Growth Engines

At the centre of crop growth models, a plant growth engine dictates the processes involved in the production of biomass from the capture of carbon dioxide, absorption of solar radiation and uptake of water. There are three main crop growth engines that can be distinguished, *viz*. carbon-, radiation- and water-driven engines (Steduto, 2006). They share a common disadvantage with regard to the effort required to obtain sufficient data to build a model (Hofstee, 2013). Moreover, the reality that models attempt to represent can be complex and thus, the use of assumptions to simplify the real world can lead to uncertainties and errors. In the following subsections, the three growth engines are discussed in more detail.

3.3.1 Carbon-driven

For the carbon-driven growth engine, crop growth is based on the assimilation of carbon by leaves through photosynthesis (Todorovic *et al*., 2009). The simulation of crop growth and phenological development are controlled by solar radiation, air temperature, atmospheric carbon dioxide and the availability of water limits those processes. The carbon-driven growth engine follows pathway **(a)** as presented in **Figure 3-1**.

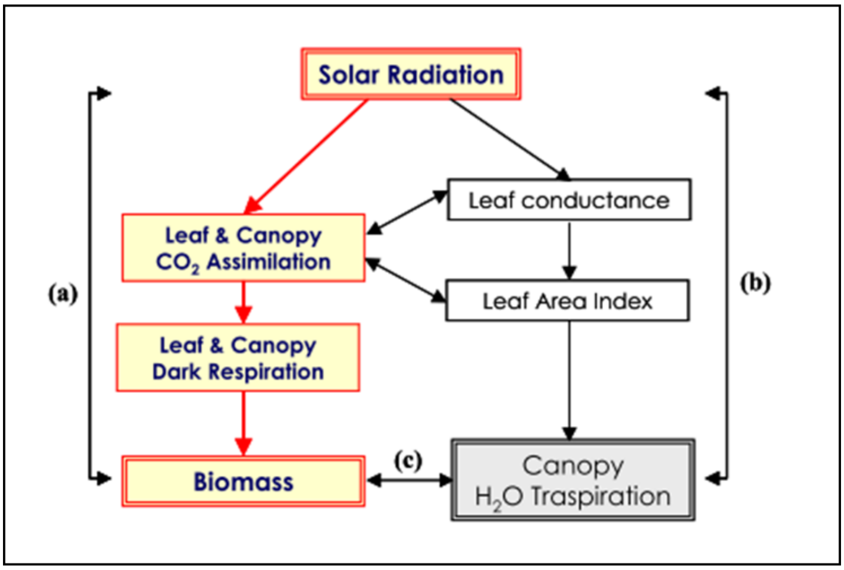

Figure 3-1 Processes involved in the production of biomass in carbon-driven crop models is via pathway (a) (Steduto, 2006)

According to Steduto (2006), the advantages of carbon-driven growth engines is their ability to describe the system in a hierarchical way. Therefore, higher level responses (biomass production) are a result of the underlying integration of lower level processes (i.e. interception of radiation). Carbon-driven crop models are thus suitable for investigating the following effects on crop growth, *viz.* leaf area, location (i.e. latitude), crop row orientation, diffuse and direct light, elevated carbon dioxide and other low-level processes (Steduto, 2006). Such models often have a complex structure and therefore, require many input parameters (Todorovic *et al.*, 2009). Models that belong to this type of growth engine include the WOrld FOod Studies (WOFOST) (Diepen *et al.*, 1989; Boogaard *et al.*, 1998) and the American CROP GROwth (CROPGRO) models (Boote *et al.*, 1998; 2002).

3.3.2 Radiation-driven

Radiation-driven models, initially developed in the 1970s (e.g. Sinclair *et al.*, 1976), simulate biomass production as a function of intercepted solar radiation. Unlike carbon-driven models, there are no lower underlying processes that represent intermediary steps deemed essential to producing biomass. Rather, these intermediary steps are incorporated into a single coefficient called the radiation use efficiency, i.e. RUE or Ɛ (Steduto, 2006). The radiation-driven growth engine also follows path **(a)**, but bypasses the intermediary steps associated with carbon-driven models (**Figure 3-2**).

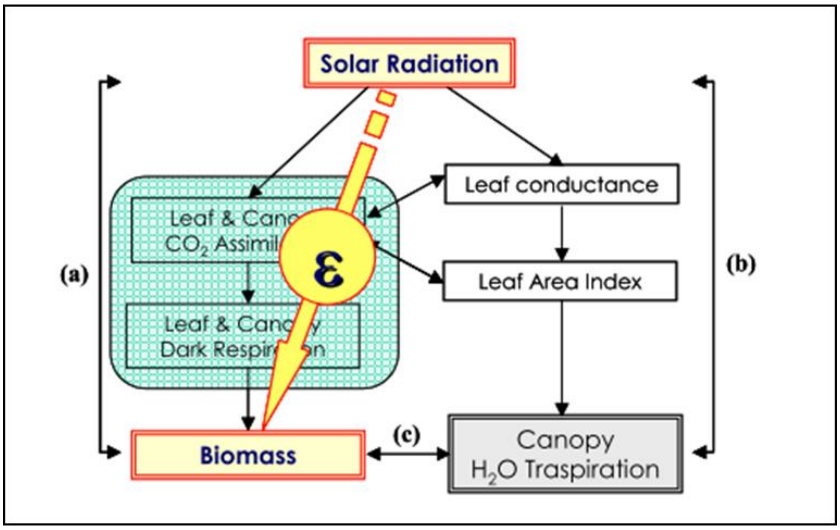

Figure 3-2 Processes involved in the production of biomass in radiation-driven crop models is via pathway (a), but bypasses the intermediary steps (Steduto, 2006)

Radiation-driven crop models have an advantage over carbon-driven models in that they are less complex and require fewer input variables (Todorovic *et al*., 2009). This reduction in parameters is mainly due to the introduction of the RUE term, which is derived from the slope of the relationship between above-ground biomass production and interception of photosynthetically active radiation (PAR). RUE values have been determined for different crops and locations, allowing the models to be applicable across a broad range of climates (Gallagher and Biscoe, 1978; Gosse *et al*., 1986; Kiniry *et al*., 1989). However, when the modelled crop is under water stress and nutrient deficient conditions, the slope of the above-mentioned relationship loses its linearity, which results in errors in the estimation of total above-ground biomass production.

Another disadvantage of this growth engine is inconsistency in the variability (i.e. non-stationarity) of RUE values that have been observed for different crops, locations and years (Steduto, 2006). Steduto (2006) stated that this is mainly caused by various factors which affect RUE, *viz*:

- variability in carboxylation capacity of leaves (e.g. nitrogen changes, stomatal response to vapour pressure deficit and leaf water potential),
- ratio differences between diffuse and direct light, and
- diversity in biomass sampling.

Models that belong to this group include the following: the CERES (Crop Environment REsources Synthesis) models for various crops such as rice (Alocilja and Ritchie, 1991) and wheat (Ritchie *et al*., 1998); the EPIC (Erosion Productivity Impact Calculator; Williams *et al*., 1984; Jones *et al*., 1991), STICS (Simulator mulTIdisciplinary for Crop Standard; Brisson *et al*., 1998; 2003) and CROPSYST (CROPping SYSTem; Stockle *et al*., 1994; 2003) models.

3.3.3 Water-driven

The water-driven engine is depicted by pathway **(c)** as indicated in **Figure 3-3**. Their approach avoids explaining the underlying hierarchical processes and thus, results in a structure that is much less complex and thus, requires fewer input parameters (Steduto *et al*., 2009). This approach to crop modelling was initially noted by de Wit (1958) who reported that a linear relationship exists between seasonal transpiration and biomass production. This relationship is linear in nature and its slope is represented by the biomass water productivity (WP or w_p) parameter. This parameter is conservative (unlike RUE), which accounts for the robustness of water-driven crop models compared to carbon- and radiation-driven crop models (Steduto, 2006).

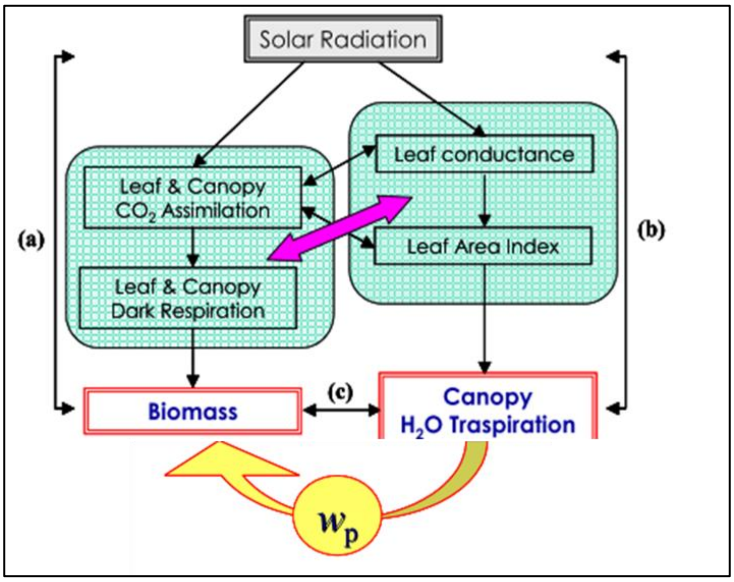

Figure 3-3 Processes involved in the production of biomass in water-driven crop models is via pathway (c) (Steduto, 2006)

The main advantage of such models is the ability to normalise the WP parameter for climate (both evaporative demand and atmospheric carbon dioxide). Thus, the model can have a wider applicability, both spatially and temporally, allowing for the modelling of future climate scenarios (Steduto *et al*., 2007; Steduto *et al*., 2009; Mabhaudhi, 2012). According to Steduto (2006), one disadvantage of this model type is the difficulty of deriving actual transpiration.

CROPSYST consists of both a solar- and water-driven growth engine, making it a more complex than models that comprise of a single growth-engine, whereas AquaCrop (Raes *et al*., 2009; Steduto *et al*., 2009) is only water-driven. CROPSYST requires more crop input parameters (i.e. 40) compared to AquaCrop (33). Some of AquaCrop's parameters can easily be observed in the field such as the percentage of canopy cover, soil texture, nutrient input and other biomass-related physiological inputs (Todorovic *et al*., 2009). Fewer parameters equate to less complexity, especially when parameterising or calibrating a model for various crops under different climatic conditions. The additional parameters required by CROPSYST are a disadvantage because they may not always be readily available (Vanuytrecht *et al*., 2014). For example, scientific research is limited in less developed countries, which makes it difficult to derive values for location-specific crop parameters. Regardless of AquaCrop's fewer input parameters, studies by Todorovic *et al*. (2009) and Saab *et al*. (2015) have shown that its performance has not been affected. In addition, they indicated that AquaCrop could simulate final yield, biomass and WUE competitively well when compared to CROPSYST and WOFOST. Other studies such as those by Heng *et al*. (2009) and Mainuddin *et al*. (2010) have shown the robustness AquaCrop's performance when calibrated properly.

3.4 Model Selection

Based on the main objective of this study and on the above discussion of different crop growth engines, a water-driven model was deemed appropriate for this study. Of the two water-driven models presented, AquaCrop was the preferred model due to its robustness and simplicity as well as its effectiveness in regions where water is a limiting factor (Raes *et al*., 2009). Mabhaudhi (2012) also used the AquaCrop model for determining drought tolerance and water use for specific crops. In addition, AquaCrop (version 4) is equipped with a variable WP parameter that not only considers crop response to CO_2 via a multiplier (f_{CO2}), but also to crop sink strength (see **section 4.3**). Furthermore, AquaCrop was tested against Free Air Carbon Enrichment (FACE) experiments, which measure crop responses to elevated CO_2 conditions (Vanuytrecht *et al*., 2011; 2012).

AquaCrop has previously been parameterised and tested for the selected biofuel feedstocks (e.g. sugarcane and sugarbeet). More specifically, AquaCrop was parameterised for sugarcane using crop and climate data collected in South Africa. However, for the purposes of this study, AquaCrop was not parameterised but rather calibrated and fine-tuned for local conditions. The difference between parameterisation, calibration and validation is described in **subsection 3.4.3**.

3.4.1 Description of AquaCrop

Simulating a crop's response to water stress has long remained one of the most difficult phenomena in crop modelling. The difficulty has mainly been due to the variability of water deficits in terms of intensity, duration and time of occurrence (Hsiao, 1973; Bradford and Hsiao 1982). Thus, empirical production functions became the most practical way of assessing crop yield in relation to water use. FAO's Irrigation and Drainage Paper No. 33 titled "Yield Response to Water" (Doorenbos and Kassam, 1979) reported the following approach that has been used for decades:

$$\left(\frac{Y_x - Y_a}{Y_x}\right) = K_y\left(\frac{ET_x - ET_a}{ET_x}\right) \qquad \textbf{Equation 3-1}$$

where Y_x and Y_a = maximum and actual yield respectively,

ET_x and ET_a = maximum and actual evapotranspiration, respectively and

K_y = factor relating relative yield loss to reduction in evapotranspiration.

For example, FAO's irrigation scheduling model called CROPWAT uses a similar approach as shown in **Equation 3-1**. However, the understanding of soil–water–plant relations has improved over time. Coupled with this, the need for improved water productivity in agriculture has led to the development of a simulation model for field and vegetable crops. This model is the AquaCrop model, which is a canopy level, deterministic type of model that evolved from the CROPWAT model (Steduto *et al*., 2012).

The following reasons given by Steduto *et al*. (2009) detail AquaCrop's evolution from the previous CROPWAT approach:

- Evapotranspiration (ET) has been separated into soil water evaporation (E) and crop transpiration (Tr);

- AquaCrop uses a simple canopy growth and senescence model as a basis for the estimation of Tr and its separation from E;
- The model calculates final yield (Y) from the product of final biomass (B) and harvest index (HI); and
- The model segregates the effects of water stress into four components, *viz*. canopy growth, canopy senescence, Tr and HI.

AquaCrop segregates ET into E and Tr, which is especially useful for incomplete ground covers since E (which does not contribute to crop growth) can have a confounding effect. AquaCrop simulates biomass (B) by using **Equation 3-2**, the core of its growth engine:

$$B = WP \cdot \Sigma Tr \qquad \textbf{Equation 3-2}$$

WP is the water productivity parameter (i.e. biomass production *B* per unit of cumulative transpiration ΣTr) that can be normalised (see **subsection 3.3.3**). In AquaCrop, the evaporative demand is normalised by dividing the daily Tr with reference crop evaporation (ET_o). Atmospheric CO_2 is normalised by applying a multiplier (f_{CO2}), which is dependent on ambient CO_2 levels in the year 2000 (reference year) as well as the year in which the crop is grown (Vanuytrecht *et al*., 2014). Other improvements from **Equation 3-1** (in CROPWAT) to **Equation 3-2 (**in AquaCrop) include the time step used. The relationship in **Equation 3-1** operates on a seasonal time step, whereas **Equation 3-2** operates on a daily time step. According to Acevedo *et al*. (1971), a daily time step is closer to approaching the actual time scale of crop responses to water deficits.

3.4.2 Model structure and processes

Figure 3-4 represents the structure of AquaCrop and its associated processes. The solid lines represent the direct links between variables and processes and the dotted lines indicate the feedbacks. The climate component of AquaCrop requires four weather inputs that are necessary to run the model, *viz*. rainfall, maximum temperature, minimum temperature and reference crop evaporation (ET_o). Values of historical carbon dioxide (from the Mauna Loa Observatory in Hawaii) are included within the model structure (Steduto *et al*., 2009).

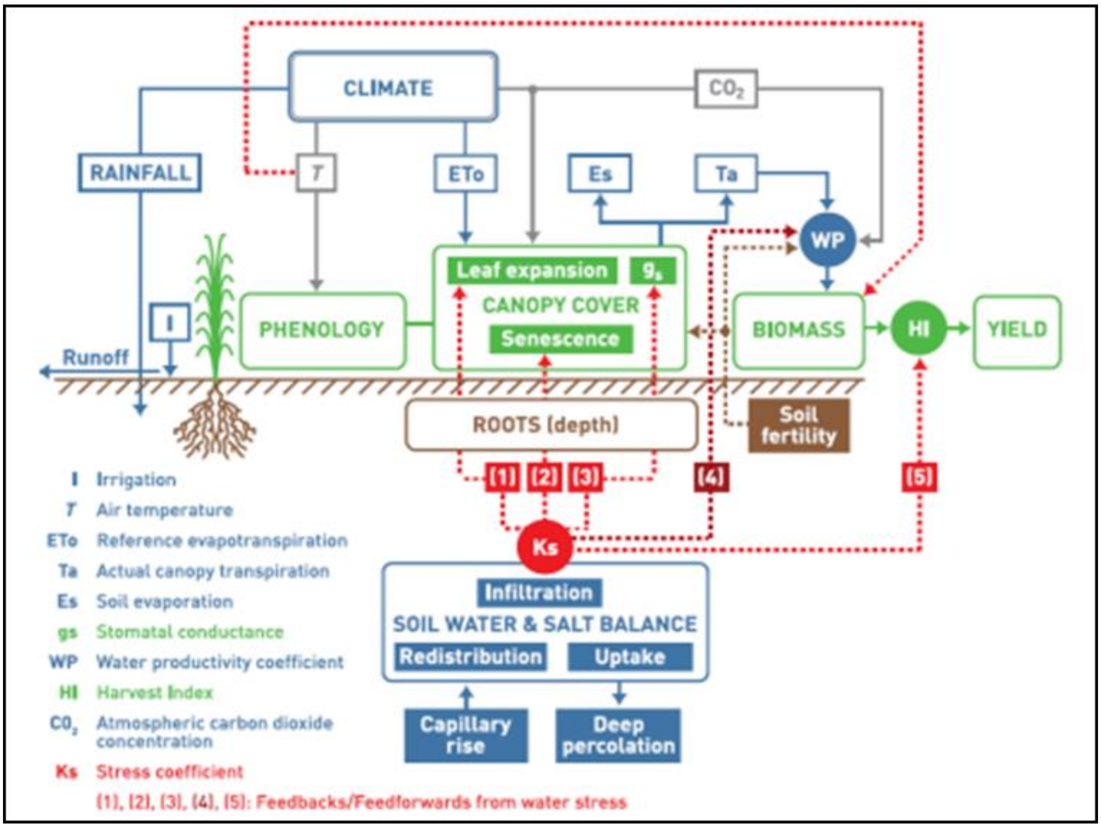

Figure 3-4 Diagram of the AquaCrop model showing main components of the SPAC and the parameters driving the phenology, canopy cover, transpiration, biomass production and final yield (Steduto *et al.*, 2012)

The AquaCrop model can also accept rainfall, temperature and ET_o in monthly or mean decade records, which are then approximated into daily value when the model is run (Raes *et al.*, 2009). This option gives flexibility to users especially in regions where daily data are limited or not freely available. AquaCrop derives the water that infiltrates into the soil by subtracting the runoff generated from the rainfall. Rainfall and ET_o are required to determine the soil water balance of the root zone. The carbon dioxide level influences the WP parameter and thus, the crop's growth rate. Temperature values drive or influence the phenology (crop development) component in the model. AquaCrop uses thermal time to calculate the growth stages of the crop as described by McMaster and Wilhelm (1997), with the exception that no adjustment is made of the minimum temperature when it drops below the base temperature. This is believed to better represent the damaging or inhibitory effects of cold on plant processes.

The crop system has five main components related to the phenology, canopy, root system, biomass production and harvestable yield. The crop grows over its specified cycle through leaf expansion and by deepening its rooting system. When water is limited, the crop responds to water stress through any of the following feedbacks:

- a reduction in leaf expansion;
- closure of stomata, or
- increased senescence.

Water stress may also affect the WP and harvest index (HI) parameters, thus resulting in a lower attainable yield. Both E and Tr are affected by the extent of canopy cover. The Tr and WP are then used to calculate the biomass *B* (**Equation 3-2**). The harvestable portion of the biomass (i.e. yield *Y*) is calculated using the *HI* (**Equation 3-3**).

$$Y = B \cdot HI \qquad \textbf{Equation 3-3}$$

The soil component of the model allows the user to input a soil texture class for up to five different soil horizons (Raes *et al*., 2009). Soil texture is based on the particle size distribution as per the USDA triangle (Soil Conservation Service, 1991). The model can then estimate the hydraulic characteristics associated with each textural class. Estimated values are useful when such data are unavailable, but user-specified values for the location are preferable, especially for model calibration. The hydraulic characteristics include the drainage coefficient, hydraulic conductivity at saturation, as well as volumetric water contents at saturation, field capacity and permanent wilting point. The model also performs a daily water balance within the soil component. The water balance includes processes of runoff, infiltration, redistribution, deep percolation, capillary rise, water uptake by roots, evaporation and transpiration (Steduto *et al*., 2009).

3.4.3 Calibration and validation

Parameterisation is a higher-level adjustment of model parameters than calibration (Farahani *et al*., 2009). It involves defining the necessary parameters (e.g. by data collection) within a model before being used for a particular purpose. Farahani *et al*. (2009) notes that these terms are at times used interchangeably in some literature. In the context of this document and similar to the approach by Kunz *et al*. (2015b), parameterisation refers to the original development of new crop parameter files, which was undertaken by the model developers for sugarcane and sugarbeet. In this study, certain parameters were calibrated (i.e. fine-tuned) to better represent local growing conditions.

Calibration and validating of the AquaCrop model requires the information presented in **Table 3-1**. Calibration is the refinement or adjustment of parameters that are already in the model so that simulated yields agree with observations at a given location (Merriam-Webster, 1998; Farahani *et al*., 2009). Model validation often refers to the comparison of model output against an independent dataset that was not used to calibrate the model (Augusiak *et al*., 2014). Model verification determines whether the model implements the assumptions correctly and that the model is error-free (Sargent, 2011).

Table 3-1 Information and data required by AquaCrop to simulate crop growth, yield and water productivity (after Steduto *et al*., 2012)

Crop	Climate and Et	Soil	Irrigation and soil water
• Plant density • Planting and harvesting dates • Date of emergence • Date of crop senescence • Maturity date • Crop life cycle length • Seeding rate and germination % • Periodic measurements of leaf area index and above-ground biomass over the season • Signs and dates of water stress • Rooting depth • Grain/tuber/stem yield • Reference harvest Index	• Daily minimum and maximum temperature • Daily minimum and maximum relative humidity • Daily average wind speed • Daily solar radiation • Daily rainfall data • Measured ET (optional)	• Soil textural class and depth of each soil horizon • Layer restrictive to root growth and depth • Indication of slope (via the curve number) • Indication of soil fertility • General fertilisation practice • Kind, rate and timing of fertiliser application • Field capacity and permanent wilting point of each soil horizon • Soil water holding capacity • Saturated hydraulic conductivity	• Water application method and approximate irrigation schedule • Estimate of soil water content at planting based on measurements • Amount of water applied at each irrigation • Measured or estimated soil moisture content for different soil depths at planting • Periodic measurements of soil water content at various depths of the root zone

The model parameters in **Table 3-1** can be collected via different techniques and methods (see **Chapter 6**). These methods can be classed as primary data, secondary data and simulation modelling. Primary data are data gathered directly from the material/s being investigated. Such data have not been analysed or interpreted by another person. The main advantage of using primary data sources is that they are considered to be stronger than secondary sources (Hofstee, 2013). The disadvantages of primary data collection are related to associated cost and time. Secondary data pertains to primary data that another party has collected, interpreted or analysed. Consequently, utilising such data can provide significant savings in cost and time (Hofstee, 2013). However, errors incurred during the primary collection and data analysis can be carried over by the secondary user. Furthermore, secondary sources may not always be detailed enough (i.e. the quantity of data may be insufficient), as was the case in this study.

3.5 Gaps in Literature

As noted in **subsection 2.4.1**, sugarbeet is a new crop in South Africa and hence, it is not a commonly grown in the country. This implies that AquaCrop model parameters for sugarbeet have not been calibrated for local growing conditions. This presents an opportunity to develop such parameters for this crop. In addition, the potential impacts of climate change of sugarbeet production in South Africa are unknown, which needs to be addressed as climate change can negatively impact the production of bioethanol from sugarbeet.

3.6 Summary

Crop yield models are applied widely in agriculture for the purposes of estimating yields. The literature review has shown that there are three classes of such models, *viz*. carbon-driven, solar-driven and water-driven models. The latter was selected in this study because such models simulate yield in response to water availability. Hence, the AquaCrop model was chosen based on its robustness and simplicity. The next chapter discusses AquaCrop's suitability for climate change studies.

4 CROP RESPONSE TO CLIMATE CHANGE

This chapter discusses the potential impacts of climate change on crop productivity. The benefits of using AquaCrop in climate change studies is also presented.

4.1 Background

Agricultural crops are directly dependent on suitable climatic conditions for optimum yield production. Therefore, any changes in atmospheric carbon dioxide concentrations ([CO_2]), air temperature and precipitations patterns are bound to affect future water resources and crop production (Easterling and Apps, 2005; Vanuytrecht *et al*., 2011). In addition, the ratio of blue (i.e. runoff) and green water (i.e. ET) will be altered, resulting in changes in soil water availability, which will also affect crop yields.

The simulation of crop yield can predict both the sign and magnitude of the overall impact that may result from climate change (Tubiello *et al*., 2002). For example, studies have indicated that mean seasonal temperature increases of 2-4°C may result in optimal temperature ranges of crops being exceeded and thus, future crop yields may decrease (Adams *et al*., 1998; Wheeler *et al*., 2000; Battisti and Naylor, 2009; IPCC, 2014a). However, such negative impacts can be counteracted by the effects of increased [CO_2]. This is particularly true for C3 crops, which is discussed next in more detail.

4.2 C3 vs C4 Crops

It is a well-known that [CO_2] coupled with management factors interact in complex ways to determine the overall impact of climate change on crop production (Zhao and Li, 2015). Changes in temperature and precipitation patterns could either have a positive or negative impact on agriculture. In general, increases in [CO_2] will enhance the growth and yield of most agricultural plants (Allen *et al*., 1997; Kimball *et al*., 2002; Vanuytrecht *et al*., 2014; Zhao and Li, 2015). This phenomenon is known as CO_2 fertilisation (Vanuytrecht *et al*., 2011). This effect is manifested differently in C3 and C4 crops. Rising [CO_2] generally stimulates C3 photosynthesis more than C4 (Lara and Andreo, 2011). Studies such as those by Ainsworth and Ort (2010) as well as Sultan *et al*. (2013) have indicated that C3 (e.g.

sugarbeet) crops are more responsive to elevated [CO_2] compared to C4 crops (e.g. sugarcane). For C4 crops, increased [CO_2] will not affect biomass production much at all. However, elevated [CO_2] increases WUE by decreasing stomatal conductance and transpiration (Ainsworth *et al*., 2002; Vanuytrecht *et al*., 2012).

The process of carbon fixation is different for C3 and C4 crops and thus, changes in [CO_2] affects them differently. Lara and Andreo (2011) stated that C4 species have evolved in a high CO_2 environment enabling them to have a higher nitrogen and WUE compared to C3 species. Therefore, photosynthetic carbon assimilation in C4 species is somewhat saturated. Photosynthesis in C3 species is known to operate at less than optimal CO_2 levels and thus, can show dramatic increase in carbon assimilation, growth and yields (Lara and Andreo, 2011).

C3 and C4 crops are also suited to different climatic conditions. C4 plants are more adapted to hot and dry climates and thus, lose less water via evapotranspiration relative to C3 species (Sage and Monson, 1999; Gillies, 2008). Even when stomata are closed (i.e. due to heat stress), photosynthesis can still continue. The opposite takes place in C3 plants, where higher temperature results in a process called photorespiration (oxygen is used instead of carbon dioxide for photosynthesis), resulting in reduced photosynthetic activity (Gillies, 2008). Therefore, under higher temperatures and lower [CO_2] levels, C4 crops have an advantage. However, they can benefit from increased [CO_2] levels under drought conditions as shown by Gillies (2008). C3 crops benefit largely from elevated [CO_2] under most conditions, and thus have an advantage over C4 crops. Additionally, increased [CO_2] decreases photorespiration in C3 crops, even under heat stress (Raines, 2011).

Based on the available literature related to impacts of elevated [CO_2], there are fewer studies for C4 crops compared to C3 crops. This is due to the lack of response of C4 crops to rising [CO_2], which has translated in a lack of interest (Lara and Andreo, 2011). Nevertheless, based on the reviewed literature in this study, differences in yields and WUE between sugarcane (i.e. C4) and sugarbeet (i.e. C3) due to changes in [CO_2] and climate (i.e. temperature and rainfall) are anticipated.

4.3 Modelling CO_2 Effects

With the inception of crop modelling some four decades ago, several earlier crop models could simulate plant responses to [CO_2], but most were originally developed to simulate present climate conditions. The introduction of crop models with CO_2 as an input variable appeared in the early 1970s and 1980s (Acock *et al.*, 1971; Thornley, 1976; Charles-Edwards, 1981; Goudriaan *et al.*, 1985). These models could describe the dependency of photosynthesis on light and CO_2 at canopy and leaf level. Tubiello and Ewert (2002) reviewed the evolution and different types of crop models used in climate change studies involving crop response to [CO_2]. AquaCrop has been used in impact studies for various crops such as maize (Masanganise *et al.*, 2012), durum wheat (Soddu *et al.*, 2013) and cotton (Voloudakis *et al.*, 2015).

4.3.1 Normalisation of WP

As described in **subsection 3.4.1**, the *WP* parameter in AquaCrop is normalised by ambient CO_2 levels. This allows the model to account for the effects of increasing CO_2 on crops. The normalised WP parameter values are thus different for C3 and C4 crops. They range between 15-20 g m^{-2} for the C3 crops and 30-35 g m^{-2} for C4 crops (Raes *et al.*, 2011).

4.3.2 Crop sink strength

Compared to other crop yield models, AquaCrop takes into consideration the sink strength (f_{sink}) of crops which can be adjusted due to crop characteristics and field management. This is important since crops that have strong sinks respond better to increased [CO_2] and vice-versa, thus giving a better presentation of expected future yields. The study by Vanuytrecht *et al*. (2011) showed that "variation in future yield potential associated with sink strength could be as high as 27% of the total production". Vanuytrecht *et al*. (2011) presented the f_{sink} ranges of various crops in the AquaCrop database based on Free Air Carbon Enrichment (FACE) experiments. Since multiple environmental factors affect the sink strengths of crops, the current values are not definite (Ainsworth and Rogers, 2007; Leakey *et al*., 2009). Nonetheless, the developers of AquaCrop have taken a step in the right direction by including the f_{sink} of crops in the model.

Adjustments of f_{sink} for current climate conditions should be carried out with caution because the literature (e.g. Vanuytrecht *et al*., 2014) indicates that such adjustments may not be necessary. There are no FACE experiments that have been undertaken for sugarcane and hence, its f_{sink} range is yet to be determined. However, research institutions such as the South African Sugarcane Research Institute (SASRI) can possibly undertake such experiments for sugarcane.

4.3.3 Summary

Climate change is a widely studied topic and its predicted impacts on agricultural crops, based on simulation modelling, is an accepted plausible reality. The importance of crop response to increasing [CO_2] is evident in the literature. Since the process of carbon fixation in C3 and C4 crops is different, they will respond in dissimilar ways to climate change. Therefore, based on the literature, it is expected that sugarbeet (C3 crop) will have a bigger response to CO_2 changes compared to sugarcane (C4 crop). Modelling the impacts of increased CO_2 can help improve the understanding of likely impacts on crop yield and WUE of sugarcane and sugarbeet.

5 CLIMATE CHANGE PROJECTIONS

In this chapter, the importance of different downscaling techniques is discussed as well as the use of multiple GCMs in reducing uncertainty in model output. Such approaches allow crop modellers to use future climate scenarios at a regional or local scale.

5.1 Background

It is widely accepted that climate change may threaten global food security (Donatelli *et al*., 2012). However, climate change is linked with uncertainty and its potential impacts are estimated using climate projections developed from a plethora of global climate models or GCMs. Regardless of the uncertainties involved, studies have indicated that [CO_2] has been increasing since the industrial revolution and continue to do so on an annual basis. According to Tubiello and Ewert (2002), [CO_2] is approximately 30% higher today (at 399 ppm) compared to pre-industrial times. By the year 2100, it is estimated to reach at least 750 to 1300 ppm if no effective mitigations are employed (IPCC, 2014a). Increased [CO_2] is linked to the high probability of climate change (Tubiello and Ewert, 2002). Extreme events (i.e. droughts, variability in rainfall patterns) are tied to the dynamics of the changing climate.

5.2 Global Climate Models

Most impact studies rely on GCMs to provide future climate scenarios (Hewitson and Crane, 2006). GCMs are complex tools that consist of a set of mathematical equations operating at a spatial resolution of 100-300 km (Vanuytrecht *et al*., 2014, Wibig *et al*., 2015). They describe climate at a set of "grid points" which are distributed spatially at the same density over land and ocean (Wibig *et al*., 2015). These models are only able to capture climate features at an atmospheric level, at scales ranging between 1000 to 2500 km, i.e. about eight grid point distances (Grotch and MacCracken, 1991; von Storch *et al*., 1993). However, the more relevant climatic processes (e.g. cloud formation and rainfall) occur at a much smaller scale in reality and hence, such process are not adequately modelled by GCMs. Therefore, outputs from GCMs cannot be applied directly at a field scale (Baron *et al.,* 2005). Downscaling techniques have been developed to provide climate change impacts at a regional and catchment level (see **section 5.3**).

5.2.1 Ensemble approach

All techniques developed to derive regional-scale climate information are associated with uncertainties (Wibig *et al*., 2015). The spread in model output is an indicator of the level of uncertainty, which can be related to differences in model structure, model parameterisation and initial conditions. According to Weigel *et al*. (2008), uncertainties can be grouped into two classes:

- "Uncertainties in model initialisation, for example due to incomplete data coverage, measurement errors, or inappropriate data-assimilation procedures; and
- Uncertainties and errors in the model itself, for example due to the parametrization of physical processes, the effect of unresolved scales, or imperfect boundary conditions (Buizza *et al*., 2005; Schwierz *et al*., 2006; Weigel *et al*., 2007)."

Uncertainty in modelling can be reduced by using climate change information from multiple GCMs (Maraun *et al*., 2010; Benestad, 2011). For climate change studies, an ensemble approach to modelling has become widely popular (Kharin and Zwiers, 2002; Yun *et al*., 2003; 2005). There are two types of ensemble techniques found in literature, *viz.* 1) an ensemble of predictions obtained from one model, and 2) an ensemble of predictions obtained from multiple models (Kharin and Zwiers, 2002). The first approach is usually applied in numerical weather forecasting, whereas the latter approach involves the use of different GCMs for future climate forecasting (Sachindra *et al*., 2013). In this study, the terms ensemble GCM approach and multi-model ensemble are used interchangeably.

The multi-model ensemble approach often outperforms single model simulations and their predictions tend to be more accurate (Knutti *et al*., 2010; Warner 2011; Sachindra *et al*., 2013). Of importance is knowing that every model performs well for different applications and no model is best suited for all applications (Christensen *et al*., 2010). Therefore, the careful selection of each GCM model in an ensemble approach is important.

5.2.2 SRES CO_2 scenarios

Before undertaking future climate simulations, a scenario of possible carbon emissions must be selected. Due to many influencing factors, different CO_2 scenarios have been developed, which are referred to as the Special Report on Emissions Scenarios (or SRES scenarios).

These scenarios were developed by the Intergovernmental Panel on Climate Change (IPCC) (Nakićenović *et al*., 2000). The SRES scenarios relate to six possible outcomes with regards to future development of the world population and economy. Each SRES scenario predicts an increase in greenhouse gases in the atmosphere resulting in higher global temperatures, leading to changes in the climate. These scenarios are within the four "families", namely the Al (with three scenarios, e.g. A1B) as well as A2, B1, and B2 (each with one scenario). The AquaCrop model is bundled with four of the six possible future CO_2 trajectories, i.e. A1B, A2, B1 and B2 (**Figure 5-1**).

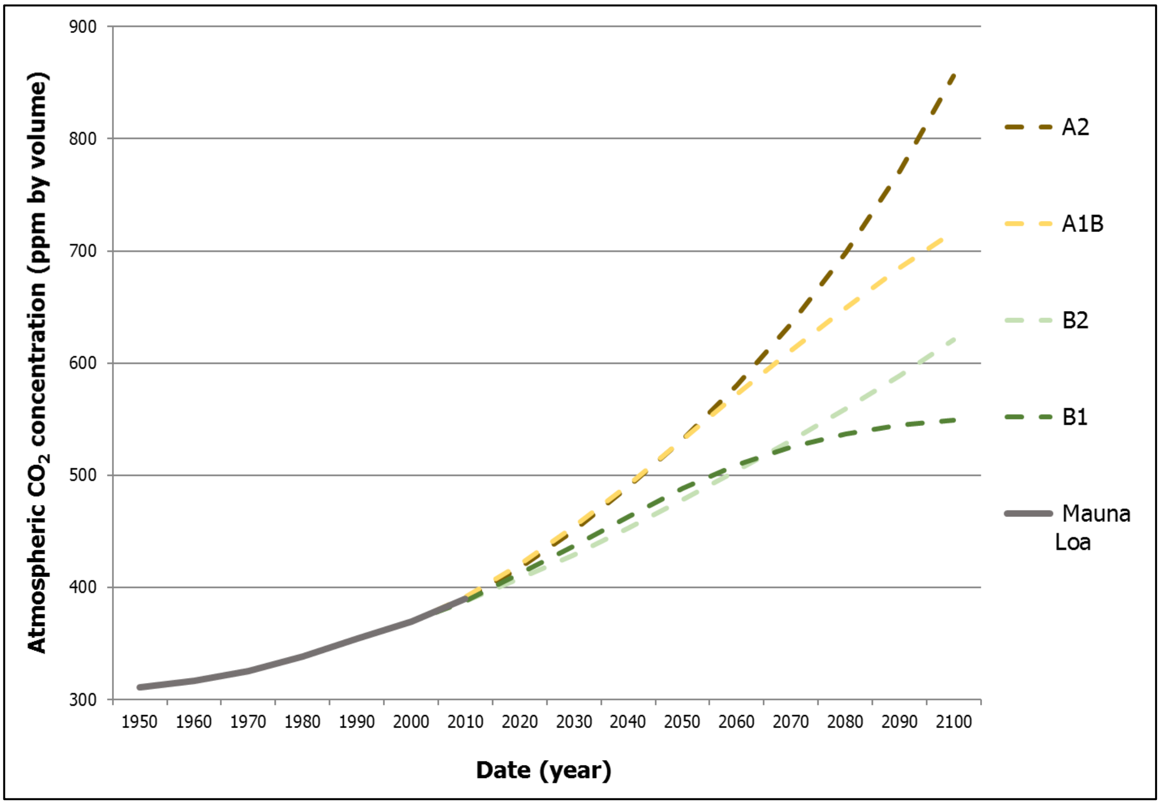

Figure 5-1 Possible SRES CO_2 trajectories with reference to observed values measured at Mauna Loa (data source: AquaCrop version 4, 2012)

For this study, the A2 scenario was selected. This is known as the "business-as-usual" pessimistic outlook of the future in which greenhouse gas emissions will continue to rise. By 2100, this is expected to result in mean global temperatures being up to 2.4°C to 5.4°C higher than the present time (IPCC, 2007). Such temperature increases, coupled with CO_2 increases, could impact the climate and hence, would affect agricultural crop production. The IPCC (2014a) notes that stabilising temperature increases in the future would require moving away from the "business-as-usual" scenario. Such a move may result in limiting annual temperatures to below 2°C (as per the Paris Agreement) relative to pre-industrial times (Han-Chen *et al*., 2017). That equates to atmospheric concentrations reaching 450 ppm in the year 2100. Therefore, based on the A2 scenario, the simulations in this study are likely to show annual temperature increases well above the desired 2°C.

5.3 Downscaling Techniques

In essence, downscaling involves a process where large-scale climate variables are linked with small-scale variables (Wibig *et al*., 2015). There are two types of downscaling techniques that exist, namely dynamical and statistical downscaling. The former technique nests a high-resolution regional climate model (RCM) into the GCM and the latter technique statistically represents desired fields from the lower resolution GCM data (Haylock *et al*., 2006).

Regardless of the level of resolution that GCMs can be downscaled to, a level of uncertainty will always exist. Changes in the environment such as the vegetation, atmospheric gases, ocean and air temperatures all lead to variations in the climate. Some of these can be predicted with a high level of accuracy while others cannot, such as land-use change and atmospheric composition, specifically greenhouse gases (Wibig *et al*., 2015). The following subsections briefly discuss each downscaling technique and its associated advantages and limitations.

5.3.1 Dynamical downscaling

The use of RCMs in climate change studies dates back to 1989, when Dickinson *et al*. (1989) used a dynamical approach for modelling the climate over a western region of the United States. To date, RCM climate change simulations have been used across all continents (Wibig *et al*., 2015). For example, RCM output to drive crop yield models has been used in studies by Oettli *et al*. (2011) and Zacharias *et al*. (2015).

Using dynamical downscaling, long term climate simulations can be carried out at spatial resolutions of 50 to 10 km for a specific region with lateral boundary conditions coming from observation-based datasets (Nemeth, 2010; Kienzle *et al*., 2012; Wibig *et al*., 2015). Since the spatial resolution of RCMs is much better than GCMs, RCMs are more suited for representing local conditions. Lateral boundary conditions differentiate GCMs and RCMs as the latter model cannot operate on a global scale. RCMs are thus driven by winds, temperature, and humidity imposed at the boundaries of the domain and sea surface temperatures, supplied by a GCM (Maraun *et al.*, 2010). One of the major drawbacks to dynamical downscaling is the high computational costs (IPCC, 2007).

Since RCMs receive boundary conditions from GCMs, the quality of output from these models is highly dependent on the GCMs. The aim of the RCM is to correct local climate misinterpretations (e.g. topographic influences) and not large-scale atmospheric flow. Therefore, poor atmospheric flow representation (which affects local climate conditions) from a GCM will manifest in the data produced by RCMs. This can ultimately lead to RCMs being biased towards a hotter/cooler and a wetter/drier climate. This obviously has a knock-on effect in climate change impact studies. According to Maraun et al. (2010), systematic biases are a big disadvantage of dynamical downscaling. Systematic biases are a combination of systematic errors from the driving GCMs as well as the RCM. It is therefore important to understand model bias in GCMs and RCMs before undertaking impact assessments (Zacharias *et al*., 2015). Various methods to correct model biases have been discussed by Maraun *et al*. (2010) but are beyond the scope of this study.

A major advantage of dynamical downscaling is their usability in any region of the world (Wibig *et al*., 2015). This is however not the case with statistical downscaling which requires good quality data for calibration purposes (discussed further in **subsection 5.3.2**). However, each RCM is different in its representation of various atmospheric processes. Hence, it is important to use outputs from different RCMs. In addition, developing methodologies that exploit each model's strengths is important in an ensemble approach (Leith and Chandler, 2010).

5.3.2 Statistical downscaling

The statistical downscaling approach is a technique that bridges the gap between the large-scale output from GCMs and local-scale input requirements of simulation models (Wibig *et al.*, 2015). There are two statistical approaches as suggested by Rummukainen (1997), namely model output statistics (MOS) and perfect prognosis (PP). Only the latter technique is discussed in this document.

PP methods identify a statistical relationship between an independent atmospheric variable and various dependent variables related to the local or regional climate. The reference (i.e. historical) climate is used to determine this relationship (Maraun *et al*., 2010). This approach is computationally cheap in comparison to dynamical downscaling (Shin *et al*., 2009, Wibig *et al*., 2015). The main rationale behind the method is the use of empirical knowledge via the inclusion of observational data. The performance of this approach is largely dependent on the selected predictor, in that it must be able to capture changes in the climate. A drawback of PP methods is their under-representation of temporal variability. According to Wibig *et al*. (2015), another disadvantage of PP approaches is their lack of spatial coherence, especially when numerous climate models are used at a particular location.

5.4 Summary

GCMs are important tools and the majority of climate change studies rely on them for simulations of future climate scenarios. However, there is uncertainty associated with climate change simulations and now most studies use climate change information from multiple GCMs to reduce that uncertainty. GCMs do not capture the climatic processes that occur at finer scales which are important in the context of climate change. This limits their applications at such scales. Therefore, downscaling techniques have been developed to improve impact study simulations at a regional and catchment levels. Overall, the literature review has shown the benefits of using outputs from multiple GCMs and using different downscaling techniques.

Chapter 6 discusses various methods and tools that were used to collect data for input into the selected crop yield model. The type of methods used was dependent on the availability of equipment and on the advantages they offered. **Chapter 6** also presents the GCMs that were selected and the two downscaling techniques employed for the different GCMs. The various sources that provided future climate scenarios are also acknowledged.

6 MATERIALS AND METHODS

The research designs used in this study were carefully selected for their ability to give reliable results, regardless of their limitations. The following three research designs were used:

1) field experiment and laboratory analyses (i.e. primary data collection),
2) secondary data (for model calibration and validation), and
3) model simulations (to assess the impacts of climate change on crop yield).

The methodology is therefore split into three broad categories. The first category (**sections 6.1** to **6.5**) describes the field work and laboratory analysis that was undertaken to generate a primary dataset that was used to calibrate the AquaCrop model for sugarbeet. During 2013, a field experiment was conducted at UKZN's research farm (Ukulinga) and soil samples were analysed in a laboratory at UKZN to determine soil water retention parameters. The second category (**section 6.6**) describes the calibration and validation of the crop model for sugarcane using secondary datasets. In addition, secondary datasets were also used to test the calibration for sugarbeet. This approach helped answer the first research question (i.e. what the attainable yield of sugarbeet and sugarcane is?). The third category (**sections 6.7** and **6.8**) describes the data and simulations used to assess the impacts of climate change on yield and WUE of the two selected feedstocks. The methodology begins with a description of each experimental site where primary and secondary datasets were sourced as well as a description of the experiments designs used to generate the datasets. **Table 6-1** below presents the data sources for the work undertaken in this study.

Table 6-1 Sources of data used in this study

Data	Undertaken by	Source	Reference
Climate data for sugarbeet	Dr. M Mengistu	ARC weather station	n/a
Climate data for sugarcane	SASRI	SASRI	n/a
Soil water content	Dr. M Mengistu and Mr. O Mokonoto		Kunz *et al.* (2015)
Total evaporation	Dr. M Mengistu and Mr. O Mokonoto		Kunz *et al.* (2015)
Crop establishment	Mr. I Dodge	ACCI	Kunz *et al.* (2015)
Leaf area measurements	Mr. O Mokonoto		
Root measurements	Mr. O Mokonoto		
Final yields	Mr. I Dodge from the ACCI	ACCI	Kunz *et al.* (2015)
Soils analysis	Soil survey pit dug by Mr. Mokonoto and analyzed by the ICFR	ICFR	n/a
Soils retention parameters	Mr. O Mokonoto	UKZN Soils Laboratory	n/a
Calibration set-up and runs	Sugarbeet data compiled by Mr. O Mokonoto and Dr M Mengistu	Sugarcane data provided by SASRI	AgMIP
Validation runs	Mr. O Mokonoto	Sugarcane data provided by SASRI	n/a
Climate change runs	Mr. O Mokonoto	Historical and future climate data obtained from various sources	Schulze *et al.* (2011a; 2011b), CSAG, CSIR (Engelbrecht *et al.*, 2011)

6.1 Site Description

A primary dataset was collected for sugarbeet grown at Ukulinga during the 2013 season and used to calibrate the AquaCrop model. No field experiments were undertaken in this study to validate the model for sugarbeet, nor calibrate or validate the model for sugarcane. Rather, secondary datasets pertaining to each crop were obtained from the Agricultural Model Intercomparison and Improvement Project (AgMIP) initiative. AgMIP is made up of different international communities from climate, crop and economic modelling backgrounds. Their aim is to produce improved crop and economic models and new climate impact projections for the agricultural sector (Rosenzweig *et al*., 2013). In total, three AgMIP datasets were utilised in this study as follows (Singels, *pers. comm*., 2013):

- The La Mercy dataset (1989-1990) was used to calibrate AquaCrop for sugarcane.
- The Pongola (1968-1971) and the Komatipoort datasets (2011-2012) were then used to validate the model for both sugarbeet and sugarcane.

The secondary datasets were provided by SASRI, based at Mt. Edgecombe in KwaZulu-Natal. A description of each experimental site where the primary and secondary datasets were measured is given in the subsections that follow.

6.1.1 Ukulinga

Ukulinga is the University of KwaZulu-Natal’s research farm in Pietermaritzburg and is approximately 7 km from the University campus (30˚24'22"E; -29˚40'04"S, altitude 800 m a.s.l). The mean annual precipitation (MAP) at Ukulinga is 750 mm, with most of the rainfall occurring in the summer months, particularly in January and February (Kunz *et al*., 2015a). Ukulinga generally experiences warm to hot summers and mild winters. February (26.5°C) and July (8.0°C) are the warmest and coldest months, respectively (Kunz *et al*., 2015a). The soils at the experimental site are classified as Westleigh soil form (Soil Classification Working Group, 1991). A soil survey undertaken in August 2010 revealed a mostly clay loam texture with depths varying between 0.6 to 1.0 m across the trial site (Kunz *et al*., 2015a).

6.1.2 La Mercy

The La Mercy sugarcane site (31°07'48"E, -29°34'12"S, altitude 72 m a.s.l) is approximately 6.7 km west of Tongaat in KwaZulu-Natal and experiences a subtropical climate. Based on AgMIP climate data from 1980 to 2009, the MAP is 1004 mm, the mean annual maximum temperature is 25.6°C and the mean annual minimum temperature is 15.4°C. Rainfall occurs throughout the year, with most occurring between October to February. As per the FAO soil classification, the soils are classified as Brunic luvisol (FAO, 2015). They have a depth of 1.65 m and a Curve Number (CN) of 65, indicating a medium probability for runoff. The AgMIP dataset, provided by Singels (*pers. comm*., 2013), did not specify the texture of the soils.

6.1.3 Pongola

The Pongola site (31°35'31"E, -27°24'50"S, elevation of 308 m a.s.l) is 6.5 km south west of Pongola town. The site is also classified as subtropical and hence, temperatures are similar to La Mercy. The mean annual maximum temperature for the site is 26.7°C and the mean annual minimum temperature is 14.9°C. However, the MAP is lower at 585 mm. The soils at the study site are deep, measuring up to 2.72 m. They are classified as Shorrock soils and have a higher CN of 73 (thus a higher potential for runoff). The AgMIP dataset was again provided by Singels (*pers. comm.*, 2013).

6.1.4 Komatipoort

The Komatipoort site (31° 52'E, -25° 37'S, altitude 187 m a.s.l) is about 24 km south west of Komatipoort town in the Mpumalanga Province. Based on the AgMIP dataset, the annual maximum and minimum temperature averages are 30.5°C and 14.2°C respectively. The MAP of the study site is 769 mm and the soils are fairly shallow, measuring a depth of 0.6 m. The clay content decreases with depth from 36% (0.25 m) to 28% (0.60 m). The soils are classified as Shortlands soils. The AgMIP dataset was also provided by Singels (*pers. comm.*, 2013).

6.2 Trial Description

A description of each experimental site is given in the subsections below for the two selected biofuel feedstocks. The experimental sites had different layouts and designs, cultivars, planting and harvesting dates as well as different agronomic practices.

6.2.1 Sugarcane

One rainfed sugarcane cultivar (cultivar NCo376), ratooned over eight treatment dates across the year, was used at La Mercy and Pongola. Cultivar NCo376 was released in 1955 in South Africa and it has been reported to produce high yields across different climatic conditions (Zhou, 2013). NCo376 is a high population cultivar and has a low sucrose content. It has a thermal time of 203°C days (ratoon crop) from start to emergence and a base temperature of 10°C (Zhou *et al*., 2003; Jones, 2013). The Komatipoort trial consisted of three sugarcane cultivars spread over six irrigated treatments. The three sugarcane sites used a row spacing ranging from 1.2 to 1.5 m.

6.2.1.1 La Mercy

The La Mercy experimental dataset (1989 to 1990) from AgMIP consisted of eight rainfed ratoon treatments. A row spacing of 1.2 m was applied across all treatments. Treatments one to four were ratooned in 1989, followed by treatments four to eight which were ratooned in 1990 (**Table 6-2**). Harvesting took place 18 months later in each of the eight treatments.

Table 6-2 Ratooning and harvesting dates for the La Mercy sugarcane treatments

Treatment Number	1	2	3	4	5	6	7	8
Ratooning Date	01-06-89	01-08-89	01-10-89	01-12-89	01-02-90	01-04-90	01-06-90	01-08-90
Harvest Date	02-10-90	05-12-90	05-02-91	03-04-91	04-06-91	31-07-91	01-10-91	03-12-91

Dates of fertiliser application were not recorded in the AgMIP dataset. However, the AgMIP dataset indicates that 140 kg per hectare of nitrogen, 30 kg per hectare of phosphorus and 140 kg per hectare of potassium were applied at start of tillering.

6.2.1.2 Pongola

The ratooning of sugarcane in Pongola (1968 to 1970) was also divided into eight treatments with a row spacing of 1.4 m. The Pongola treatment dates are shown in **Table 6-3**. The sugarcane from each treatment was harvested 16-17 months after ratooning. The AgMIP Pongola dataset showed the crop was irrigated to avoid water stress using an overhead sprinkler system. However, no mention of fertiliser application was made in the AgMIP dataset.

Table 6-3 Ratooning and harvesting dates for the Pongola sugarcane treatments

Treatment Number	1	2	3	4	5	6	7	8
Ratooning Date	17-12-68	11-02-69	08-04-69	30-06-69	29-07-69	23-09-69	18-11-69	13-01-70
Harvest Date	05-05-70	30-06-70	25-08-70	20-10-70	15-12-70	09-02-71	06-04-71	29-05-71

6.2.1.3 Komatipoort

The AgMIP Komatipoort dataset consisted of three irrigated sugarcane cultivars (N31, N19 and 04G0073) which were planted on the 12 of October 2011 with a row spacing of 1.5 m.

N31 is a high yield sugarcane cultivar (compared to NCo376) with a low sucrose content and became available in South Africa in 1997 (SASRI, 2006). Sugarcane cultivar N19 was released in South Africa in 1986 and grows well in the North Coast and Zululand regions. N19 is a high sucrose cultivar and has good yields across a range of soils, particularly under rainfed conditions (SASRI, 2006). Cultivar 04G0073 is a high-fibre cane, characterised by thin stalks and long narrow leaves (Ngxaliwe, 2014). The six Komatipoort treatments were all planted and harvested on the same date (12/10/2011 to 26/10/2012). The AgMIP dataset made no mention of the planting density of each of the sugarcane cultivars.

At Komatipoort, each treatment involving three cultivars received both 50% and 100% of total irrigation demand using a drip irrigation system (i.e. six treatments). Nitrogen (120 kg per hectare) and phosphorus (100 kg per hectare) were applied to each treatment one month after planting.

6.2.2 Sugarbeet

6.2.2.1 Ukulinga

The trial was conducted in an 80 by 80 m plot, which provided the minimum fetch required to measure crop water use using a micrometeorological technique (**Figure 6-1**). Land preparation at Ukulinga included ploughing and disking. The sugarbeet trial was established and maintained by Mr Ian Doidge and other support staff from African Centre for Crop Improvement (ACCI), based at UKZN. Although sugarbeet EB0809 (planted at Ukulinga) is a sub-tropical variety, it is not well suited to hot conditions, especially when daily maximum temperatures reach 26°C (Kunz *et al*., 2015b).

Figure 6-1 Sugarbeet trial at Ukulinga research farm (Google Earth, 2013)

Prior to planting, the seed was initially treated with Trichoderma (a type of fungi) to make the plants more resilient to fungal infections (Ha, 2010). Sunshine Seedlings produced the sugarbeet seedlings for the trial, which were not transplanted the day they were delivered to the research farm. This allowed the seedlings to slowly adjust or harden to the outside weather conditions. Transplanting began on the 21st of May 2013 and harvesting took place between the 6th and 12th of December 2013 (i.e. ~7 month growing season).

A non-automated drip irrigation system operating at 120 kPa (non-compensated) was installed to maintain optimum soil water conditions and thus, maximise yield. The delivery rate of each dripper, spaced at 300 mm apart, was 1 litre per hour. The seedlings were transplanted between the dripper holes in order to minimise below-ground disease incidence. The dripper lines were spaced 0.5 m apart and thus; plant spacing was 0.3 m x 0.5 m (i.e. 66667 plants per hectare).

From previous trials, the land on which the sugarbeet was grown was known to be susceptible to weeds. Therefore, regular weeding was done using hand hoes to ensure the field remained weed-free, minimising competition for resources. Goltix was also used as a herbicide to combat weed growth. It was applied twice during the season at a dilution rate of 2.5 litres per hectare. In addition, two preventative fungicides, *viz*. Moncozeb and Difenaconozole (Difence) were applied to minimise possible leaf spot (i.e. *Cercospora*) outbreaks. Mocozeb was applied at 2 kilograms per hectare and Difence at 300 ml per hectare.

6.2.2.2 Komatipoort

Sugarbeet (variety EB0809) was grown at Komatipoort with a row spacing of 0.75 m and 0.20 m between plants in order to achieve a planting density of 66 667 plants per hectare (Francois *et al*., 2015). The crop was planted on the 12th of October 2011 and harvested on the 26th October 2012. Similar to the three sugarcane cultivars at Komatipoort, the sugarbeet had two irrigation treatments (i.e. 50% and 100% of total irrigation demand), with water applied using a drip irrigation system. Agronomic practices included the application of nitrogen (120 kg per hectare), phosphorus (75 kg per hectare) and potassium (75 kg per hectare) on the 23rd of May 2012.

6.3 Instrumentation

Different instruments were used to collect data related to the climate, soil water status as well as crop growth and water use, which were then analysed in order to prepare the necessary input files required by the AquaCrop model. Climate data were collected using automatic weather stations (AWSs) situated near the field experiments. Reference crop evaporation (ET_o) calculations were undertaken using the Penman-Monteith equation following procedures in the FAO Paper No. 56 as described in Allen *et al*. (1998). This technique estimates ET_o for a hypothetical, short grass surface using climatic inputs of solar radiation, air temperature, relative humidity and wind speed.

6.3.1 Sugarcane

AWSs were used to collect climate data at the sugarcane field experiments. The following daily climate variables were recorded, *viz*. solar radiation, minimum and maximum air temperature, minimum and maximum relative humidity, rainfall, wind speed and dew point temperature. The location of each AWS is given in **Table 6-4** below.

Table 6-4 Location of the AWS used for the sugarcane field experiments

Site	Station Name	Co-ordinates	Distance from Site
La Mercy	SASRI Tongaat	31°08'46"E, -29°34'30"S	5km W
Pongola	Pongola	31°35'31"E, -27°24'50"S	0 km
Komatipoort	SASRI Research Station	31°07'48"E, -29°34'12"S	0 km

6.3.2 Sugarbeet

The following subsections describe the instrumentation used at the Ukulinga sugarbeet trial.

6.3.2.1 Climate

An AWS situated near the sugarbeet trial was used to measure daily climatic variables. This included rainfall, minimum and maximum air temperature, minimum and maximum relative humidity, solar radiation, wind speed, wind direction and reference crop evaporation. Due to extreme weather events (e.g. hail) damaging the field equipment, some of the climatological variables were patched (by Dr Michael Mengistu) using data from an on-site weather station maintained by the Agricultural Research Council. Less than 10 percent of the original dataset was patched, thus making the data reliable for use in the crop model.

6.3.2.2 Soil water content

Dobriyal *et al*. (2012) reviewed different methods of estimating the soil water content. Instruments such as neutron probes, time domain reflectometry (TDR) probes, tensiometers, frequency domain reflectometry, gypsum block measurements, pressure plates and the gravimetric method can be used to estimate soil water content (Dobriyal *et al*. 2012). For example, Farahani *et al*. (2009), García-Vila *et al*. (2009) and Karunaratne *et al*. (2011) used neutron probes to measure the soil water content. However, TDR and the gravimetric method have also been utilised in other studies where AquaCrop was applied (Geerts *et al*. 2009; Todorovic *et al*., 2009). TDR results are usually accurate within an error limit of approximately 1% (Anisko *et al*., 1994; Chandler *et al*., 2004). Dobriyal *et al*. (2012) concluded that TDR is more economical and provides accurate results when compared to the other methods. Calibrations are not required for specific soil types, thus allowing it to be used in different environments (Ferrara and Flore, 2003). However, the TDR technique is very sensitive if there is poor contact between the probes and the soil, which then results in erroneous measurements (Dobriyal *et al*., 2012). Thus, it was necessary to install the probes correctly and to ensure there was full contact with the soil medium.

Soil water retention characteristics can be measured using pressure plate cells. According to Mavroulidou *et al*. (2009), this technique is the most common method utilised in the fields of soil science and hydrology.

A Campbell Scientific TDR100 system (Campbell Scientific, Logan UT, USA) was used to measure the volumetric soil water content at Ukulinga. The TDR system consisted of a TDR100 Time Domain Reflectometer, eight CS605 TDR probes, a Campbell Scientific CR1000 data logger and SDMX50 coaxial multiplexers. A pit was dug to insert the eight probes. The probes were inserted at depths of 10, 20, 40 and 60 cm on opposite walls of the pit. This allowed for a comparison of the readings and infilling of data, should a probe fail. See **Figure 10-1** and **Figure 10-2** in **APPENDIX A** which shows the pit that was dug and the location of the TDR instrumentation.

6.3.2.3 Total evaporation

Total evaporation can be measured using a soil water budget method (Farahani *et al*., 2009; Abedinpour *et al*., 2012). However, techniques such as the eddy covariance and surface renewal can also be used to estimate crop water use (Mengistu and Savage, 2010; Mengistu *et al*., 2012). The surface renewal system was used for crop water measurements (i.e. sum of soil water evaporation, transpiration and intercepted water by the canopy) at the Ukulinga sugarbeet trial. The surface renewal method determines total evaporation by calculating the latent heat flux density (*LE*) as a residual of the shortened energy balance equation as shown in **Equation 6-1** (Mengistu *et al*., 2012; McElrone *et al*., 2013):

$$LE = R_n - G - H \qquad \textbf{Equation 6-1}$$

where

LE = latent heat flux density (W m^{-2}), related to the phase change of water to vapour from the crop surface;

R_n = net irradiance (W m^{-2}), which is the radiant flux received per unit area from the sun,

G = soil heat flux density (W m^{-2}), which is the energy conducted in and out of the ground; and

H = sensible heat flux (W m^{-2}), i.e. the energy flux density from the surface to the air and vice-versa.

The latent heat flux density is divided by the latent heat of evaporation (L=2.45 MJ kg^{-1}) to obtain the mass flux density of water vapour from the surface (i.e. total evaporation) (McElrone *et al*., 2013). The surface renewal method used fine wire thermocouples to measure high frequency air temperatures at the surface-atmosphere interface (McElrone *et al*., 2013). One unshielded type-E fine-wire thermocouple (75-µm diameter), placed at a height of 0.5 m above the crop, was used to measure air temperature at Ukulinga, from which estimates of sensible heat flux were obtained. The surface renewal technique was calibrated using the more complex eddy covariance system (McElrone *et al*., 2013), as described by Kunz *et al*. (2015b).

Net irradiance was measured using a Rebs Q*7 net radiometer (REBS, Seattle, Washington, USA) situated at a height of 1.5 m. Two Hukse flux plates (HFP01-15, Delft, The Netherlands) were used to measure soil heat flux density at a depth of 80 mm and a system of parallel-thermocouples at depths of 20 and 60 mm were used to calculate the heat stored above the plates (Kunz *et al*., 2015b).

6.4 Data Collection at Ukulinga

At the Ukulinga sugarbeet trial site, Mr Ian Dodge from the ACCI helped to establish and maintain the sugarbeet crop. In addition, Dr Michael Mengistu assisted with data collection to determine crop water use (see **subsection 6.3.2.3**). During crop establishment, the frequency of collection of crop growth data was weekly. From the vegetative growth stage onwards, measurements were carried out fortnightly. However, soil water status and weather data were recorded every 30 minutes and downloaded from the data loggers on a weekly basis. Crop and soil data were collected using various techniques depending on the availability of field equipment and other resources (e.g. access to a soils laboratory).

6.4.1 Leaf area measurements

In AquaCrop, canopy development (an important feature in the model) is expressed through canopy cover (CC) and not via the leaf area index (LAI). A LAI-2200 plant canopy analyser (LI-COR, USA) can be used to measure the LAI (Hyer and Goetz, 2004). The LAI-2200 does not require calibration, as does other instrumentation (e.g. AccuPAR LP-80 ceptometer). Limitations of the LAI-2200 include the effect of non-uniform cloud cover and direct sunlight on LAI measurements. However, such limitations can be overcome by following procedures described in the manual (LI-COR, 2010), as was done in this study.

Before transplanting, a random sample of ten sugarbeet seedlings was taken for determination of seedling leaf area using an LI-3100C Portable Leaf Area Meter (LI-COR, USA). Once the meter has been calibrated properly, it has a combined accuracy and precision of 99% (LI-COR, 2010). Following successful crop establishment, an LAI-2200 plant canopy analyser (LI-COR, USA) was used to measure LAI, with the first reading taken 42 days after transplanting. Measurements were taken weekly until maximum LAI was reached. After that, measurements were taken fortnightly due to slower canopy cover development.
Canopy cover simulation is an important feature of AquaCrop because its expansion, ageing, senescence and conductance influence plant transpiration, which then determines biomass production. The latter is then used to calculate yield in the model via the harvest index (Steduto *et al*., 2012). Therefore, estimates of CC need to be accurate for good simulations of crop development. The LAI measurements collected on a weekly to bi-weekly basis were used to estimate CC using a regression equation (see **subsection 6.6.2.1**). This procedure has been followed by García-Vila *et al*. (2009), Hsiao *et al*. (2009) and Karunaratne *et al*. (2011).

6.4.2 Chlorophyll content

A Minolta SPAD 502 chlorophyll meter (Konica Minolta, Osaka, Japan) was used to measure sugarbeet's chlorophyll content index. Measurements were taken from the upper surface (i.e. adaxial) of the mature leaves and are based on comparing leaf transmittance at two wavelengths, *viz*. 650 nm and 940 nm. The obtained values are proportional to the chlorophyll content of the leaves (Manetas *et al*., 1998). The chlorophyll meter's design is based on the assumption that changes in the ratio of transmittance between the two wavelengths are purely based on chlorophyll levels. However, this is not always the case, since certain plants change leaf colour at different development stages (Manetas *et al*., 1998).

6.4.3 Rooting depth

The root system in AquaCrop is simulated through its effective rooting depth and water extraction pattern (Steduto *et al*., 2009). The effective rooting depth is the soil depth where the majority of plant roots reside. The depth of roots can either be estimated or measured. Mini-rhizotrons have been used in many areas to study root development, root turnover, root parasitism and proliferation of fungal hyphae (Faget *et al*., 2010). Majdi (1996) reviewed the application and limitations of this technique and concluded that it is a simple, non-destructive method to use. If this device is unavailable, destructive sampling can be used to measure root growth (e.g. Abedinpour *et al.*, 2012).

The root length of seedlings was measured at transplanting to determine the minimum rooting depth. Transparent access tubes (made of clear perspex) were inserted into the soil profile and then a scanner was inserted into the tubes to record images at various depths in order to ascertain the maximum rooting depth. However, the use of a mini-rhizotron camera was not successful in this study because the images that were obtained were blurred and thus, could not be used to measure root development. Therefore, the maximum rooting depth was obtained via destructive sampling (See **Figure 10-3** in **APPENDIX A**).

6.4.4 Soil water content

The TDR technique was used because (a) it is not labour intensive, and (b) it allows for continuous volumetric measurements of soil water content (see **subsection 6.3.2.2**). Soil water conditions were monitored on a weekly basis using this system to help guide when to irrigate the sugarbeet crops (see **APPENDIX B**).

6.4.5 Phenological growth stages

Phenological growth stages such as time to flowering and senescence and maturity as well as planting and harvest dates were observed (i.e. not measured). Hence, these stages were noted separately on a spreadsheet for input into the AquaCrop model.

6.4.6 Biomass and yield

Periodically, wild animals trampled and ate some of the sugarbeet plants, while hail damaged the sensors used to collect climatological data. By implication, damaged plots were not used for measuring final crop yield. Fresh and dry biomass can be determined by weighing samples with an accurate scale. The literature indicates that the drying of samples should be done over 48 hours at temperatures of between 65 to 75°C (Farahani *et al.*, 2009; Todorovic *et al.*, 2009; Karunaratne *et al.*, 2011; Abedinpour *et al.*, 2012).

Destructive sampling was used for taking periodic measurements of leaf, stem and tuber mass (dry and fresh) to measure biomass growth. Fresh and dry biomass of sugarbeet samples were determined by weighing samples on a scale (accurate to 3 decimals of a gram).

A sample was deemed dry after reaching constant mass with oven drying for over 48 hours at temperatures that approximated 70°C. Final biomass, yield and the harvest index (HI) were all determined at harvest.

6.5 Soil Laboratory Analysis

For soil texture, samples were obtained from three different depths (20, 40 and 60 cm) using a soil auger (by Mr Mokonoto), then carefully placed into labelled plastic bags and sent to the Institute for Commercial Forestry Research (ICFR) at UKZN for textual analysis. A second batch of soil samples was also collected, albeit at different depths of 0 to 30 cm and 30 to 60 cm for comparison purposes.

Undisturbed soil samples were collected from a 1 by 1 m pit within the study site for measurements of the soil water retention parameters and saturated hydraulic conductivity at the UKZN soil physics laboratory (Kunz *et al*., 2015b). The soils samples taken at the pit were deemed representative of the sugarbeet plot. Six soil cores (steel cylinders) in total were inserted at appropriate depths (20, 40 and 60 cm) in the soil profile, then carefully removed using minimal force so that the soil structure was not disturbed.

6.5.1 Soil water retention parameters

Soil water parameters (i.e. total porosity/saturation, field capacity/drained upper limit and permanent wilting point/lower limit) for three soil samples were estimated using the outflow pressure method as explained in **APPENDIX C**. This method is designed to measure soil water parameters between 0 and 100 kPa, from which estimates of total porosity (0 kPa) and field capacity (33 kPa) were obtained from three soil samples. A high-pressure pot operated at 1500 kPa of pressure was also used to determine the permanent wilting point of each soil sample.

6.5.2 Saturated hydraulic conductivity

The saturated hydraulic conductivity of the other three soil samples was determined using the constant head method (**Figure 6-2**). This method works by applying Darcy’s law (**Equation 6-2**) across the permeameter pressure ports. This law describes the basic flow of liquids in permeable materials (Gliński *et al*., 2011).

$$Ks_{ij} = \left(\frac{\Delta l_{ij}}{H_i - H_j}\right) \times \left(\frac{Q}{A}\right)$$ **Equation 6-2**

where,

KS_{ij} = saturated hydraulic conductivity of the soil between port i and j (cm s^{-1}),

I_{ij} = length of the soil material between ports i and j (cm),

$H_{i \text{ and } j}$ = total hydraulic head at port i and j (cm),

Q = volumetric outflow rate (cm^3 s^{-1}) and

A = total cross-sectional area of the column (cm^2).

This technique was selected due to the following advantages: 1) it is simple and easy to set up and 2) is a direct application of Darcy's law, thus giving reliable results that mimic field conditions (Lorentz *et al*., 2001). However, it has some pitfalls, *viz*. 1) the soil material can sometimes be disturbed, thus giving a false reflection of field conditions; 2) the manometer tubes can periodically block due to air bubbles, which will affect the accuracy of results; and 3) the soil must have a uniform structure to get a consistent hydraulic conductivity across the ports. The reader is referred to Lorentz *et al*. (2001) for the steps that were taken to calculate the saturated hydraulic conductivity using this method.

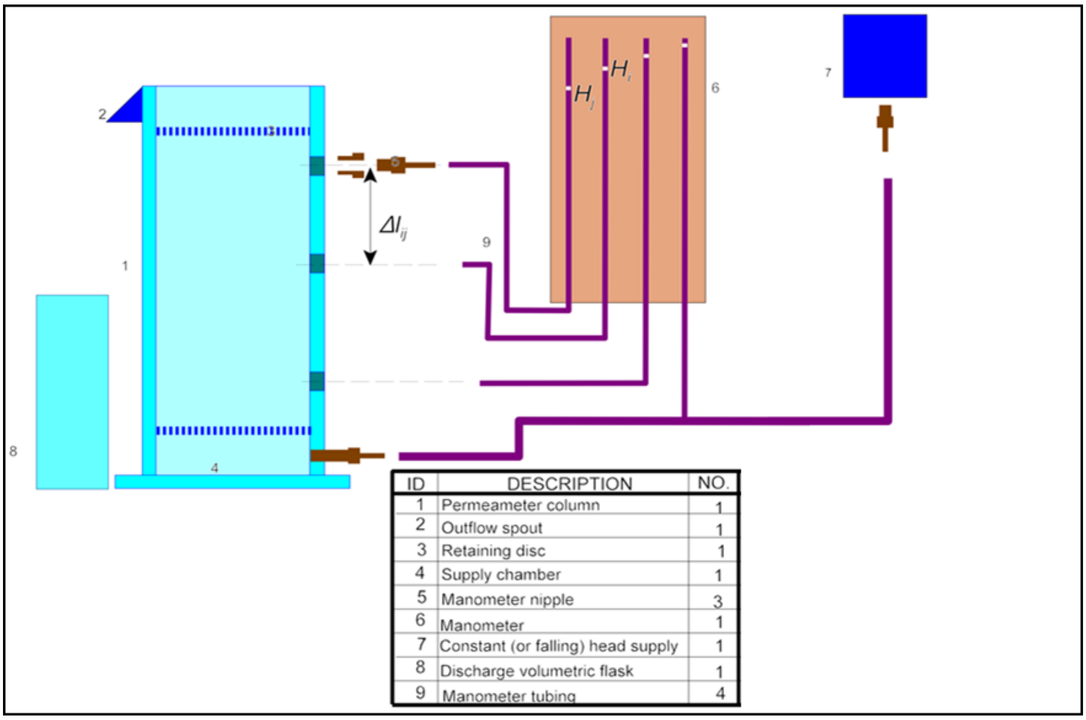

Figure 6-2 A diagram of the constant head method for measuring the soil hydraulic conductivity of undisturbed soil samples (after Lorentz *et al*., 2001)

6.6 Model Calibration and Validation

The AquaCrop model was selected for this study based on its advantages over other crop yield models (see **section 3.4**). AquaCrop is already parameterised for sugarbeet, sugarcane and other herbaceous crops. The model developers at FAO obtained experimental data from South Africa to parameterise the model for sugarcane. The sugarbeet parameters were derived using data from Foggia (Italy). However, the model was calibrated for these two crops by fine-tuning certain parameters for local conditions, as explained in the subsections that follow. A table indicating the parameters that were adjusted is presented in **APPENDIX D**. However, conservative parameters (i.e. type 1) were not adjusted directly, but indirectly when a type 3 parameter was adjusted in the model. For example, adjusting the maximum canopy cover parameter (i.e. type 3) led to a subsequent change in the canopy growth coefficient (i.e. type 1).

6.6.1 Sugarcane

The AgMIP La Mercy dataset (see **subsection 6.2.1.1**), obtained from SASRI, was used to calibrate the AquaCrop model (Singels, *pers. comm*., 2013). A total of eight simulations (for each planting date) were produced using the model's default crop parameter file (i.e. the parameterised version) and then repeated using the calibrated (i.e. adjusted) parameters. It is important to note that these sugarcane simulations were for rainfed growing conditions.

Crop parameters that are changed in the calibration process were not adjusted when the model was validated. This process facilitated the testing of how well the model was calibrated. Model validation was carried out using other AgMIP datasets for sugarcane obtained from trials conducted at Pongola (1968 to 1971) and Komatipoort (2011 to 2012), both of which were irrigated trials. By using secondary data, more time was spent on sugarcane calibration and validation. An added advantage is saving of financial resources related to costs associated with field experiments.

6.6.2 Sugarbeet

The calibration for sugarbeet was undertaken using observed soil, crop and climate data obtained in this study at Ukulinga, as described in the subsections that follow. Two sugarbeet simulations were also produced using 1) AquaCrop's default crop parameter file, and 2) the calibrated crop file developed in this study. It is important to note that the sugarbeet simulations were for irrigated conditions. Furthermore, model validation was also carried out using an AgMIP dataset obtained from SASRI for the Komatipoort trial (2011 to 2012).

6.6.2.1 Canopy cover

Measured leaf area just after emergence was input into AquaCrop (see **subsection 6.4.1**) as seedling leaf area. The model used this value, together with the planting population to compute initial canopy cover (CCo). Unlike most other crop models, AquaCrop expresses canopy size as canopy cover and not LAI. **Equation 6-3** from Hsiao *et al*. (2009) was used to convert LAI to canopy cover. The equation was formulated using an empirical relationship, via regression, between canopy cover and LAI of maize (Hsiao *et al*., 2009). Other regression equations exist in the literature, such as **Equation 6-4** given by García-Vila *et al*. (2009). A general relationship between intercepted solar radiation at midday and LAI was used to derive **Equation 6-4** using a canopy extinction coefficient of 0.77 for cotton (Charles-Edwards *et al*., 1986; Orgaz *et al*., 1992). A comparison of the two equations is given in the results (see **subsection 7.1.1.2**). The canopy cover values were then used to develop parameters for maximum canopy cover (CCx) and the time taken to reach CCx.

$$CC = 1.005 \times [1 - exp(-0.6 \cdot LAI)]^{1.2} \qquad \textbf{Equation 6-3}$$

$$CC = \frac{1 - e^{-\frac{LAI}{1.3}}}{1 + e^{-\frac{LAI}{1.3}}} \qquad \textbf{Equation 6-4}$$

6.6.2.2 Time to senescence

The time taken for the crop to begin senescing is another important physiological indicator and thus, is required as an input by AquaCrop. Measurements of leaf chlorophyll content (see **subsection 6.4.2**) were related to the time taken for the plant to begin senescing (i.e. decrease in chlorophyll content).

6.6.2.3 Rooting depth

AquaCrop also requires data describing root growth (i.e. minimum and maximum rooting depths) to adequately simulate the extension of the root system and water extraction throughout the simulation phase. The minimum (Z_n) and maximum (Z_x) effective rooting depth parameters were obtained from measurements described in **subsection 6.4.3**.

6.6.2.4 Estimation of fresh yields

The mass of fresh and dry tubers was used to convert simulated dry yields to fresh weight (see **subsection 6.4.6**). In addition, a general conversion factor of 0.20 to 0.25 was provided by Raes *et al*. (2011), which represents the ratio of kg of dry matter to fresh weight. Hence, dry yields are multiplied by a conversion factor ranging from 4-5 to obtain fresh tuber yields.

6.6.2.5 Soil water balance

AquaCrop outputs the soil moisture content at different depths in the soil profile. In this study, the volumetric soil water content measured using TDR (see **subsection 6.4.4**) was compared to model outputs. This was undertaken to determine the accuracy of the model's soil water balance calculations.

6.6.2.6 Input climate file

From daily measurements of climate variables made using the AWS (see **subsection 6.3.2.1**), only rainfall, minimum and maximum temperature and ET_o were used to create an input climate file for AquaCrop. The mean annual atmospheric CO_2 concentrations from 1902 to present, which were measured at the Mauna Loa Observatory in Hawaii, are stored within the model.

6.6.3 Model performance

Model performance was evaluated using statistical indicators such as difference or measures of error (Willmott *et al*., 1985). The performance of the model in relation to it simulating observed values was assessed using statistical methods. The statistics consisted of the coefficient of determination (R^2), the root mean square error (RMSE) as well as its components, i.e. the unsystematic RMSE ($RMSE_u$) and the systematic RMSE ($RMSE_s$). Willmott's Index of Agreement (IoA) was also used to evaluate model performance.

The IoA was used to further indicate the degree to which the model accurately simulated the observed values (see **Equation 6-5**). The closer IoA is to 1, the greater the agreement between the observed and predicted values.

$$\text{IoA} = 1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum\left[\left|P_i'\right| + |O_i'|\right]^2}$$ **Equation 6-5**

where

$P_i' = P_i - O_i$,

$O_i' = O_i - \bar{O}$ whereby $\bar{O}$ is the observed mean.

The R^2 was used to indicate the goodness of fit between simulated and observed values, although its applicability and usefulness is dependent on the sample size (i.e. number of observations). Therefore, when the sample size is small, it can be a poor indicator of model performance. Willmott (1982) suggested the use of RMSE, which is deemed to be amongst the best statistical indicators for evaluating model performance. The RMSE is particularly useful as it summarises the mean difference in the same units of observed and predicted values.

Willmott (1982) also suggested the use of its components, *viz*. $RMSE_s$ and $RMSE_u$. The performance of the model was deemed adequate when $RMSE_u$ was similar to RMSE and when $RMSE_s$ approached zero. **Equation 6-6**, **Equation 6-7** and **Equation 6-8** indicate how RMSE and its components were derived.

$$RMSE_U = n^{-1}\left[\sum_{i=1}^{n}(P_i - \hat{P}_i)^2\right]^{1/2}$$ **Equation 6-6**

$$RMSE_s = n^{-1}\left[\sum_{i=1}^{n}(\hat{P}_i - O_i)^2\right]^{1/2}$$ **Equation 6-7**

$$RMSE = (RMSE_U + RMSE_S)$$ **Equation 6-8**

$$\hat{P}_i = (a + b \cdot O_i)$$ **Equation 6-9**

where

n = number of observations,

i = number of specific observations,

P = predicted variable,

O = observed variable and

$\hat{P}_i$ = derived from **Equation 6-9**, where a is the intercept and b is the slope of the least squares regression.

6.7 Assessment of Climate Change Impacts

Following the model simulations and validation at a field scale, AquaCrop was applied at a quinary level (a fifth level division of a primary catchment) to assess the impact of climate change on crop response. Additionally, this allowed for the results to be compared with other studies where crop simulations were undertaken at the same scale such as those by Mabhaudhi *et al*. (2018). The following subsections describe the data and simulations undertaken for this assessment.

6.7.1 Quaternary and quinary catchments

A quaternary catchment represents is a fourth-level division of a primary drainage basin. There are 1946 quaternary catchments in southern Africa, which were originally delineated by the former Department of Water Affairs and Forestry (DWAF). Each quaternary catchment has then been subdivided into three quinary sub-catchments according to altitude criteria (Schulze and Horan, 2007; 2011), which produced a total of 5838 quinaries (see **subsection 6.7.2**). Hence, each quaternary was sub-delineated into an upper, middle and lower quinary of unequal area (but of similar topography) using “natural breaks” in altitude by applying the Jenks’ optimisation procedure (Schulze and Horan, 2007; 2011).

Determining the quaternary catchments encompassing the two study sites was important because each quaternary has different climate and soils data (see **subsection 6.7.2**). Using a Geographic Information System (GIS), it was determined that La Mercy and Ukulinga are located in quaternary catchments U30D and U20J respectively. At a quinary level, La Mercy is located in sub-catchment 4719 and Ukulinga in sub-catchment 4697 (**Figure 6-3**). However, climate change simulations were undertaken for all three sub-catchments per quaternary (see **subsection 6.7.3.2**). The altitude range of each quinary is provided in **Table 6-5** below. As expected, the standard deviations are low, indicating that the altitudes across the quinaries are relatively homogenous.

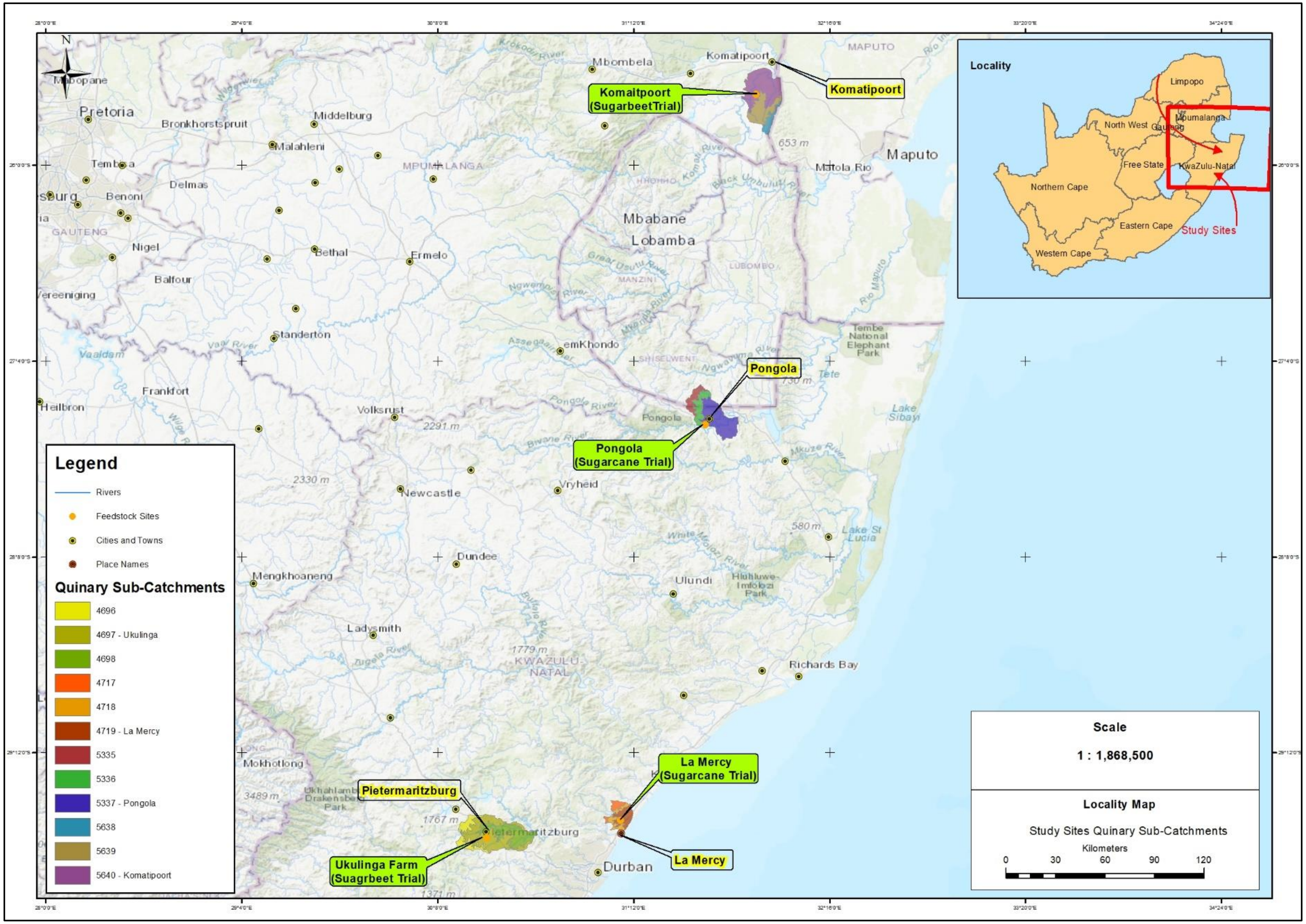

Figure 6-3 Location of the study sites in relation to the quinary sub-catchments

Table 6-5 Altitudinal range for the quinaries used in this study (Schulze and Horan, 2007; 2011)

Quinary	Min (m)	Max (m)	Mean (m)	Median (m)	Std. dev
4696	858	1431	1024	1006	102
4697	603	931	761	752	65
4698	314	745	566	593	84
4717	127	332	206	200	40
4718	10	160	100	95	25
4719	1	103	50	52	20

6.7.2 Historical climate

The quinary sub-catchment database consists of 50 years (1950-1999) of daily rainfall, maximum and minimum temperature and reference crop evaporation for each of the 5838 quinaries. A summary of how this database was developed is provided next. However, the reader is referred to Schulze *et al*. (2011b) for a more detailed description.

6.7.2.1 Rainfall

A representative rainfall driver station with a continuous (i.e. no missing values) record of daily data from 1950 to 1999 was assigned to each quaternary catchment as described by Schulze *et al*. (2005). The rainfall driver station previously selected to represent the parent quaternary catchment was initially chosen to represent the three quinary sub-catchments. However, errors in rainfall station data affecting 33 quinaries were discovered and corrected (Schulze *et al*., 2011b), which reduced the total number of unique driver stations to 1061.

Multiplicative rainfall adjustment factors were applied to the driver station to render the daily rainfall more representative of that quinary. In this way, a unique 50-year daily rainfall record is available for each of the 5838 quinaries. The adjustment factors were derived by spatially averaging all one arc minute (~1.7 x 1.7 km) gridded estimates of median monthly rainfall (determined by Lynch, 2004) located within each quinary boundary. The ratio of the sub-catchment averaged median monthly rainfalls to the driver station's median monthly rainfalls was then calculated to arrive at 12 monthly adjustment factors (**Table 6-6**).

Table 6-6 Monthly rainfall adjustment factors for quinaries representative of La Mercy and Ukulinga (Schulze *et al*., 2011b)

Sub-catchment	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
4717	0.97	1.06	1.03	0.91	1.18	0.68	0.84	0.64	0.82	0.93	1.03	0.99
4718	0.93	1.06	1.01	0.92	1.12	0.65	0.90	0.64	0.84	0.90	0.97	0.93
4719	0.92	1.05	1.00	0.93	1.24	0.72	0.89	0.64	0.84	0.86	0.95	0.92
4696	1.57	1.53	1.59	1.55	1.25	1.09	1.14	0.92	1.21	1.53	1.37	1.64
4697	1.26	1.26	1.31	1.22	1.12	0.93	1.02	0.77	1.03	1.23	1.08	1.31
4698	1.17	1.13	1.19	1.12	1.07	0.84	1.01	0.74	0.99	1.08	0.98	1.18

Note: Driver station 0240073 W used for Ukulinga (sub-catchment 4697), Driver station 0241302 W used for La Mercy (sub-catchment 4719).

Generally, the driver station used for sub-catchment 4717 to 4719 tends to over-estimate the respective sub-catchments monthly rainfall and hence, the rainfall has been adjusted down by an average factor of 0.92. On a month to month basis, the May and August months have the largest and lowest adjustment factors, respectively. For sub-catchments 4696 to 4698, the selected driver station tends to under-estimate the monthly rainfall across the sub-catchments. Hence, an averaged adjustment factor of 1.2 was applied by Schulze *et al*. (2011b). The reader is referred to Schulze *et al*. (2011b) for more information regarding the derivation of the rainfall adjustment factors.

6.7.2.2 Temperature

Schulze and Maharaj (2004) developed an extensive database of 50 years of estimated daily maximum and minimum temperature for each one arc minute grid point in southern Africa (i.e. 429 700 grid points in total). Representative grid points from this database were then selected to represent each of the 5 838 quinary sub-catchments. This selection was determined by first calculating the average altitude of each quinary by spatially averaging all gridded altitudes from the 200 m Digital Elevation Model located within each sub-catchment boundary. The grid point with a similar altitude to that of the sub-catchment mean and located closest to the sub-catchment centroid, was then selected to represent that quinary (Schulze *et al*., 2011b).

6.7.2.3 Reference crop evaporation

The 50-year record of estimated daily maximum and minimum temperature assigned to each quinary was then used to derive ET_o using the Penman-Monteith technique as described by Schulze *et al*. (2011b). Daily estimates of solar radiation and vapour pressure deficit were derived by Schulze and Chapman (2007) and Chapman (2004), respectively. Owing to the lack of observed wind speed data for southern Africa, a constant value of 1.6 m s^{-1} is assumed for all quinaries (Schulze *et al*., 2011b).

6.7.3 Future climate

Future climate projections for this study were obtained from the Council for Scientific and Industrial Research (CSIR) in Pretoria and from the Climate Systems Analysis Group (CSAG) in Cape Town. These climate projections are all based on atmosphere-ocean Global Climate Models (GCMs). A GCM ensemble approach was used in this study as it promotes a reduction in uncertainty. In this study, a total of six GCMs were considered which were forced using the A2 CO_2 emission scenario (**Table 6-7**). Two commonly used downscaling approaches were applied to the GCMs as described next.

Table 6-7 Names of the GCMs used in this study and the availability of climate projections derived from each GCM using two different downscaling techniques

Abb.	Model	Downscaling	
		Statistical	Dynamic
CSI	CSIRO-Mk3.5	√	√
GF0	GFDL-CM2.0	√	√
GF1	GFDL-CM2.1	√	√
MIR	MIROC3.2-MEDRES		√
MPI	MPI-ECHAM5	√	√
UKM	UKMO-HADCM3		√

6.7.3.1 Downscaling to regional level

The two downscaling approaches applied to the GCMs listed in **Table 6-7** were statistical and dynamical. These techniques are described in detail in **section 5.3**.

<u>Statistical downscaling</u>

Four of the six GCMs were statistically downscaled to station level (Hewitson and Tadross, 2011; Schulze *et al*., 2011a). This involved using a self-organising map (SOM) technique as described by Hewitson and Crane (2006). Unlike the climate projections from the dynamically downscaled technique, the statistically downscaled dataset is not continuous. Rather, it is split into two-time periods representing the 1) present (1961-1999) and 3) distant future (2081-2100) (Schulze *et al*., 2011a). From the 40-year present record, a 20-year period (1971-1990) was extracted to allow comparison with the two future 20-year periods. The last year in each 20-year sequence (i.e. 1990 and 2100) was not simulated due to lack of weather data in the corresponding year.

Dynamical downscaling

Six GCMs were dynamically downscaled by the CSIR (Engelbrecht *et al*., 2011; Kunz *et al*., 2014) using the conformal-cubic atmospheric RCM model (McGregor, 2005), developed by the Australian Commonwealth Scientific and Industrial Research Organisation. This produced a total of 499 grid-based "pixels" over southern Africa, each 0.5º in size. For each pixel, daily rainfall as well as maximum and minimum temperature data from 1961 to 2100 is available. Therefore, the six GCMs have a long continuous climate data record of 140 years. As noted earlier, the end year (i.e. 2100) of the 140-year data was not simulated.

6.7.3.2 Downscaling to catchment level

The grid-based (0.5º and 0.25º grid size) output from the six GCMs was further "spatially downscaled" to the quinary sub-catchment level (Kunz *et al*., 2014). This was achieved by using a GIS to select a representative pixel to drive the hydrology of each sub-catchment. By implication, each pixel "drives" the hydrology of more than one quinary. However, because La Mercy and Ukulinga are located in different sub-catchments, the pixel selected to represent each study site was different. Hence, quinary sub-catchments 4717 to 4719 were used for La Mercy and quinaries 4696 to 4698 represent Ukulinga (Kunz *et al*., 2014). The downscaling to a catchment level is described in further detail by Lumsden *et al*. (2011).

For each quinary, the dominant lapse rate region (derived by Schulze and Maharaj, 2004) was identified using GIS. Adiabatic lapse rates available for each of the 12 regions were then used to adjust for the altitudinal difference between the pixel and the quinary (i.e. spatially averaged altitude of the quinary was compared to that of each 0.5º x 0.5º pixel). Daily reference crop evaporation estimates (i.e. Penman-Monteith) were derived from the GCM temperature data. However, a wind speed of 2.0 m s^{-1} was assumed for all quinaries as suggested by Shuttleworth (2010) and solar radiation was derived by Schulze and Chapman (2007). In summary, 10 climate files containing daily rainfall, temperature and reference crop evaporation from 1961 to 2099 (i.e. 139 years) exist for each quinary (6 in total).

6.7.3.3 Rising CO_2 concentrations

As mentioned in earlier in this section, the A2 emission scenario was used. The A2 scenario represents the "business as usual" scenario in which the rate of greenhouse gases is not curtailed into the future (see **subsection 5.2.2**). A file with atmospheric carbon dioxide values from 1961 to 2099 for the A2 scenario exists within AquaCrop. Since the carbon dioxide estimates end in the year 2099, it also explains why the final year of the future climate record (i.e. 2100) was not simulated.

6.8 Model Simulations

The model simulations for both feedstocks were undertaken for rainfed conditions. However, calibration simulations for sugarbeet included irrigated conditions. The same irrigation schedule (see **APPENDIX B**) was applied to the crop in each season (i.e. May and September) for both the baseline and future simulations. The irrigation amount shown in **APPENDIX B** was held constant to better understand the effects of the changing climate on crop response, without introducing another variable (i.e. irrigation effect), which would have made the interpretation of the result more difficult. Therefore, changing the irrigation amount for sugarbeet would not have allowed a direct comparison of the baseline with the future simulations.

Furthermore, there are two options to run the AquaCrop model, namely for 1) a single simulation for one season to obtain one yield estimate, or 2) multiple simulations for successive years, i.e. multiple yield estimates. The latter option was chosen, which resulted in a large number of yield simulations. However, AquaCrop can only do successive simulations for up to 128 years and therefore, split simulations (i.e. 128 years and 11 years) for each quinary were done when using the dynamically downscaled climate datasets.

The typical planting and harvest were manually set for each yield simulation. For sugarcane, two planting dates (i.e. April and February) were selected, based on highest attainable yields at La Mercy. Higher sugarcane yields are expected in the warmer planting season (i.e. February). A sixteen-month growing season was assumed, which is typical for farms situated along the KwaZulu-Natal North Coast. A winter (i.e. June) planting of sugarbeet was assumed, together with a seven-month growing season. However, an autumn (e.g. May) planting is considered the “norm” for the Cradock region in the Eastern Cape (Maclachlan, 2012). A spring (i.e. September) planting date was also considered. These two planting dates (i.e. May and September) were chosen to allow a comparison of a summer and winter planting of the crop. For sugarbeet, the cooler planting season (i.e. May) is anticipated to have higher yields.

Soils information (i.e. soil water retention characteristics, soil depth and saturated hydraulic conductivity) from the La Mercy AgMIP dataset was assumed to be the same across all three quinaries (4717-4719). The same assumption was applied in the other quinaries (4696-4698) using soils information collected at Ukulinga. Thus, differences in yields simulated by AquaCrop are mainly a result of climatic variations due mainly to altitudinal differences between the quinary catchments (see **Table 6-5**).

The model was then run to assess the impact of climate change on feedstock yield and water use using 10 GCM climate files (i.e. six dynamically and four statistically-downscaled GCMs). Secondly, the effects of altitudinal differences on simulated yield were determined by running the model for each of the six quinaries. The seasonal yields and water use values were analysed to calculate the mean statistic and the coefficient of variation for each quinary. The model was also run to assess the sensitivity of crop growth to increasing CO_2 concentrations (see **subsection 6.7.3.3**). Finally, the total number of simulations undertaken were as follows:

- 2 crops *x* 6 dynamically downscaled GCMs *x* 6 quinaries (3 per crop) *x* 2 planting dates for periods 1961-2099 (139 years), plus
- 2 crops *x* 4 statistically downscaled GCMs *x* 6 quinaries (3 per crop) *x* 2 planting dates for periods 1961-1999 and 2081-2099.

6.8.1 Baseline simulations

Using 30 years of historical data is a World Meteorological Organisation standard procedure. According to Steduto *et al*. (2012), a minimum of 30 years of input climate record is recommended for long-term assessments of productivity (e.g. yield). The disadvantages in using extended climatic datasets of 139 years in crop modelling is 1) the simulations take much longer to run (which limits the amount of simulations or scenarios that can be considered) and 2) the need to split the simulation into two separate runs (i.e. 128 and 11 year runs due to a limit in AquaCrop).

In this study, baseline conditions were determined using 50 years (1950-1999) of daily historical climate data in order to calculate the long-term attainable yield of both sugarbeet and sugarcane for each quinary. Following that, a 30-year (1961-1990) simulation was produced to evaluate its approximation to the 50-year simulation. In other words, a comparison was made to see if there would be any major differences in mean yield or WUE using 30 years of data instead of 50 years. These results are presented in **section 7.2**.

6.8.2 Present climate

Before undertaking any model simulations using future climate scenarios, the yields and WUE simulated for the present climate (1961-1990) were compared to the yields and WUE simulated for the baseline (i.e. historical) for the same period. This was done by running simulations using the same record length of climate data for the same 30-year period. From the four GCMs (i.e. CSI, GF0, GF1 and MPI) that were common to both downscaling techniques, a mean yield value was calculated for the comparison. Simulations were produced for all six quinaries and for two planting dates per crop. These results are presented in **section 7.3**.

6.8.3 Future climate

AquaCrop was run for a 30-year period using the dynamically downscaled climate data for all six GCMs for each crop assumed to be grown in three quinaries. Further simulations were undertaken for the different time periods (present and distant future) using the statistically downscaled climate data available for each of the four GCMs. An analysis was done to evaluate the percentage change in both crop yield and WUE using both downscaling techniques between the present and future climate. This was done for the dynamically downscaled GCMs by calculating the percentage change in mean yield (and mean WUE) obtained for the present (1961-1990) and future (2070-2099) 30-year periods. For the statistically downscaled GCMs, a 20-year period was used to calculate the percentage change from the present (1971-1990) to the future (2081-2099) period. The averaged outputs (i.e. yield and WUE) from each GCM run and the calculated percentage changes were used to assess the impacts of climate change. These results are presented in **section 7.4**. This exercise was then repeated for the GCMs common to both downscaling techniques (i.e. four in total) and the results are given in **section 7.5**.

6.8.4 CO_2 effects

AquaCrop considers the sink strength (i.e. ability to hold CO_2) of crops and their responsiveness to changing CO_2 concentrations. In order to quantify how responsive the crops are to rising CO_2 levels (i.e. the so-called "CO_2 fertilisation effect"), the CO_2 value was initially kept constant at 369.41 ppm for the six dynamically downscaled GCMs, i.e. for the simulation period (1961-2099). This is the reference CO_2 value used by the model that was measured at Mauna Loa (Hawaii) in the year 2000. The six simulations were compared to model output derived with changing CO_2 levels as per the A2 emission scenario (see **subsection 6.8.3**). Hence, the water productivity parameter only changes for simulations beyond 2000, i.e. WP normalised by CO_2 concentrations which are different from the reference value. The differences in yields and WUE between the simulations with a fixed CO_2 and increasing CO_2 levels were also expressed as percentage differences. These results are presented in **section 7.6**.

6.8.5 MAP and MAT effects

Analyses of mean annual precipitation (MAP) and mean annual temperature (MAT) climate data were undertaken in order to better understand the influence of the changing climate on the yield and WUE of sugarcane and sugarbeet. This analysis was repeated for all 6 quinaries and completed for the simulation periods shown in **Table 6-8**. These results are presented in **section 7.7**.

Table 6-8 Simulation periods used for the two downscaling techniques

Simulation Period	Statistically downscaled GCMs	Dynamically downscaled GCMs	Baseline (Historical) Climate
Present	1971-1990	1961-1990	1961-1990* 1950-1999
Future	2081-2100	2071-2100	

*Compared against the present period simulations

6.9 Summary

In summary, the following methods were applied, *viz*. 1) experiments and laboratory analyses (i.e. collection of primary data for model calibration); 2) analysis of secondary data (for model calibration and validation); and 3) simulation modelling (to assess the impacts of climate change on yield and WUE). In other words, different methods were used to collect data in order to adjust AquaCrop's parameters to represent local conditions for two biofuel feedstocks. The datasets included soils, crop and climate parameters and variables which contribute towards the description of the SPAC. Field experiments and analyses of soil and crop samples in a laboratory were used for collecting primary data to calibrate AquaCrop for sugarbeet. Field experiments were not undertaken to validate the model for sugarbeet.

Rather, secondary data obtained from the AgMIP initiative (via SASRI) were used to validate the model for sugarbeet as well as calibrate and validate the crop model for sugarcane.

A quinary sub-catchment database containing 50 years of historical data as well as future climate projections for up to six GCMs was used to assess the impacts of climate change on crop response. However, the same soils data (i.e. field-based) were used for model simulations pertaining to the calibration, present and future runs. However, GCM output is at a coarse scale that cannot be applied directly at a field scale. Hence, climate change scenarios applicable at the catchment level were derived from two downscaling techniques (i.e. statistical and dynamical). This approach facilitated a comparison of yield and WUE results obtained from the two downscaling techniques. The impact of rising CO_2 levels on crop response was quantified by running the crop model both with and without the CO_2 fertilisation effect. Finally, an analysis of MAP and MAT was completed to better understand the influence of the changing climate on the yield and WUE of sugarcane and sugarbeet. The following section presents and discusses the results that were obtained using the approaches described in this chapter.

7 RESULTS AND DISCUSSION

This chapter discusses the results of the calibration and validation of AquaCrop for sugarcane and sugarbeet. The first section (**section 7.1**) assesses the model's ability to adequately simulate the yield and WUE of both feedstocks after the calibration process (see **subsection 7.1.1**). Following that, the results of the model validation procedure are discussed in **subsection 7.1.2**. AquaCrop's ability to simulate soil water content is presented in **subsection 7.1.3**.

Thereafter, **sections 7.2** to **7.5** present the long-term attainable yield and WUE of each feedstock that was simulated for baseline conditions, as well as those derived using the present and future climate projections. **Section 7.6** discusses the effects of CO_2 on the productivity of both feedstocks. **Section 7.7** presents the results of projected changes in MAP and MAT from the present to the future and the associated impacts on crop production. Lastly, **section 7.8** presents the final thoughts, particularly on the planting dates, altitudinal influence and CO_2 fertilisation effect.

7.1 Model Performance

As noted in the previous chapter, AquaCrop has predetermined parameters (i.e. default crop files) for both sugarbeet and sugarcane. The AgMIP experimental dataset from La Mercy (1989-1990) was used to calibrate the model for sugarcane (cultivar NCo376), while the Ukulinga dataset (2013) was used to calibrate the model for sugarbeet (variety EB0809). Two independent datasets were then used for validating the model. The Pongola AgMIP dataset (1968-1971) used the same sugarcane cultivar, whilst the Komatipoort AgMIP dataset (2011-2012) had three different cultivars (N31, N19 and 04G0073) under two different irrigation treatments. The AgMIP dataset for sugarbeet grown at Komatipoort was also used to validate the model for sugarbeet. It is worth noting that a preliminary version of the calibrated parameter files for sugarcane and sugarbeet was used by Kunz *et al.* (2015c). The model was run at a national scale using the quinary sub-catchment climate database to obtain spatial estimates of long-term attainable yields for both feedstocks.

7.1.1 Model calibration

The parameters that were changed in the model in relation to the default values are presented in **APPENDIX D**. Certain parameters (related to phenological growth stages) were initially input in calendar days, then converted to growing degree days (GDD). Certain default parameters were not adjusted for the following reasons. Firstly, the model developers consider them to be conservative, i.e. not affected by changes in time, climate and geographic location (Steduto *et al*., 2012). Secondly, a lack of experimental data (especially in the AgMIP dataset) prevented parameter adjustments.

7.1.1.1 Sugarcane

Unlike the Ukulinga dataset that had only one season's data, the La Mercy dataset had eight treatments of sugarcane that were transplanted in different months between June 1989 and August 1990. Hence, average values were used for the harvest index (i.e. 65%) and maximum canopy (90%), which were deemed representative of the crop for different growing seasons.

<u>Canopy cover</u>

In this study, sugarcane cultivar NCo376 was used in the calibration. Using the default crop parameter file, a relatively poor goodness of fit and agreement between simulated and observed canopy cover was obtained for seven of the eight treatments (refer to columns “Def” in **Table 7-1**).

Table 7-1 Performance of the AquaCrop model in simulating percentage canopy cover of sugarcane using the default (Def) and calibrated (Cal) crop parameter files, for eight different treatments (i.e. planting dates)

Treatment	Statistical indicators									
	R^2		RMSE (%)		$RMSE_s$ (%)		$RMSE_u$ (%)		IoA	
	Def	Cal	Def	Cal	Def	Cal	Def	Cal	Def	Cal
1	0.04	0.00	8.65	7.62	7.24	6.64	4.72	3.74	0.37	0.92
2	0.34	0.27	14.81	13.21	13.87	12.66	5.20	3.79	0.24	0.78
3	0.04	0.02	6.71	8.13	6.56	7.90	1.41	1.92	0.49	0.95
4	0.13	0.02	7.60	8.96	7.27	8.76	2.22	1.92	0.34	0.95
5	0.88	0.88	6.17	4.29	5.86	4.07	1.91	1.37	0.83	0.94
6	0.08	0.29	9.66	9.36	8.52	8.99	4.55	2.61	0.56	0.93
7	0.00	0.16	15.17	14.50	14.82	14.31	3.24	2.33	0.42	0.86
8	0.53	0.51	23.44	23.91	23.40	23.84	1.47	1.80	0.52	0.81

Treatment 5 was the only exception in which an R^2 of 0.88 and IoA of 0.83 was obtained using the default parameter file. The calibration improved the simulations, but not significantly as shown by the statistical indicators (refer to columns "Cal" in **Table 7-1**). Both R^2 and IoA values were higher, although RMSE, $RMSE_u$ and $RMSE_s$ indicate the model did not perform well in simulating the percentage canopy cover.

The reason for this is due to the lack of crop experimental data (e.g. LAI) in the early phase of the growth cycle, which would have allowed the determination of the initial canopy cover parameter (CCo). This parameter affects the time to maximum canopy cover (Steduto *et al.*, 2012). Furthermore, the frequency of data collection (i.e. LAI) was insufficient and thus, there were large gaps between measurements which made it difficult to determine the specific dates at which the crop reached maximum canopy cover. Hence, default parameter values had to be used which resulted in poor simulations with respect to the growth of the canopy cover and the final yield. In addition, AquaCrop was not able to simulate the onset of canopy senescence as indicated in treatments 6 to 8 in **Figure 7-1**.

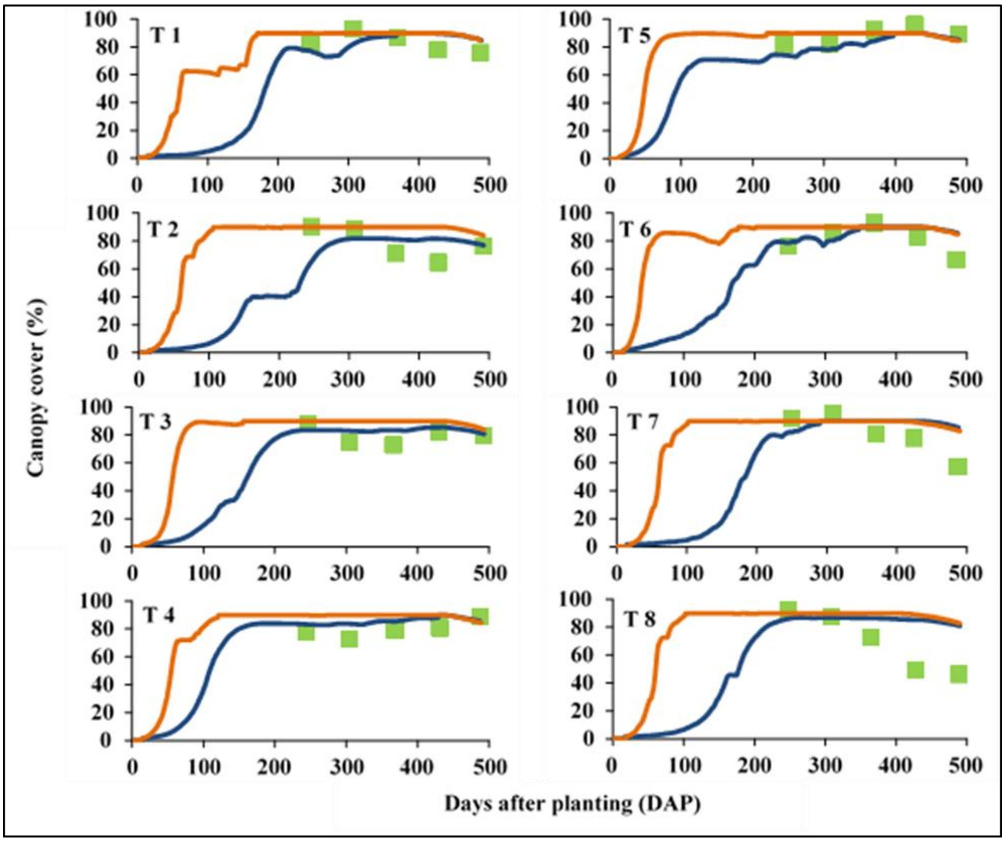

Figure 7-1 Comparison of the default (orange) and calibrated (blue) sugarcane canopy cover simulations using AquaCrop, with reference to measured values (green) for the eight different treatments (i.e. planting dates)

Final yield

Default model simulations (i.e. uncalibrated) mostly under-estimated the final yields except for treatment 2 (see **Figure 7-2**). The overall default mean dry yield (i.e. 25.1 t ha^{-1}) from the eight treatments was about 8.5 t ha^{-1} lower than the mean observed value of 33.6 t ha^{-1}. This figure also illustrates how the calibration improved the prediction of final cane yield for each of the eight treatments, especially for treatments 1 to 6. However, final yields were over-estimated in five of the eight treatments resulting in a mean dry yield that was 1.2 t ha^{-1} higher than the observed yield. **Figure 7-3** shows there is a relatively low goodness of fit between observed and simulated values. The low RMSE values in **Table 7-2** further indicate that the model performed well in simulating the final yields compared to the simulations that used default parameters.

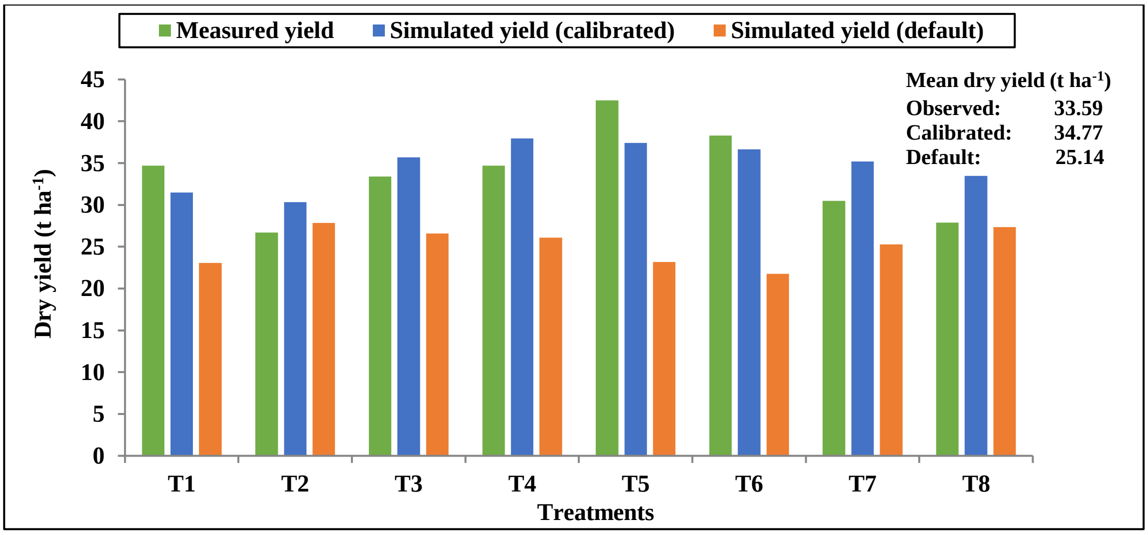

Figure 7-2 Difference between calibrated and default sugarcane dry yields in relation to measured yields

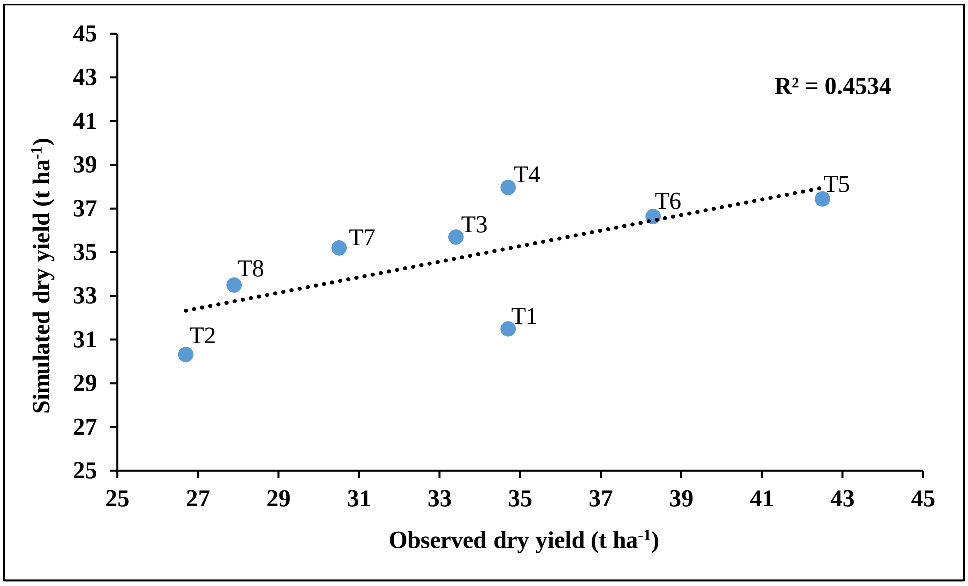

Figure 7-3 Comparison of observed and simulated sugarcane yields derived using the calibrated crop parameter file for the eight treatments

Table 7-2 Difference between observed and simulated sugarcane yields using the calibrated crop parameter file

Treatment	Dry yield (t ha^{-1})		
	Observed	**Simulated**	**RMSE**
T1	34.70	31.48	3.22
T2	26.70	30.32	3.62
T3	33.40	35.69	2.29
T4	34.70	37.96	3.26
T5	42.50	37.43	5.07
T6	38.30	36.63	1.67
T7	30.50	35.19	4.69
T8	27.90	33.49	5.59
Mean	33.59	34.77	3.68

7.1.1.2 Sugarbeet

Canopy cover

The simulation of canopy cover for sugarbeet (**Figure 7-4**) using default crop parameters over-estimated the canopy cover measured at Ukulinga. This corroborates with the statement made by the model developers that some of the parameters are not universal (Raes *et al*., 2011). Similar tendencies by AquaCrop to over-estimate values compared to observations in default (i.e. parameterised) setup mode has been reported by Paredes *et al*. (2014).

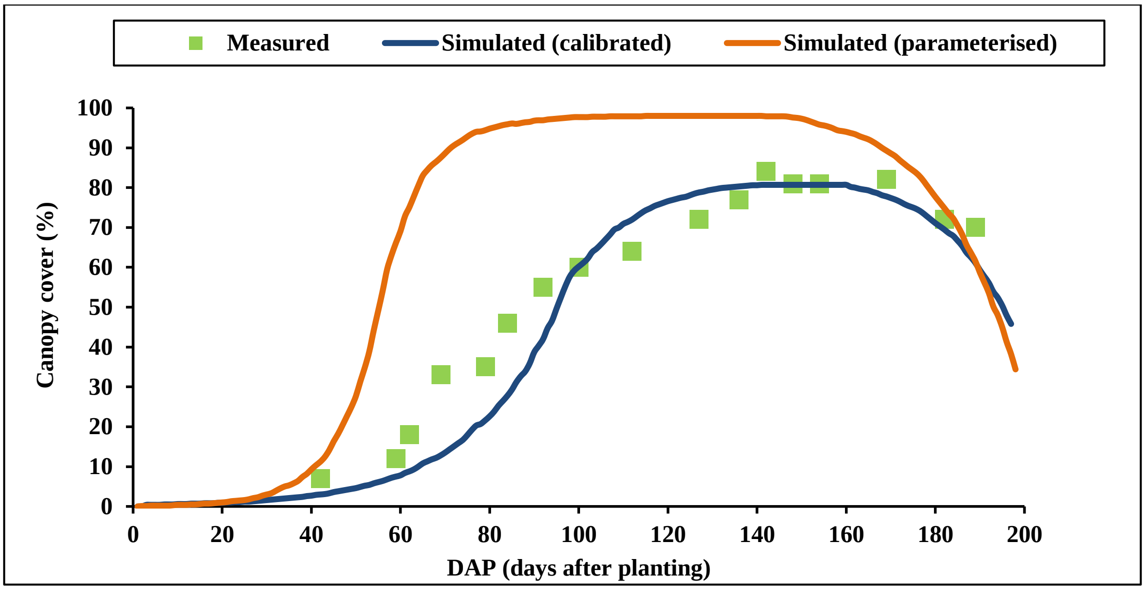

Figure 7-4 Differences between calibrated and parameterised sugarbeet canopy cover simulations in relation to measured values from Ukulinga in 2013

The percentage canopy cover of sugarbeet is presented in **Table 7-3**. Comparisons were made between two equations used to convert LAI measurements to estimates of canopy cover (see **subsection 6.6.2.1**). There is a satisfactory goodness of fit of 0.99 between the two equations as shown in **Figure 7-5**. Hence, the canopy cover estimates are similar regardless of maize being used to formulate **Equation 6-3** and cotton used to derive **Equation 6-4**. Although both equations gave similar results, **Equation 6-3** was used in this study for sugarbeet. The model then computed the canopy growth coefficient (CGC) and canopy decline coefficient (CDC).

Table 7-3 Leaf area index (LAI) measurements of sugarbeet, converted to percentage canopy cover using two different methods, for day 42 to 189 after planting (DAP)

DAP	LAI	Canopy cover (%)	
		Equation 6-3	Equation 6-4
42	0.19	7.0	7.3
59	0.30	11.6	11.5
62	0.45	17.8	17.1
69	0.85	33.2	31.4
70	0.81	31.8	30.0
79	0.90	35.3	33.4
84	1.22	45.8	43.8
92	1.54	54.8	53.2
100	1.75	60.0	58.8
112	1.95	64.3	63.5
127	2.34	71.7	71.6
136	2.72	77.4	78.0
142	3.30	84.1	85.4
148	3.04	81.4	82.4
169	3.11	82.1	83.2
182	2.36	72.0	72.0
189	2.24	69.9	69.7

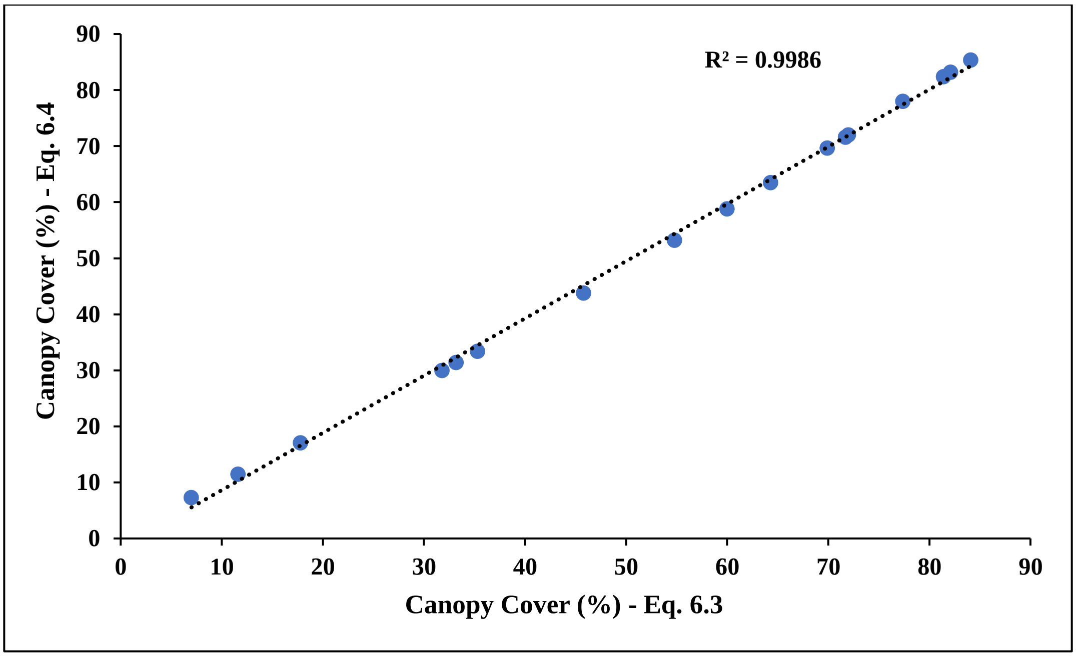

Figure 7-5 Comparison of percentage canopy cover derived using the two different methods

The statistical indicators also indicate improvements in the simulations between the default and calibrated model as shown in **Table 7-4**. The R^2 is closer to unity for the calibrated model which indicates a relatively good fit. The RMSE is 9.22% compared to 35.54% for the default parameter simulation. The low RMSE is comparatively close to values reported by Alishiri *et al*. (2014), which ranged between 5% and 11%. The model's improved performance is also illustrated by the RMSE components in which the $RMSE_s$ is closer to 0 compared to the $RMSE_s$ for the default calibrated run. Furthermore, the IoA approaches 1 highlighting the good performance of the calibrated model.

Table 7-4 Statistics showing the improvement in simulated percentage canopy cover of sugarbeet using the default and calibrated crop parameter files

Statistical indicators	Default	Calibrated
R^2	0.37	0.95
RMSE (%)	35.54	9.22
$RMSE_s$ (%)	31.05	6.09
$RMSE_u$ (%)	17.28	6.92
IoA	0.62	0.97

Crop yield

Since AquaCrop simulates yield as dry mass, the observed fresh sugarbeet mass from Ukulinga was converted to dry yield using the conversion ratio mentioned in **subsection 6.6.2.4**. A mean dry matter of 20.3% was determined for the sugarbeet trial (Kunz *et al*., 2015a), which was used to determine a dry yield value of 9.22 t ha^{-1}. However, dry matter percentages for sugarbeet typically range from 20% to 25% (Raes *et al*., 2011). For comparative purposes, the upper wet to dry ratio of 0.25 was also used to estimate a dry yield of 11.35 t ha^{-1}, which is closer to the calibrated simulation of 13.81 t ha^{-1} (and a lower RMSE of 2.46 t ha^{-1} as given in **Table 7-5**). Compared to the calibrated simulation, the default parameterised simulation over-estimated the measured yield by a larger value, with an RMSE range of 7.45 to 9.58 t ha^{-1} as shown in **Table 7-5**.

Table 7-5 Difference between simulated and observed sugarbeet yield, derived using the calibrated and default crop parameters, as well as the corresponding RMSE values

<table>
<tr><th>Conversion Ratio</th><th colspan="2">Measured yield (t ha^{-1})</th><th colspan="4">Simulated yield (dry t ha^{-1})</th></tr>
<tr><th>%</th><th>Fresh</th><th>Dry</th><th>Calibrated</th><th>RMSE</th><th>Default</th><th>RMSE</th></tr>
<tr><td>20.3</td><td rowspan="2">45.4</td><td>9.22</td><td>13.81</td><td>4.59</td><td>18.80</td><td>9.58</td></tr>
<tr><td>25.0</td><td>11.35</td><td>13.81</td><td>2.46</td><td>18.80</td><td>7.45</td></tr>
</table>

Both the simulated (especially the calibrated run) and observed sugarbeet yields are similar to values reported in recent literature. For example, Stricevic *et al*. (2011) reported a measured (irrigated) and simulated sugarbeet yield of 13.78 t ha^{-1} and 13.45 t ha^{-1}, respectively. Alishiri *et al*. (2014) varied irrigation and nitrogen input in their sugarbeet trials and obtained a measured and simulated yield of approximately 12 t ha^{-1}. The measured WUE for the 2013 sugarbeet trial ranged between 2.21 to 2.76 kg m^{-3} (Kunz *et al*., 2015a). The model over-estimated the WUE as shown in **Table 7-6**. This is expected considering the model over-estimated the observed yield.

Table 7-6 Difference between measured and simulated WUE for sugarbeet

	Simulated	**Observed**
WUE (dry kg m^{-3})	3.34	2.21 - 2.76

7.1.2 Model validation

After calibrating AquaCrop for sugarcane and sugarbeet, it was further validated using the AgMIP experimental datasets for Pongola (1968-1970) and Komatipoort (2011-2012). The same parameters in **APPENDIX D** were used in the simulations, with only the soil and climate files changed to reflect conditions at Pongola and Komatipoort. However, the simulation of canopy cover development could not be validated due to insufficient observations of this variable in the two AgMIP datasets.

7.1.2.1 Sugarcane

<u>Pongola</u>

Using the calibrated parameters, AquaCrop under-estimated the measured yield in 6 of the 8 treatments at Pongola for the same cultivar (NCo376). However, the mean simulated yield (i.e. 44.6 t ha^{-1}) is similar to the observed yield of 45.7 t ha^{-1} (**Figure 7-6**). The model's performance is reasonable as indicated by the IoA value of 0.43 and the low RMSE values. The R^2 shows there is generally a poor goodness of fit between the observed and simulated values, which may be affected by the small sample size in the dataset. **Table 7-7** presents the statistics for each treatment. The statistical indicators show that treatments 5 to 7 were well simulated by the model because the $RMSE_u$ is similar to RMSE and $RMSE_s$ is close to zero.

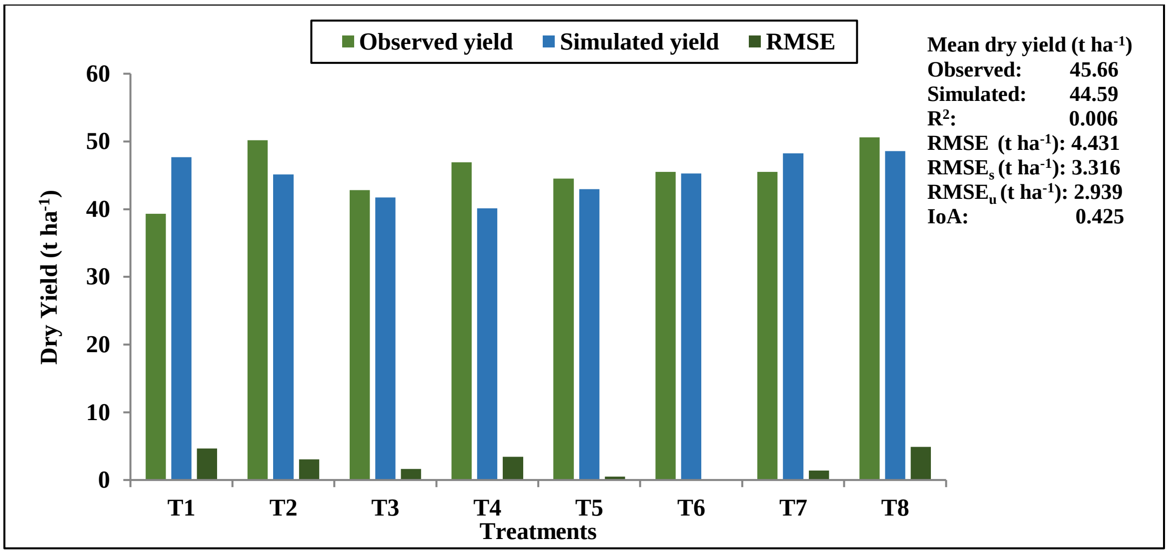

Figure 7-6 Differences between observed and simulated sugarcane dry yields at Pongola for eight treatments (planting dates from 1968-1970)

Table 7-7 Statistical indicators derived from the observed and simulated sugarcane dry yields at Pongola for eight treatments (planting dates from 1968-1970)

Treatment	RMSE (t ha^{-1})	RMSE$_s$ (t ha^{-1})	RMSE$_u$ (t ha^{-1})
1	4.660	3.425	1.234
2	3.046	3.043	0.003
3	1.656	0.485	1.171
4	3.442	0.430	3.012
5	0.489	0.018	0.471
6	0.049	0.038	0.011
7	1.411	0.038	1.373
8	4.881	3.521	1.361

Komatipoort

Three sugarcane cultivars (N31, N19 and 04G0073) were used in the Komatipoort trial and treatments 1, 3 and 5 received deficit irrigation (i.e. 50% of the total irrigation demand), whilst treatments 2, 4 and 6 received 100% of the irrigation demand. Cultivar N19 showed the largest yield improvement due to full irrigation (treatment T4 in **Figure 7-7**). When analysing the individual RMSE bars in **Figure 7-7** the statistical indicators in **Table 7-8**, cultivar N31 (T1 and T2) and cultivar N19 (T3) produced the best validation results (i.e. lower margin for error). The low RMSE values again highlight the good performance of the model, especially since the model was calibrated for cultivar NCo376 (under rainfed conditions). However, AquaCrop over-estimated the dry yield for cultivar 04G0073 for both treatments (i.e. deficit irrigation and full irrigation) and hence, performed poorly as shown by the statistics in **Table 7-8**. Although AquaCrop performed well for treatments 1 to 3, its performance was not as deemed adequate for treatments 4 to 6, which possibly contributed to a low IoA value of 0.136.

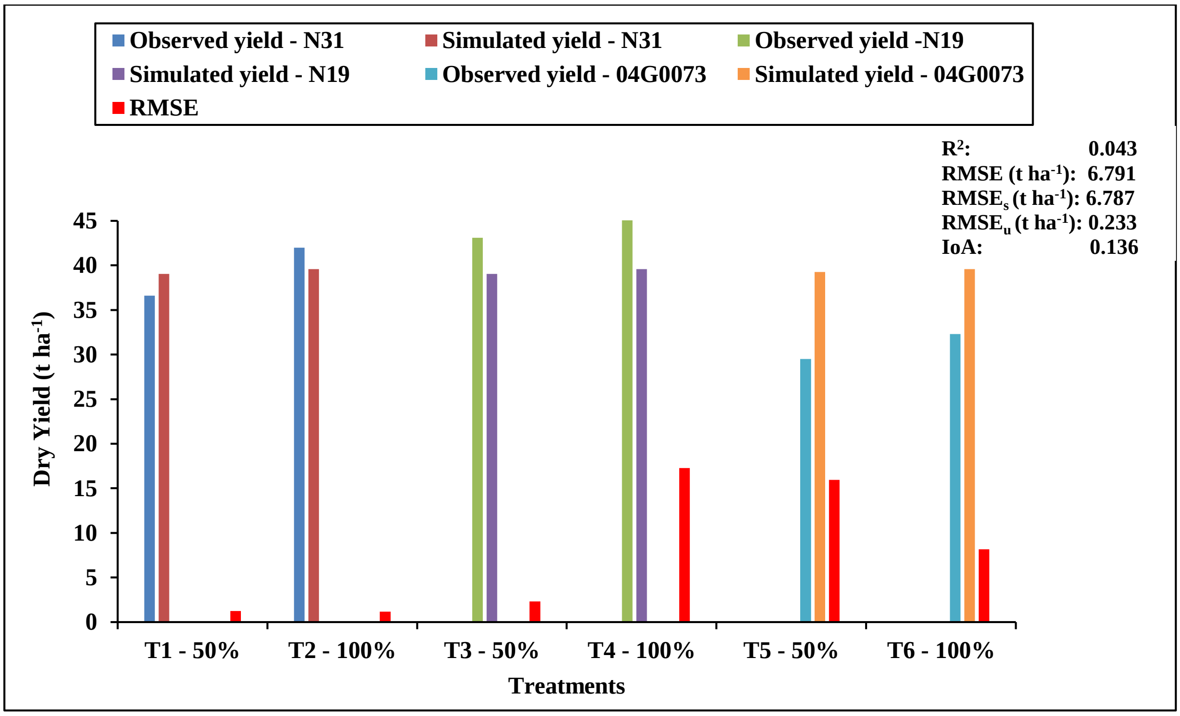

Figure 7-7 Differences between observed and simulated sugarcane dry yields at Komatipoort for six treatments (3 cultivars; 2 irrigation treatments) during the 2011/12 season

Table 7-8 Statistical indicators derived from the observed and simulated sugarcane dry yields at Komatipoort for six treatments (3 cultivars; 2 irrigation treatments) during the 2011/12 season

Treatment	RMSE (t ha^{-1})	RMSE$_s$ (t ha^{-1})	RMSE$_u$ (t ha^{-1})
1	1.254	1.241	0.013
2	1.162	1.155	0.007
3	2.329	2.311	0.018
4	17.265	17.261	0.004
5	15.933	15.933	0.000
6	8.174	8.161	0.013

7.1.2.2 Sugarbeet

One season of sugarbeet (cultivar EB0809) data from Komatipoort was used as an independent dataset to validate the calibrated model. The dataset had two different irrigation treatments (i.e. deficit irrigation and full irrigation) as indicated in **Figure 7-8**. As shown in the figure below, AquaCrop overestimated the final yields for both treatments. However, the IoA value of 0.79 indicates that there is a good agreement between the observed and simulated values. In addition, the low RMSE values suggest the model's performance is good. These results indicate that when adequately calibrated, AquaCrop can potentially be used as a decision-making tool to help farmers choose the best irrigation to apply for maximum yields.

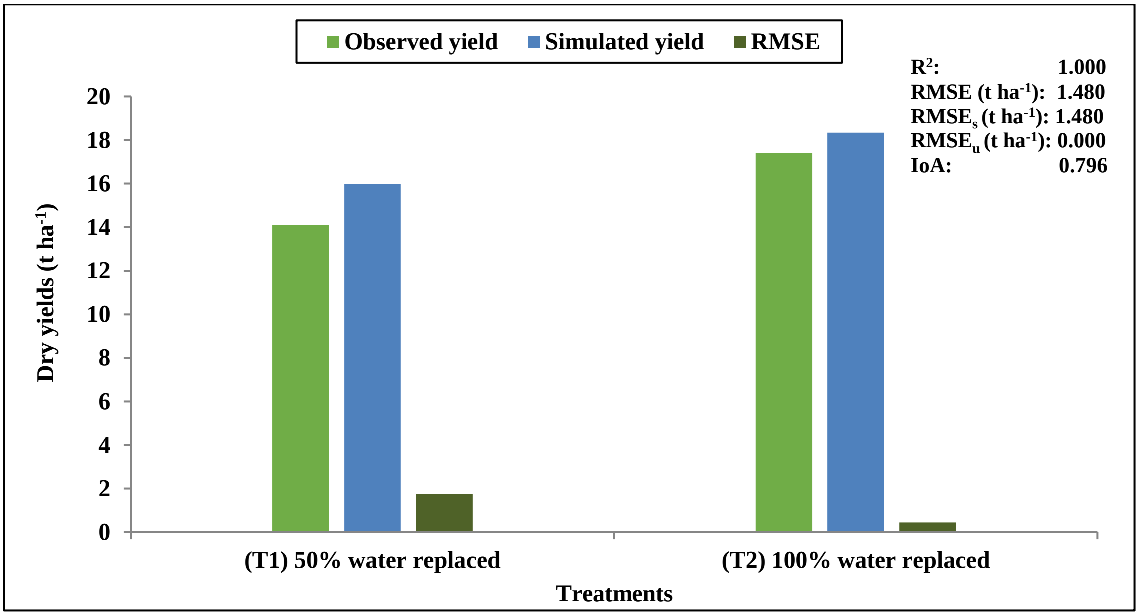

Figure 7-8 Difference between observed and simulated sugarbeet dry yields at Komatipoort in 2012

7.1.3 Soil water simulations

The results of the soil analysis described in **section 6.5** are shown in **Table 7-9**. The soil thickness corresponds to the samples which were taken at 0.2, 0.4 and 0.6 m. These parameters were entered into the AquaCrop model during the simulations.

Table 7-9 Measured soil water retention parameters and saturated hydraulic conductivity for the Ukulinga trial site

Depth (m)	Thickness (m)	Saturation	Field capacity	Wilting point	Saturated hydraulic capacity (mm d^{-1})
		Vol. %			
0.2	0.2	36.5	29.3	15.7	184.8
0.4	0.2	36.5	30.0	17.5	228.0
0.6	0.2	36.1	32.0	20.8	108.0

Simulations of the soil water content (SWC) were compared to measured values (**Figure 7-9**). The depths at which water content were simulated and measured are different because the TDR probes were inserted at 10, 20, 40 and 60 cm depths. However, AquaCrop estimates the SWC in increments of 10 cm, starting at a depth of 5 cm (i.e. 5, 15, 25, 35, 45 cm etc.). Therefore, the simulations above and below each measurement depth were averaged (i.e. 5 and 15 cm were averaged) and then compared to the measured SWC values (see **Figure 7-9**).

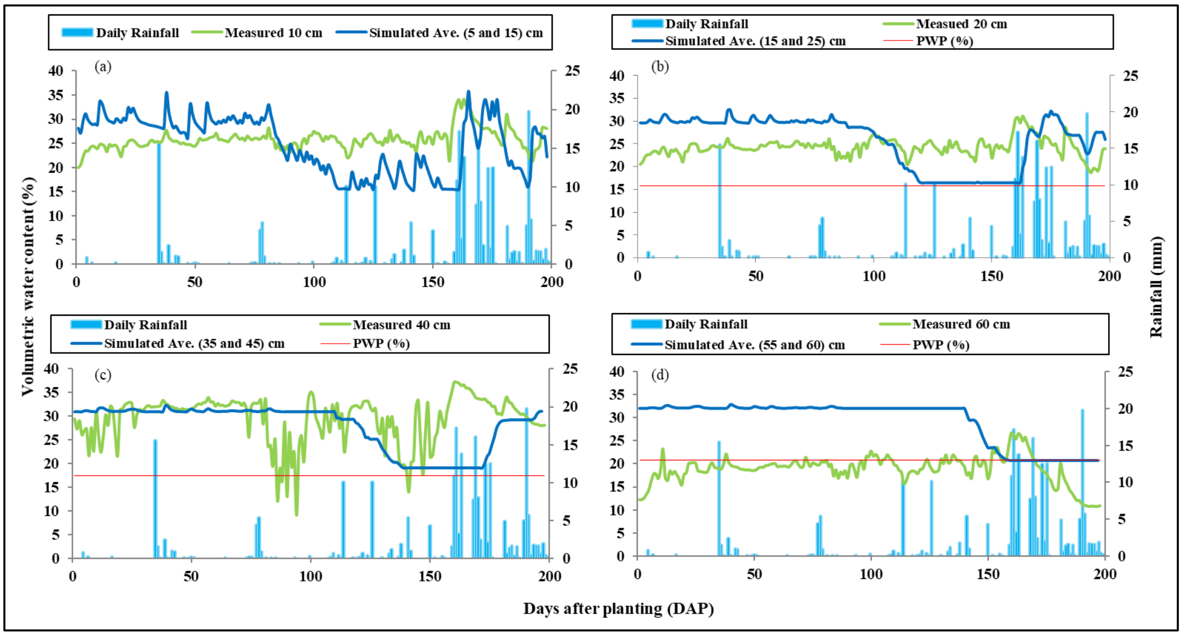

Figure 7-9 Simulations of the soil water content at varying depths for the sugarbeet trial at Ukulinga

It is important to note that the measured SWC at depths of 40 cm to 60 cm drop below 18% and 21% (**Figure 7-9**), which are the PWP values measured for the soil sample taken at 40 and 60 cm respectively (see **Table 7-9**). This can potentially be a human or systematic error, either in the measured PWP from the laboratory work or in the TDR data. For example, Dobriyal *et al*. (2012) noted that TDRs can give erroneous measurements when there is poor contact between the probes and the soil medium.

For the first 100 DAP, AquaCrop over-estimated the soil water content except at the 40 cm soil layer. The model mostly simulates the soil water content (SWC) at either FC (~30%) or PWP (~20%) with little variation in between. Between 120 DAP and approximately 165 DAP, simulations are lower when compared to measured values of SWC. According to modelled output, the crop would be water stressed, which affected canopy expansion by 16%, resulting in lower yield prediction (**subsection 7.1.1.2**).

The model does not reflect the daily fluctuation in SWC values as shown by measured (TDR) data, especially at 40 cm where the crop appears to mostly extract soil water. However, at the top soil (10 cm), which is most affected by soil water evaporation, there is a variation in the simulated SWC. The fluctuations are due to the daily variations in ET, rainfall and irrigation. The performance of the model in simulating SWC is represented statistically in **Table 7-10**. The low R^2 and IoA values indicate a poor goodness of fitness between measured and simulated values. These results concur with findings by Nyakudya and Stroosnijder (2014), who found that AquaCrop over-estimated SWC for maize.

Table 7-10 Statistical indicators for soil water simulations of the sugarbeet trial

Soil depth (cm)	Statistical indicators				
	R^2	RMSE (%)	$RMSE_s$ (%)	$RMSE_u$ (%)	IoA
10-15	0.001	6.612	2.131	6.259	0.268
20-25	0.009	6.396	3.708	5.212	0.233
35-40	0.003	7.404	5.246	5.226	0.401
55-60	0.021	9.814	8.316	5.213	0.241

On the other hand, Hadebe *et al*. (2017) showed that the model can simulate SWC well for a single layer soil beneath grain sorghum. However, a three-layer option was selected in this study, which may explain the difference in SWC results. Based on personal experience, other model users have noticed that AquaCrop performs best using a single soil layer option (Mabhaudhi, *pers. comm.*, 2017).

7.1.4 Total evaporation

Measured ET was derived by Kunz *et al*. (2015a) using a micrometeorological technique (see **subsection 6.3.2.3**). In this study, measured ET was compared to simulated ET (**Figure 7-10** and **Figure 7-11)**. The crop achieved maximum canopy cover at 140 DAP (see **subsection 7.1.1.2**). This resulted in frequent days experiencing higher evapotranspiration (ET) rates, with maximum ET measured at 179 DAP. The start of the rainy season (22 October 2013) also contributed to higher ET measurements towards the end of the season.

AquaCrop did not accurately simulate ET, as indicated by the goodness of fit (R^2 = 0.082; IoA = 0.584) indicators. During the development phase of the crop (i.e. when CC is low), the model under-estimates ET which is predominantly soil water evaporation (or E_S). Soil water evaporation occurs from the top layer of the soil (usually the first 10-15 cm) and the results in **Table 7-10** further indicate that simulations of soil water content at this depth are poor.

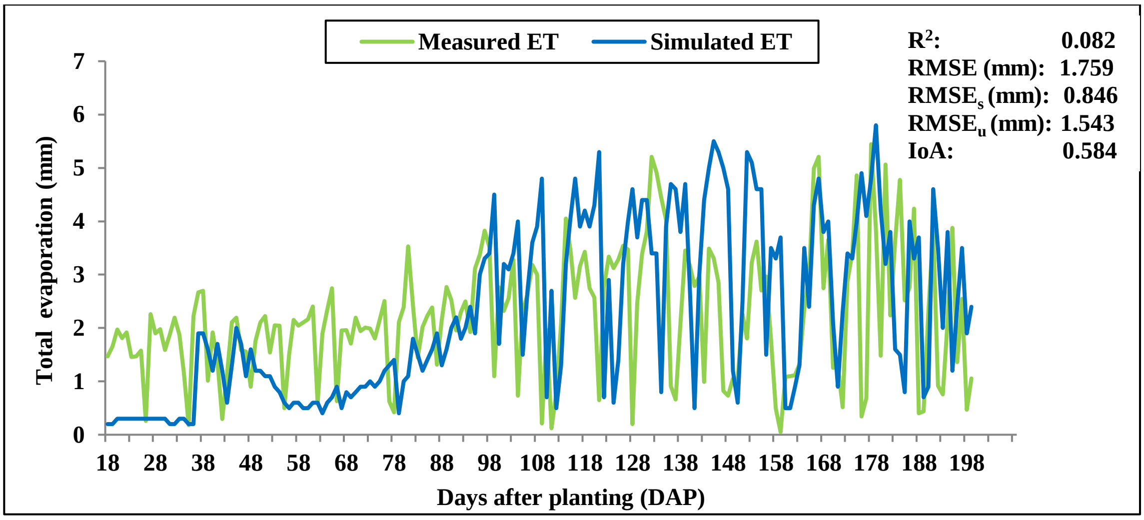

Figure 7-10 Simulations of evapotranspiration (ET) against measured values for the sugarbeet trial at Ukulinga

However, the total accumulated ET up to 199 DAP was simulated as 406 mm, which compared favourably to the estimated total of 401 mm (**Figure 7-11**). In addition, the statistical indicators, particularly the high R^2 (0.975) and IoA (0.991) values, indicate that AquaCrop performed well. Even though the accumulated ET values are similar, the daily simulations are poor and this is reflected by the high RMSE values. Based on the daily simulations, ET is generally overestimated in the latter stages of crop development (from 100 DAP) when transpiration (T_r) is dominant due to the higher CC.

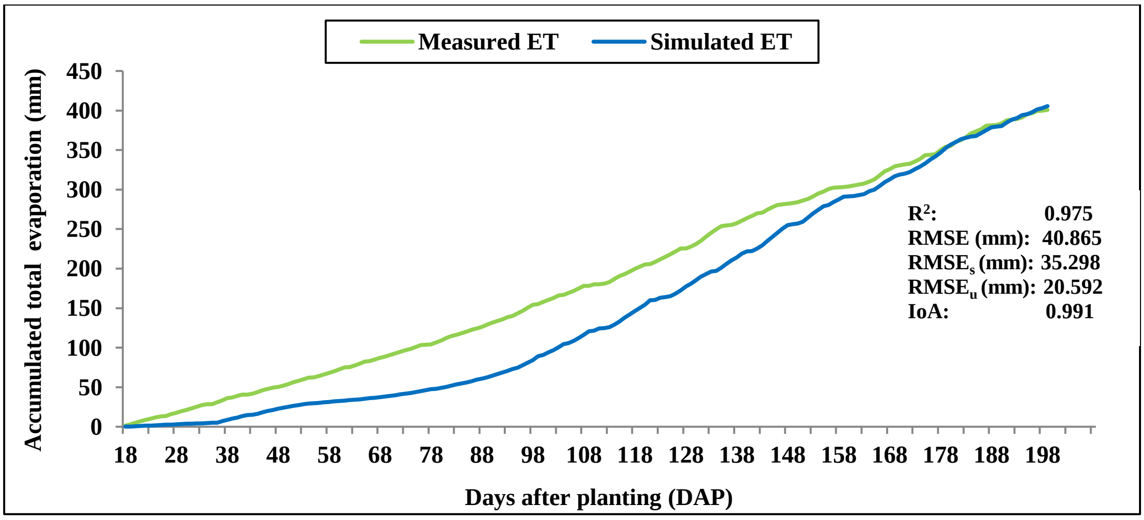

Figure 7-11 Simulations of accumulated evapotranspiration (ET) against measured values for the sugarbeet trial at Ukulinga

A study by Paredes *et al*. (2014) presented similar findings for maize in that AquaCrop tends to under-estimate E_s and over-estimate T_a, which results in biased estimations of soil water content. This is especially true given that CC is only sensitive to water stress during the vegetative phase of crop development. This implies that if CC is not affected by soil water stress, then neither is T_a. In order to improve soil water simulations, Paredes *et al*. (2014) suggested that the proportionality curves for parameters such as CC and the crop transpiration coefficient should possibly be revised to account for the effects of soil water stress, especially early on in the growing season. Measured ET incorporates soil water evaporation, transpiration and evaporation of intercepted water. However, AquaCrop does not account for canopy interception and hence, should always under-estimate ET compared to observations.

The following sections (**7.2** to **7.7**) represent an application of the calibrated crop parameter files, which were used to assess the impacts of climate change on the long-term attainable yield and WUE of both sugarcane and sugarbeet. Results for the present climate were compared to the baseline in order to evaluate the GCM's ability to predict the current climate. Furthermore, results for the future climate were compared to the present climate to evaluate each crop's response to impact of climate change.

7.2 Baseline Climate

The quinary database consisting of 50 years of climate data and the calibrated crop files (i.e. derived for sugarcane at La Mercy and sugarbeet at Ukulinga) were used in the climate change simulations. However, the soils information was assumed to be the same across all quinaries so that results largely reflected the input climate. The runs for each of the three quinaries (i.e. 4717-4719 for sugarcane and 4696-4698 for sugarbeet) were undertaken to account for altitudinal variations across each quaternary catchment (see **Table 6-5**). The 50-year climate file (1950-1999) produces 49 seasonal yields because the simulation starting in 1999 is discarded as there is no climate data in the following year (in 2000) to complete the full season. The 30-year model run (1961-1990) is unaffected because the simulation starting in 1990 is able to complete, due to the availability of climate data in 1991.

As noted in **subsection 6.2.1.1**, the La Mercy experimental dataset (1989 to 1990) comprised of rainfed ratoon treatments, whereas the Ukulinga sugarbeet was irrigated (see **subsection 6.2.2.1**). For comparative purposes, the runs were conducted for rainfed conditions.

However, for sugarbeet planted in May, an additional irrigated model run was performed to improve crop growth and yield. The two planting dates for sugarcane were selected because they produced the highest yields (see treatments T4 and T6 in **Figure 7-2** in **subsection 7.1.1.1**). For sugarbeet, winter and spring planting dates were selected.

7.2.1 Sugarcane

Figure 7-12 shows the mean yields of sugarcane (in dry t ha^{-1}) for the 50-year and 30-year simulation periods. The simulated long-term attainable yields ranged between 28.54 t ha^{-1} to 31.79 t ha^{-1} for April and 24.57 t ha^{-1} to 40.01 t ha^{-1} for February (**Figure 7-12**). Based on the coefficient of variation, sugarcane yields for the April planting are less variable over the 49-year simulation period, than compared to sugarcane planted in February (see **APPENDIX E**). Based on AquaCrop's output, April is a more suitable planting date than February.

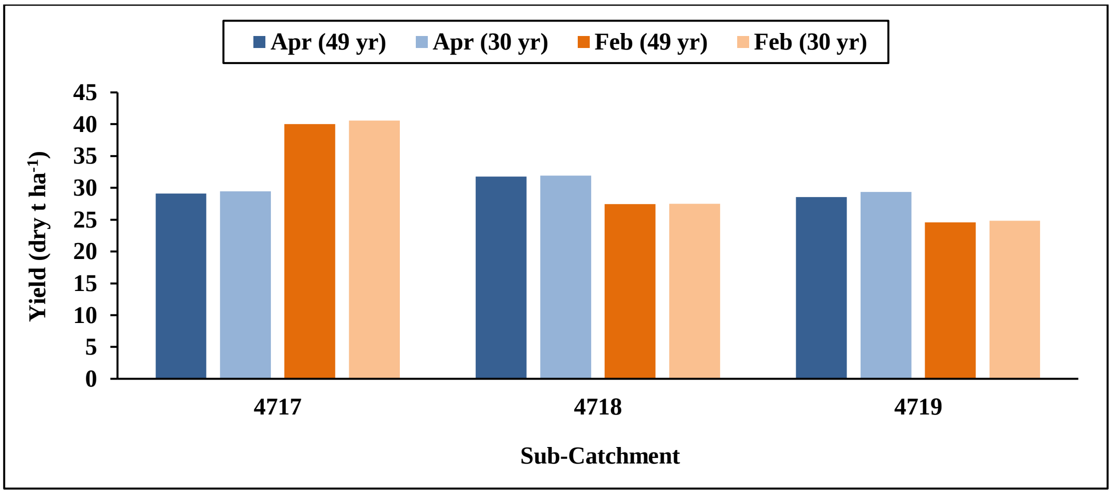

Figure 7-12 Dry yield simulations of sugarcane across the three quinary sub-catchments in quaternary catchment U30D using 30 and 50 years of historical climate data

The results indicate that the mean yield derived using only 30 years of climate data is a very good approximation of the long-term attainable yield (based on 50 years of climate data). This finding concurs with Steduto *et al*. (2012), who noted that for long-term assessments of productivity, a minimum of 30 years of input climate record is recommended. Thus, running the model with 30 years of data provides considerable saving in computational expense when compared to a 50-year simulation, with little impact on the accuracy of the long-term attainable yield.

The yields for the upper sub-catchment (i.e. lower quinary number) are expected to be higher due to wetter and cooler conditions generally associated with higher altitude sites. This is evident for the February planting, which shows higher mean yields with increasing mean altitude from the lower quinary (sub-catchment 4719, 50 m a.s.l) to the upper quinary (4717, 206 m a.s.l). For the April planting, this trend is not apparent.

Figure 7-13 shows the WUE of sugarcane for the 49- and 30-year simulations, with the 30-year simulations resembles the 49-year WUE values. WUE is generally higher in the cooler April planting season. Therefore, although February yields are higher in quinary 4717, it has the lowest simulated WUE (i.e. 2.44 kg m^{-3}). The highest long-term attainable WUE are in quinary 4718 (3.10 kg m^{-3}) and 4719 (2.77 kg m^{-3}).

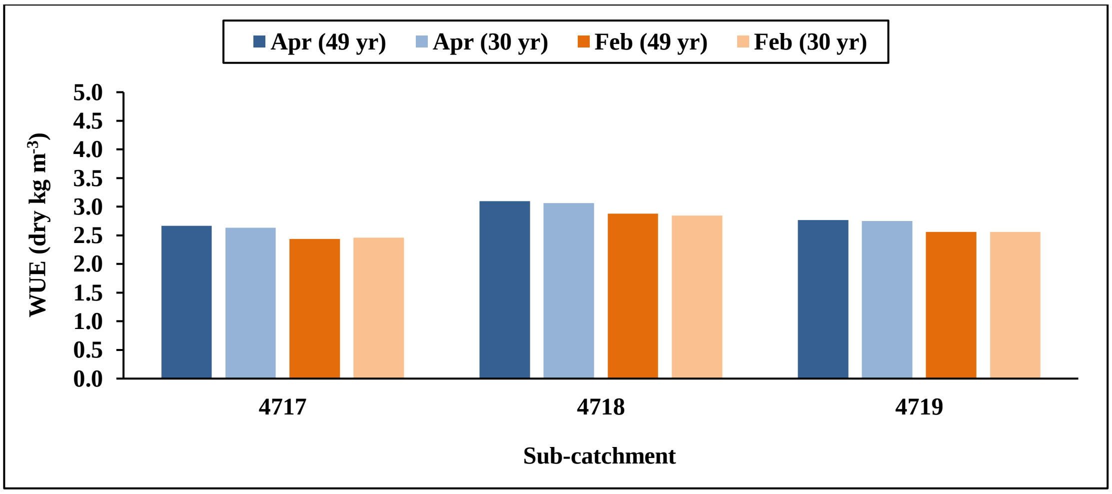

Figure 7-13 Simulated WUE of sugarcane across all three quinaries in quaternary catchment U30D using 30 and 50 years of historical climate data

7.2.2 Sugarbeet

Based on 49 years of data, long-term attainable yields of sugarbeet planted in May under irrigated conditions are estimated to be 11.97 t ha^{-1}, 11.19 t ha^{-1} and 10.62 t ha^{-1} across quinaries 4696, 4697 and 4698 respectively (**Figure 7-14**).

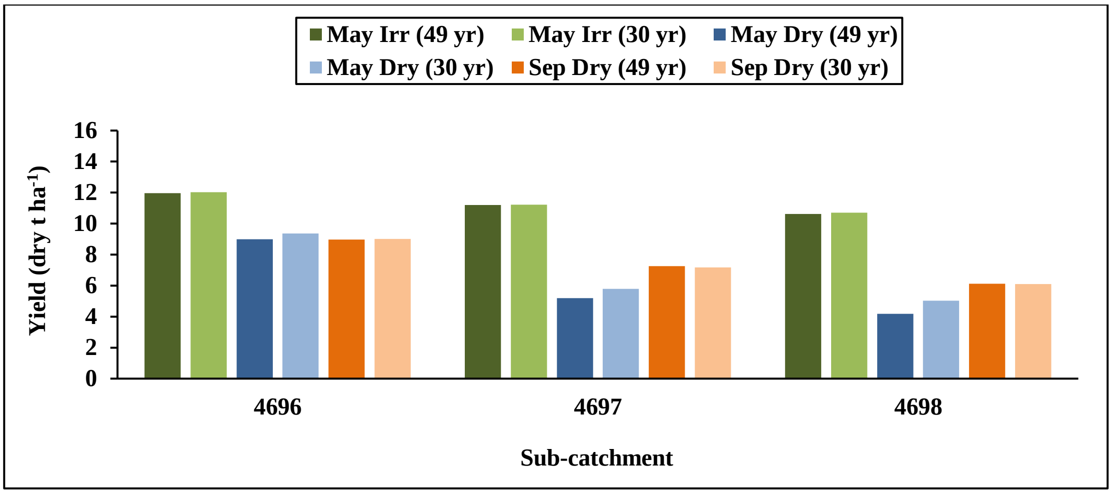

Figure 7-14 Dry yield simulations of sugarbeet across the three quinary sub-catchments in quaternary catchment U20J using 30 and 50 years of historical data

Yields are lower for simulations under dryland conditions, especially for the May (winter) planting dates compared to the September (spring) planting dates. From higher to lower mean altitudes (i.e. 1024 m to 566 m a.s.l), the rainfed yields are 9.00 t ha^{-1}, 5.20 t ha^{-1} and 4.19 t ha^{-1} for May and 8.97 t ha^{-1}, 7.26 t ha^{-1} and 6.13 t ha^{-1} for September. Lower yields in May are attributed to lower precipitation, drier soil conditions and limited transpiration, thus resulting in a lower biomass.

Sugarbeet planted in September attained the lowest WUE (2.06 kg m^{-3}) when compared to a May planting which gave the highest WUE (i.e. 2.47 kg m^{-3}). However, there is higher variability in WUE across the quinaries for a May planting (dryland conditions) over the 49-year period which can be related to the less favourable climatic conditions (i.e. dry) for crop growth over winter (see **APPENDIX E**). When the crop is irrigated, simulations show a reduction in variability and increases in both yields and WUE. Hence, supplemental irrigation is required for autumn or winter plantings, especially to help establish to crop.

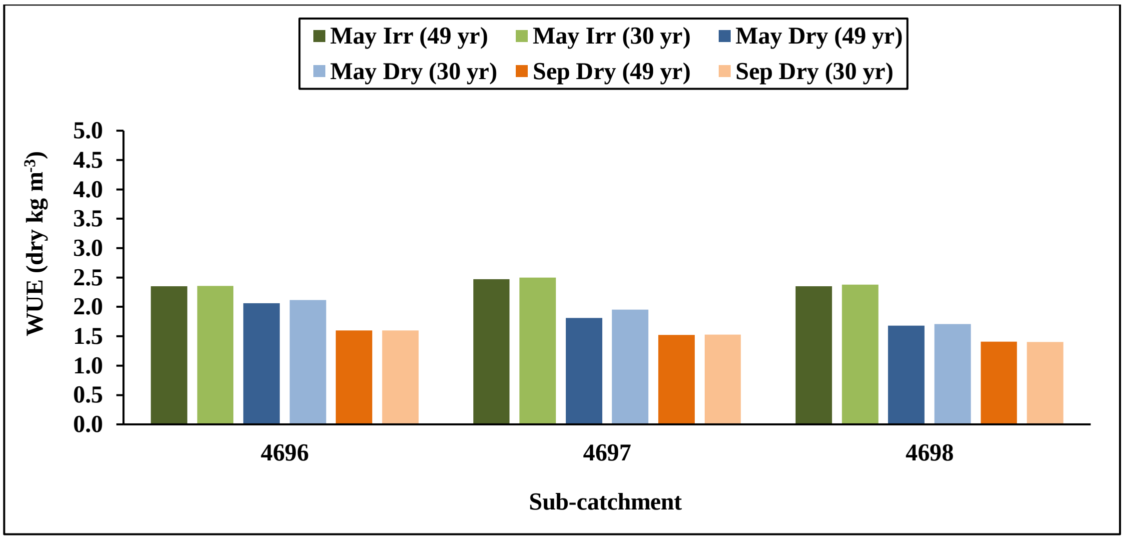

Figure 7-15 WUE simulations of sugarbeet across the three quinary sub-catchments in quaternary catchment U20J using 30 and 50 years of historical data

7.2.3 Summary

The 30-year simulations closely approximate the 49-year simulations, regardless of crop type, planting date or quinary. Thus, running the model with 30 years of data (as opposed to 50 years) provides considerable saving in computational expense, with little impact on the accuracy of the long-term attainable yield. For rainfed conditions, it is also evident that yield and WUE at the higher altitude (i.e. 1024 m a.s.l) are higher than those at the lower altitude (i.e. 566 m a.s.l). In addition, WUE is better for the cooler planting (i.e. April for sugarcane; May for sugarbeet) than the warmer planting. This is expected because crops generally use less water during the cooler season compared to summer (i.e. when conditions are hot and potential evapotranspiration rates are higher).

7.3 Present Climate

This study does not consider results of individual GCMs, but rather the mean of outputs derived using climate scenarios provided by the ensemble. Hence, the mean yield from four GCMs (i.e. CSI, GF0, GF1 and MPI) common to both downscaling techniques (i.e. statistical and dynamical) was calculated for the present climate and then compared to the baseline (i.e. historical) yields. For both downscaling techniques, yields were averaged for a 30-year period from 1961-1990.

7.3.1 Sugarcane

Compared to the baseline yields, the yields from the statistically downscaled climate scenarios are consistently lower, whilst the dynamically downscaled climate generally predicted higher yields (**Figure 7-16**). The exception is the February planting in the upper quinary (4717) where the simulated baseline yield is higher than that obtained using the dynamically downscaled climate scenarios.

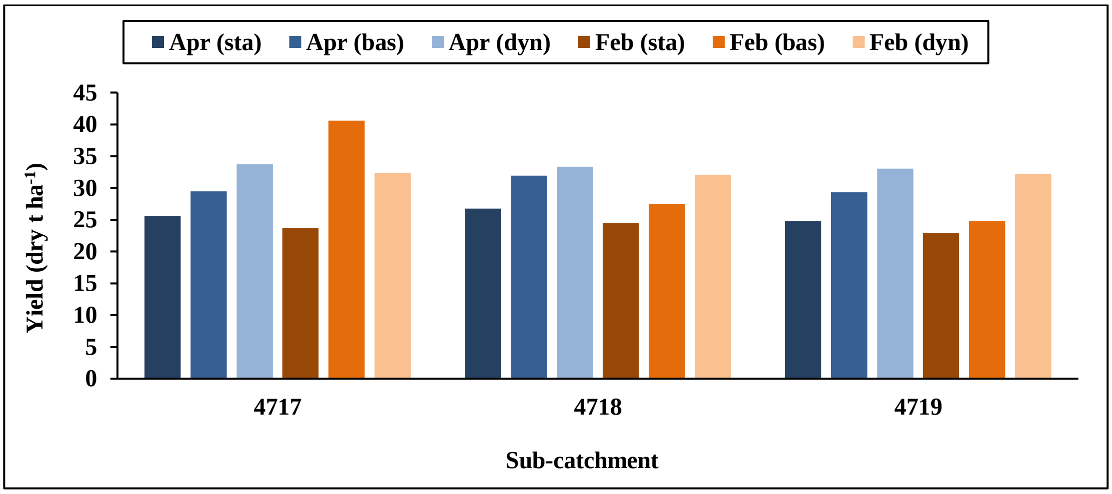

Figure 7-16 Comparisons of the baseline (bas) sugarcane yield to the present yields estimated using the statistical (sta) and dynamical (dyn) downscaled climate scenarios

According to Fowler *et al*. (2007), statistical downscaling techniques are calibrated using historically observed climate data. This implies that statistical downscaling is more suited to replicating baseline (i.e. observed) conditions than dynamical downscaling. However, this does not imply that statistical downscaling is always the better approach. Fowler *et al*. (2007) emphasised the value of dynamical downscaling in any region with complex orography (e.g. KwaZulu-Natal), considering RCMs are able to better capture the effects of orographic forcing and rain-shadow effects than compared to GCMs.

Shin *et al*. (2009) used both downscaling approaches to assess their performance in generating seasonal climate data for crop yield forecasting. The result indicated that both downscaling techniques produced better datasets than global circulation models. However, the need for improved bias correction was noted, particularly for precipitation. Shin *et al*. (2009) also highlighted that an ensemble approach helps to reduce uncertainty. Vanuytrecht *et al*. (2014) concluded that both statistically and dynamically downscaled climate scenarios should be used in climate change studies.

In terms of WUE estimations, results from both downscaling techniques underestimate the baseline WUE. This implies that the GCMs are unable to accurately predict the historical (i.e. observed) climate. However, the discrepancies between the two downscaling techniques are not significant, i.e. < 0.5 kg m^{-3} (**Figure 7-17**). Yields obtained from the statistical downscaled present climate are more similar to the baseline WUE than those obtained using the dynamically downscaled climate. As noted earlier, this is expected considering statistical downscaling is more suited to replicating baseline (i.e. observed) conditions than dynamical downscaling.

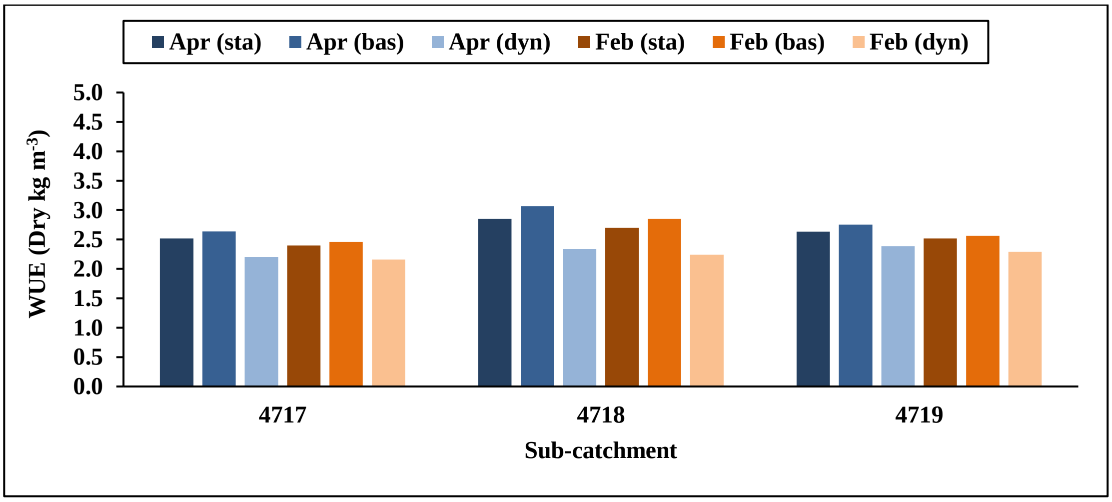

Figure 7-17 Comparisons of the baseline (bas) sugarcane WUE to the present WUE estimated using the statistical (sta) and dynamical (dyn) downscaled climate scenarios

To re-cap, the comparison of the yields and WUE of the present climate to those of the baseline are relatively good. Zhang and Huang (2013) stated that a climate model that performs well in representing the baseline period is likely to demonstrate a similar skill in simulating the future climate. Furthermore, the statistical downscaling approach gave a better comparison between the present and the baseline climate, especially for WUE estimates. However, it is important to remember that the mean of four GCMs was compared to the baseline. Various studies (e.g. Asseng *et al*., 2013) have shown that the mean derived from a GCM ensemble is a better predictor than using individual GCMs, especially if the ensemble is large. For example, if the simulated yields derived from all eight GCMs (4 statistical; 4 dynamical) were averaged, this mean yield would match more closely with the baseline yield (see **Figure 7-16**).

7.3.2 Sugarbeet

In general, the sugarbeet yield simulations for the dynamic downscaling are higher than the baseline yields (as was the case of sugarcane), except for the September planting (dryland) in the upper quinary (**Figure 7-18**). However, the statistically downscaled GCMs over-estimated the baseline yield, except for the May planting (irrigated) in the upper quinary.

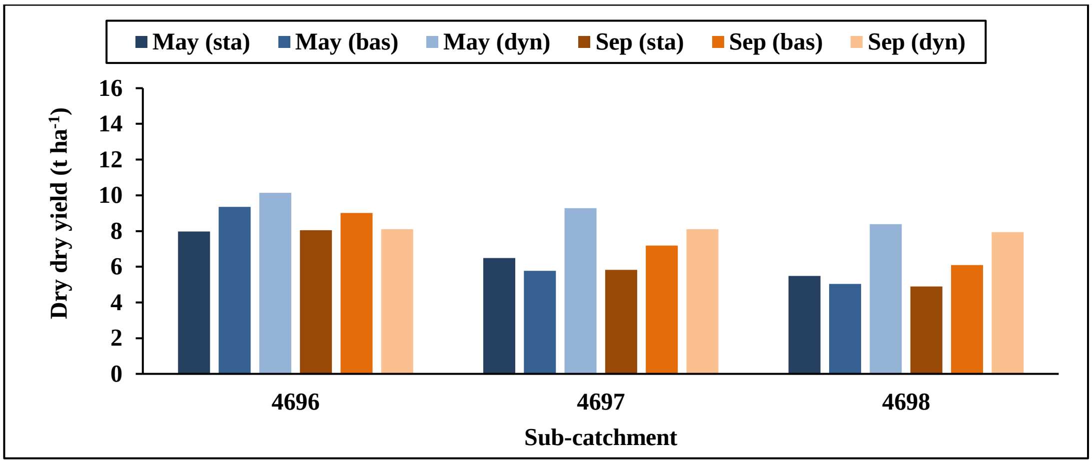

Figure 7-18 Comparisons of the baseline (bas) sugarbeet yield to the present yields derived using climate scenarios from the statistical (sta) and dynamical (dyn) downscaled climate scenarios

Trends in WUE simulations for sugarbeet (**Figure 7-19**) were similar to those for sugarcane, with the exception being the May planting (irrigated) in the lower quinary (4698). Hence, both downscaling techniques underestimate the baseline WUE. Furthermore, WUEs derived using statistically downscaled climate scenarios better match the baseline WUEs (differences range from -0.03 to 0.20 kg m^{-3}), than compared to the dynamic downscaled technique (differences range from -0.52 to 0.40 kg m^{-3}). This highlights the need for climate change studies to consider both downscaling techniques, thus producing a wider range of plausible impacts.

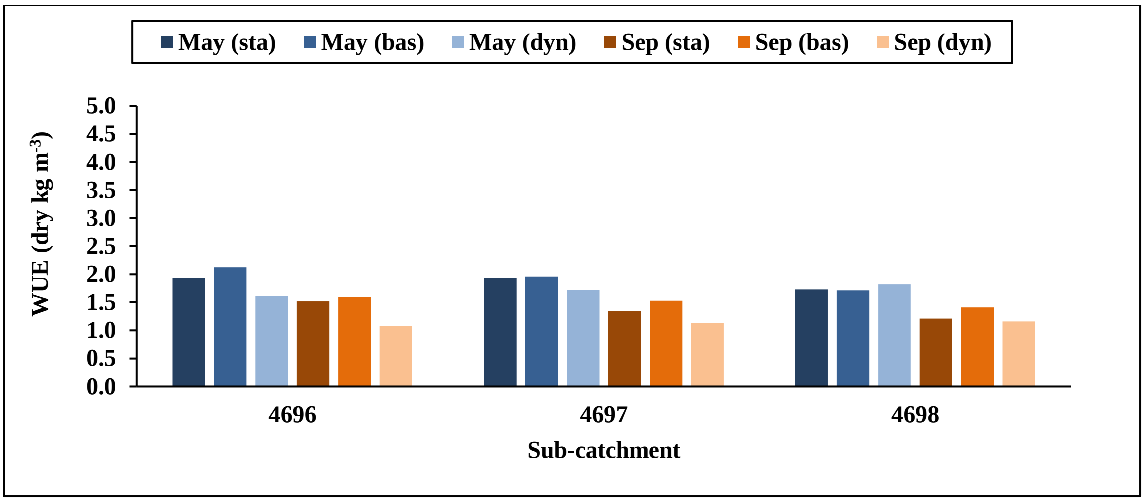

Figure 7-19 Comparisons of the present baseline (bas) sugarbeet WUE to the WUE estimated using the statistical (sta) and dynamical (dyn) downscaled climate scenarios

7.3.3 Summary

Based on the above results, the statistically downscaled model simulations better match the baseline simulations than compared to outputs derived using the dynamically downscaled climate scenarios. This is particularly true for WUE estimates than for yield estimates.

The selection on the type of downscaling technique is generally dependent on the problem to be addressed. However, in most cases, the methods are complementary and should be used together. It can be deduced that using both downscaling techniques, instead of one, provides results that are more representative of baseline conditions. Given that the downscaled climate scenarios generally mimic the baseline, this infers confidence in modelling future scenarios.

7.4 Future Climate - All GCMs

The mean yield and WUE derived from all six GCMs (see **Table 6-7**) was calculated for the future climate and compared to values for the present climate (see **section 7.3**). Future simulations were performed using input climate data from all six GCMs that were dynamically downscaled as well as the four GCMs that were statistically downscaled (see **Table 6-7**). The simulated yield and WUE for the present climate correspond to a 20-year (1971-1990) and 30-year (1961-1990) period for the statistical and dynamical downscaled scenarios, respectively. Similarly, values for the future climate also correspond to a 20-year

(2081-2100) and 30-year (2071-2100) period for the respective statistical and dynamical downscaled scenarios. The mean yields and WUEs presented in the graphs in this section were simulated using future climate projections, together with the percentage change relative to the present (not baseline) yield.

7.4.1 Sugarcane

7.4.1.1 Dynamical downscaling

Based on the results from all dynamically downscaled GCMs, the future climate projections show increases in yields and WUE. For the April planting season, quinary catchments 4717 and 4719 have a marginally higher increase in mean yields of 12.7% and 12.6%, compared to quinary 4718 with an increase of 12.2% (**Figure 7-20**). In February, mean yields increase by an average of 6% across the quinaries (range 18.4% to 18.9%) relative to April. This indicates that sugarcane planted in February may benefit more from climate change than compared to the April planting.

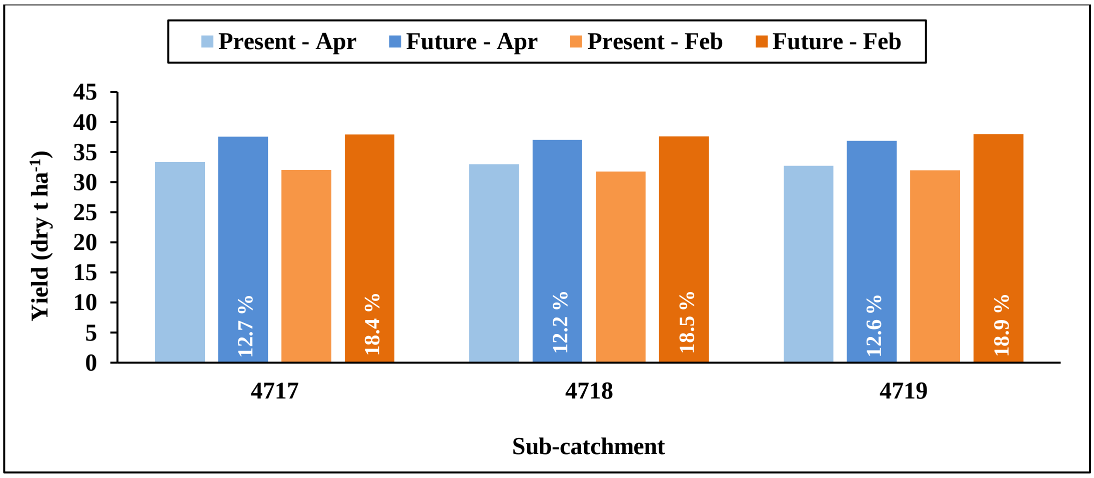

Figure 7-20 Percentage changes in sugarcane yield from present to future for April and February plantings, derived using dynamically downscaled climate data available for six GCMs

A similar trend was noted for improvements in WUE, i.e. greater for the February planting compared to April (**Figure 7-21**). However, the percentage change in WUE from present to future is much greater than the yield change, i.e. yields are simulated to increase by 18.4% to 18.9% in February, whereas WUE may increase by 56.5% to 57.8%. These results highlight the fact that impacts of climate change on crop response can be influenced by the crop's planting date.

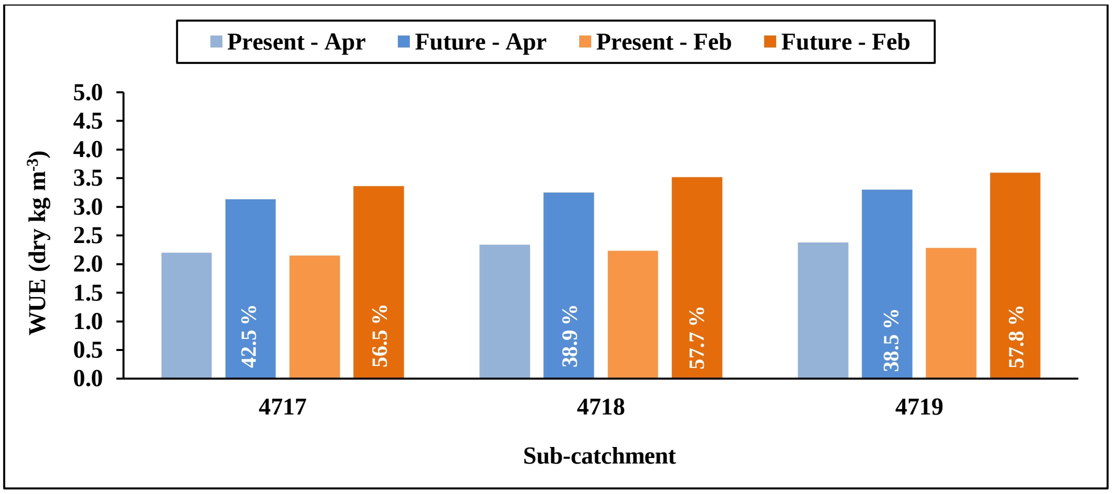

Figure 7-21 Percentage changes in sugarcane WUE from present to future for April and February plantings, derived using dynamically downscaled climate data available for six GCMs

7.4.1.2 Statistical downscaling

Using statistically downscaled GCM data, the same positive outcome of increased yields (**Figure 7-22**) and improved WUE (**Figure 7-23**) is projected for the distant future (i.e. 2081-2100). A study by Singels *et al*. (2014) showed that rainfed sugarcane yields can be expected to improve by 20% at La Mercy (e.g. sub-catchment 4719) in the distant future. The projected sugarcane yields for the April planting (13.8-17.2%) compare favourably with those derived by Singels *et al*. (2014). The latter study used different GCMs that were driven by the same A2 emission.

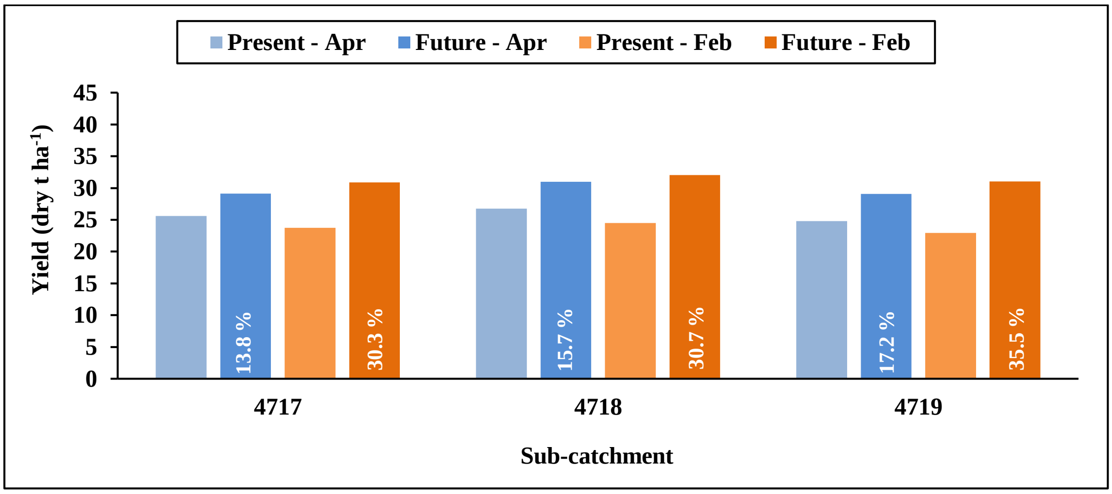

Figure 7-22 Percentage changes in sugarcane yield from present to future for April and February plantings, derived using statistically downscaled climate data available for four GCMs

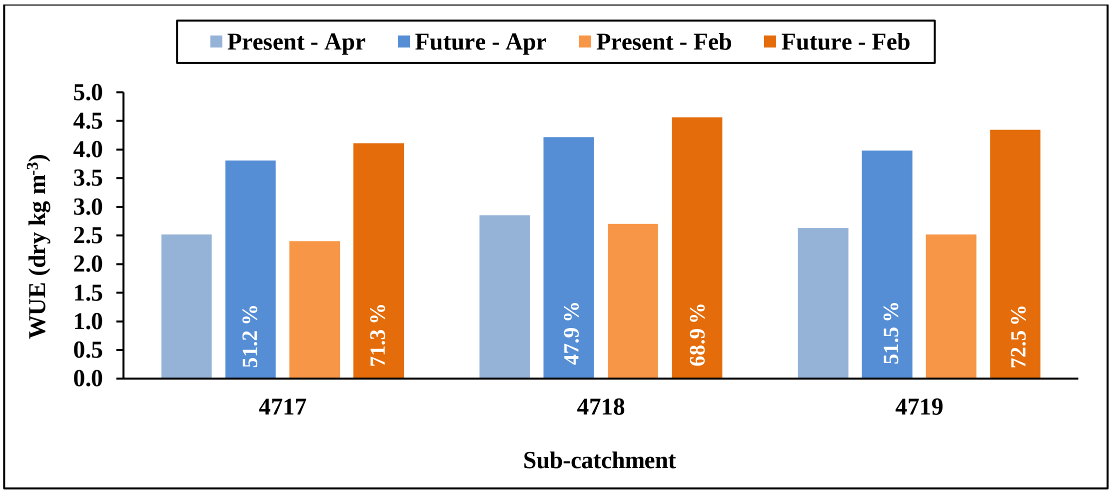

Figure 7-23 Percentage changes in sugarcane WUE from present to future for April and February plantings, derived using statistically downscaled climate data available for four GCMs

The projected increases in yield and WUE for both downscaling techniques can be attributed to favourable climatic changes in the future, such as increased temperature and the CO_2 fertilisation effect. Overall, improvements in yield and WUE projected for the future are higher when derived using statistically downscaled GCM data, than compared to the dynamically downscaled approach. Of the two planting dates, results from both the dynamical and statistical downscaled GCMs indicate that February will produce, on average, higher sugarcane yields per hectare which equates to improved WUE.

7.4.2 Sugarbeet

7.4.2.1 Dynamical downscaling

Results from the dynamically downscaled GCMs also indicate a positive outlook in future sugarbeet yields (**Figure 7-24**) and WUE (**Figure 7-25**) across all quinaries. For the May planting season, there is a 44.5% increase in mean yield at the higher altitude quinary (4696, 1024 m a.s.l), which translates into almost a two-fold increase (94.7%) in WUE. Similar to quinary 4696, the percentage increase in WUE (87.5% and 81.1%) is twice the percentage yield increase (35.4% and 36.7%) in quinaries 4697 and 4698, respectively. Hence, the mid and lower altitude (i.e. 761 m and 566 m a.s.l, respectively) quinary sub-catchments display moderately lower increases in yield and WUE compared to quinary 4696. In the future, a May planting of sugarbeet in the cooler (i.e. higher altitude) areas would produce “more crop per drop” (i.e. potentially save more water per hectare) in comparison to September planting.

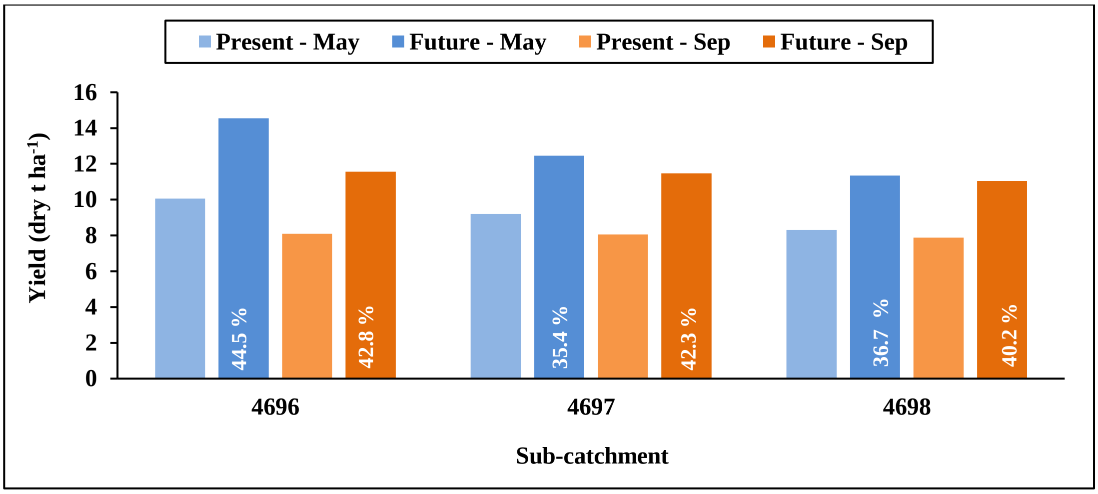

Figure 7-24 Percentage changes in sugarbeet yield from present to future for May and September plantings, derived using dynamically downscaled climate data available for six GCMs

For September, future mean yields are simulated to be 40.2% to 42.8% greater than the present yields and thus, WUEs also improve by 56.7% to 59.5% across all three quinaries. However, when compared to September, the percentage increases in WUE are more pronounced in May. Again, this shows how the planting date can influence the projected impacts of climate change on crop response.

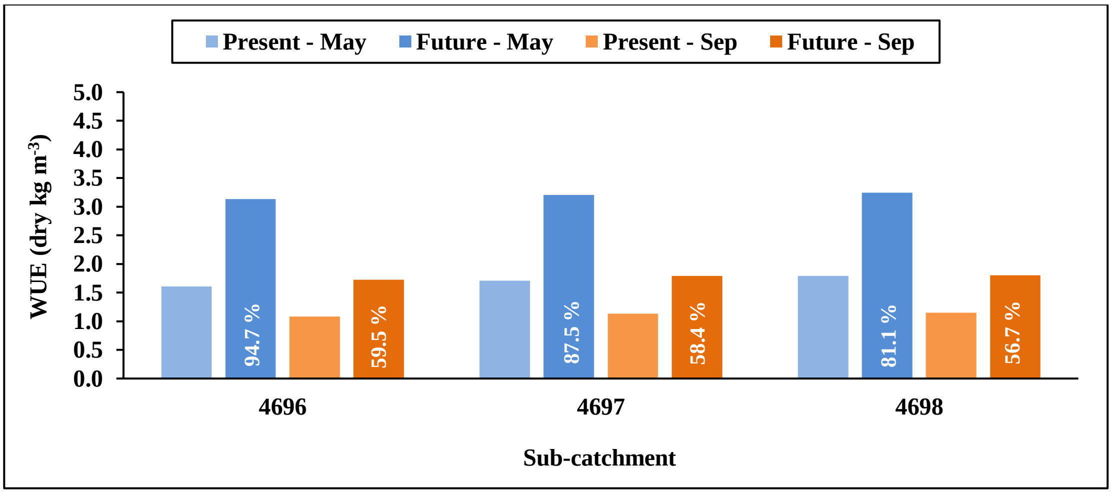

Figure 7-25 Percentage changes in sugarbeet WUE from present to future for May and September plantings, derived using dynamically downscaled climate data available for six GCMs

For the September planting of sugarbeet, the percentage increase in mean yield and WUE is greater for the higher altitude quinary, which decreases towards the lower altitude quinary. This may indicate that at the lower altitudes, growing conditions may become too hot in the future for sugarbeet growth.

7.4.2.2 Statistical downscaling

When compared to results obtained using dynamically downscaled scenarios, the statistically downscaled GCMs projected similar improvements in sugarbeet yield and WUE for the period 2081 to 2099 (**Figure 7-26** and **Figure 7-27**). For both planting seasons, the highest mean increases in yield and WUE occur in quinary catchment 4698. In May, the change in yield and WUE in quinary 4698 are simulated as 89.1% to 99.4% higher than for present conditions, respectively. Both May and September planting seasons have lower increases in yields and WUE in quinary catchment 4697 and 4696, respectively.

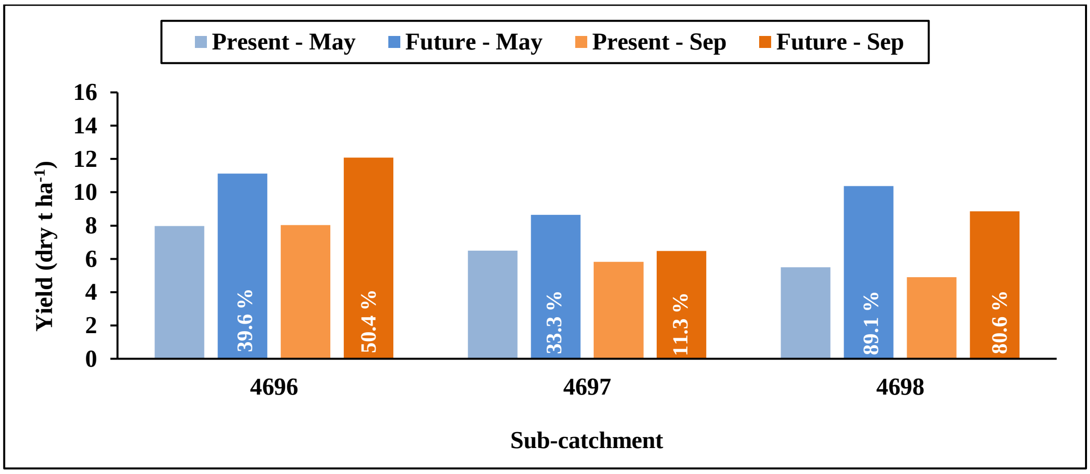

Figure 7-26 Percentage changes in sugarbeet yield from present to future for May and September plantings, derived using statistically downscaled climate data available for four GCMs

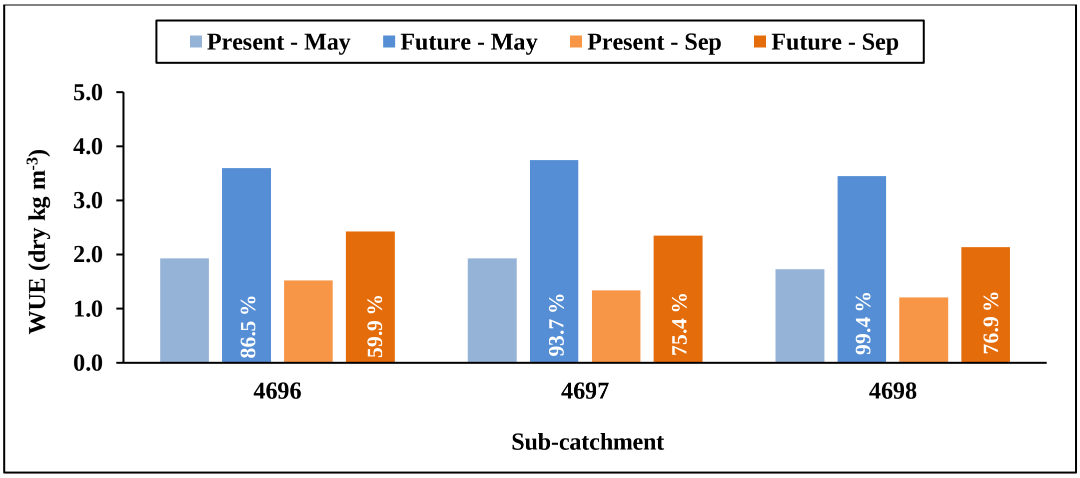

Figure 7-27 Percentage changes in sugarbeet WUE from present to future for May and September plantings, derived using statistically downscaled climate data available for four GCMs

7.4.3 Summary

Overall, the percentage increase (from present to future) in yield and WUE is higher when simulated using statistically downscaled GCMs, than compared to dynamically downscaled GCMs. In addition, projected increases in WUE are higher than changes in yield.

More specifically, irrigated sugarbeet planted in May could produce higher yields per hectare and thus, may utilise water more efficiently than compared to a September planting of the crop (dryland production). Similarly, sugarcane planted in February may benefit more from climate change, than compared to an April planting. Of particular interest is the finding that increases in yield and WUE (obtained from both dynamical and statistical downscaling) are higher for sugarbeet than compared to sugarcane. Hence, the results also indicate that sugarbeet may benefit more from the changing climate than sugarcane. This will be discussed further in **section 7.6**. The following section compares the yield and WUE simulation outputs of GCMs common to both downscaling techniques.

7.5 Future Climate - Four GCMs Common to Both Downscaling Techniques

Instead of using all six dynamically downscaled GCMs, another comparison was undertaken using the four GCMs common to both downscaling techniques. This analysis was undertaken to determine if the results are affected by the inclusion of the two additional dynamically downscaled GCMs.

7.5.1 Sugarcane

The yield increases shown in **Figure 7-28** are up to 2.0% higher when compared to those averaged from six GCMs (as shown in **subsections 7.4.1**). As expected, the improvements in mean yields are higher for February than compared to April. The percentage increase in mean WUE from present to future are higher when derived from four GCMs (**Figure 7-29**), compared to six GCMs. These increases are up to 2.9% higher for an April planting, compared to 2.4% for a February planting. Hence, similar results were obtained for sugarcane yield and WUE increases when four GCMs were used to derive the mean, compared to six GCMs.

Of more importance than the number of GCMs in an ensemble, is the influence of which GCMs are selected. This is evident from the wide range in relative yield increases from 2.8%

to 25.9% (April planting) as well as 8.8% to 27.2% for the February planting for sugarcane (see **APPENDIX F**). For the April planting, two of the six GCMs produced yield increases below 10%, three were in the range 10-20% and one GCM showed increases above 20%. In general, the GCM which produced the lowest yield increase was MIR, which was not part of the four common GCMs. This explains why percentage increases in yield and WUE were lower when all six GCMS were included in the mean calculation. This result concurs with the work of Maqsood *et al*. (2004) and Yun *et al*. (2005), who showed that the accuracy of GCMs may vary from one ensemble member to another.

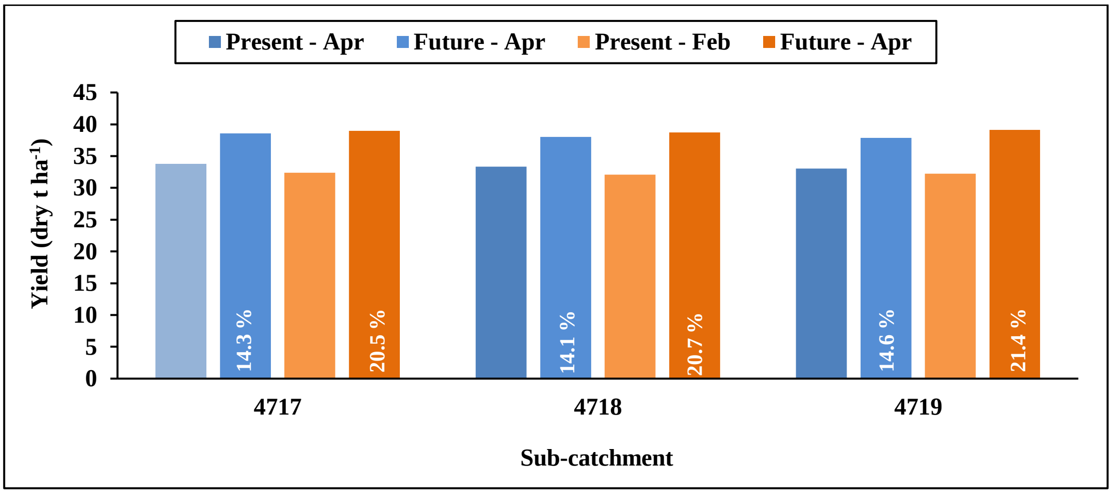

Figure 7-28 Percentage changes in sugarcane yield from present to future for April and February plantings, derived using dynamically downscaled climate data available for four GCMs

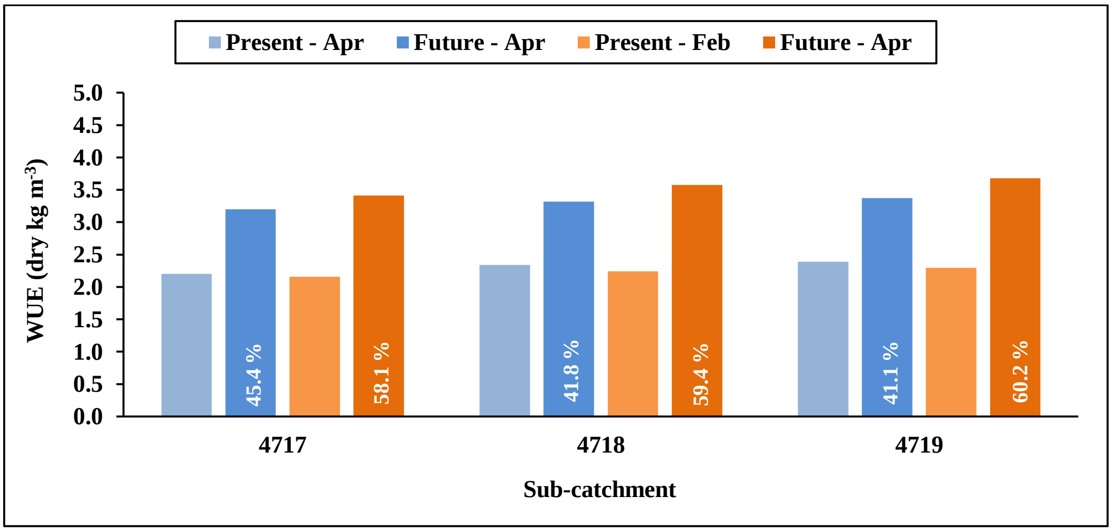

Figure 7-29 Percentage changes in sugarcane WUE from present to future for April and February plantings, derived using dynamically downscaled climate data available for four GCMs

7.5.2 Sugarbeet

As noted for the sugarcane simulations, the percentage increase in the mean yield and WUE results of the four dynamically downscaled GCMs are higher than those derived using six GCMs (**Figure 7-30** and **Figure 7-31**). The yields are up to 4.1% and 2.2% higher for the May and September plantings, respectively. Similarly, the WUEs are up to 4.1% and 2.7% higher for the May and September plantings, respectively. Similar to the findings in **subsection 7.4.2**, the highest mean percentage increase in yields (i.e. 47.1%) occurred in quinary 4696 for the May planting. As noted for sugarcane, similar results were obtained for sugarbeet yield and WUE increases when four GCMs were used to derive the mean, compared to six GCMs.

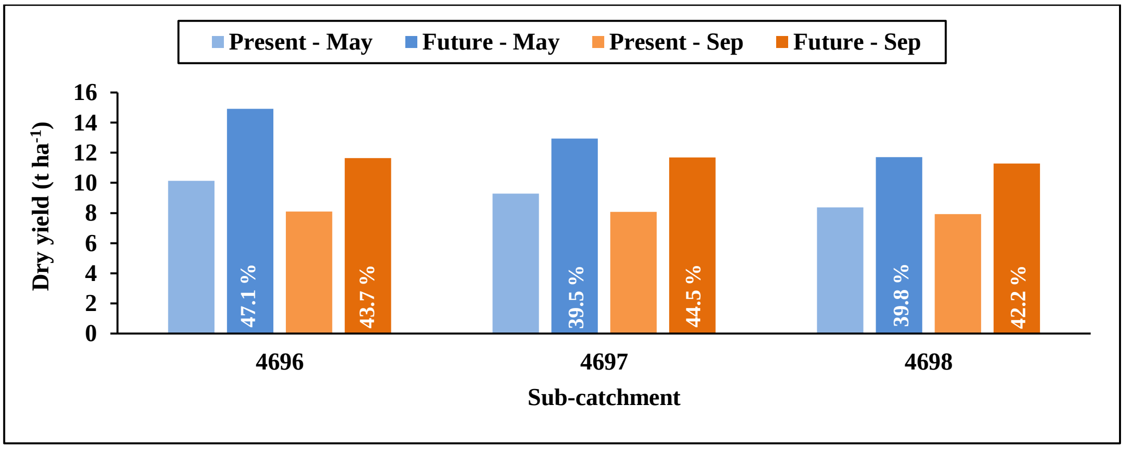

Figure 7-30 Percentage changes in sugarbeet yield from present to future for May and September plantings, derived using dynamically downscaled climate data available for four GCMs

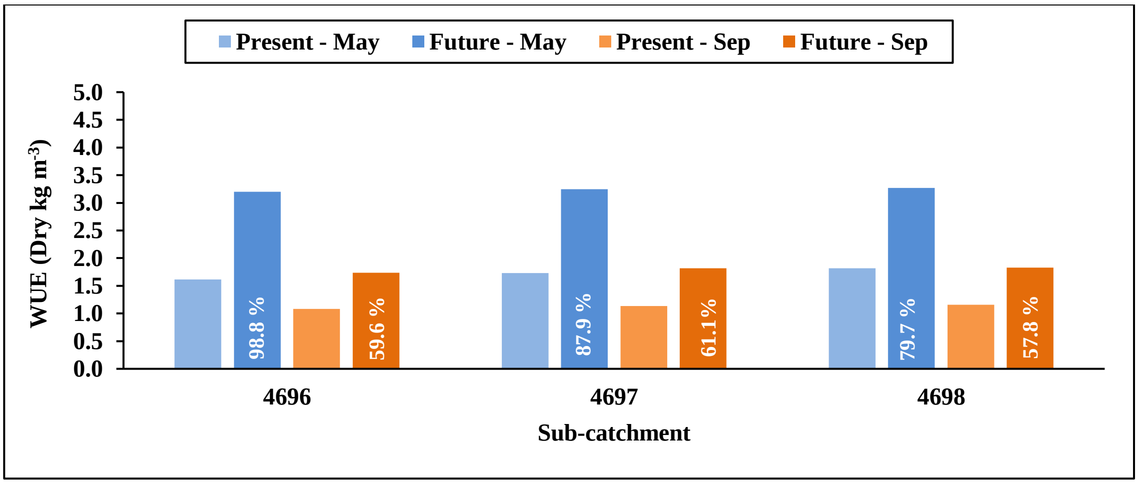

Figure 7-31 Percentage changes in sugarbeet WUE from present to future for May and September plantings, derived using dynamically downscaled climate data available for four GCMs

7.5.3 Summary

Overall, the results indicate that the percentage increase in yields and WUE using only four GCMs (see **subsections 7.5.1** and **7.5.2**) are higher than when using all six GCMs (see **subsections 7.4.1** and **7.4.2**). This highlights that there may be a threshold number of GCMs to include in an ensemble, beyond which no significant benefit is gained by including additional GCMs. However, the number of GCMs in the ensemble has a direct influence on computational expense.

7.6 CO_2 Effects

As discussed in the literature review in **section 4.3**, increased atmospheric carbon dioxide [CO_2] can improve yields of some crops and hence their WUE. This quantifiable response of crops to [CO_2], or the CO_2 fertilisation effect, has been debated in numerous papers (Zinyengere *et al.*, 2014). The results of feedstock sensitivity to [CO_2] is presented in this section, which is also dependent on the crop's ability to hold CO_2 (i.e. sink strength).

Therefore, simulations were undertaken for the six dynamically downscaled GCMs, with the CO_2 value held constant at 369.41 ppm for the entire simulation period (1961-2099). This is the reference value used in AquaCrop (Version 4), as measured at Mauna Loa (Hawaii) in the year 2000. The differences in yields and WUE between the simulations with a fixed CO_2 and increasing CO_2 levels (as per A2 scenario) were then expressed as percentage differences.

7.6.1 Sugarcane

The sugarcane simulations, as shown in **Figure 7-32** and **Figure 7-33**, indicate that a constant CO_2 has a negative impact on the yield and WUE of the crop. Overall, there is a reduction in average yields of 7 to 10% when the CO_2 fertilisation effect is nullified. This indicates that sugarcane is more stressed in the future due to the hotter and drier climate (see **subsection 7.7.2.1**). The influence of altitudinal variation across the three quinaries is not substantial, nor is the change in planting date. This type of analysis is useful in quantifying the CO_2 fertilisation effect on crop yield. According to Knox *et al.* (2010), crop simulations should consider future emission scenarios both with and without CO_2-fertilisation effects.

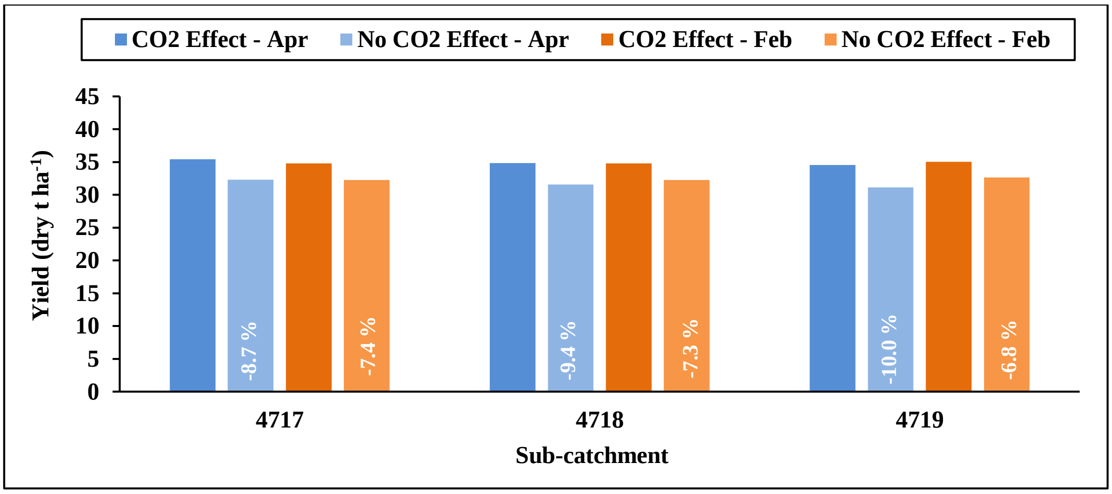

Figure 7-32 The effects of constant CO_2 on the yield of sugarcane for April and February planting dates using the dynamically downscaled data for six GCMs

WUE of sugarcane may be reduced by 6.9 to 8.4% when there is no CO_2 fertilisation taking place. Similarly, the effect of altitude or planting date does not influence the results. It can be deduced that due to the higher temperatures expected in the future, sugarcane would be under increased water stress. This may trigger stomatal closure in order to reduce water loss, which would result in a loss in yield and WUE.

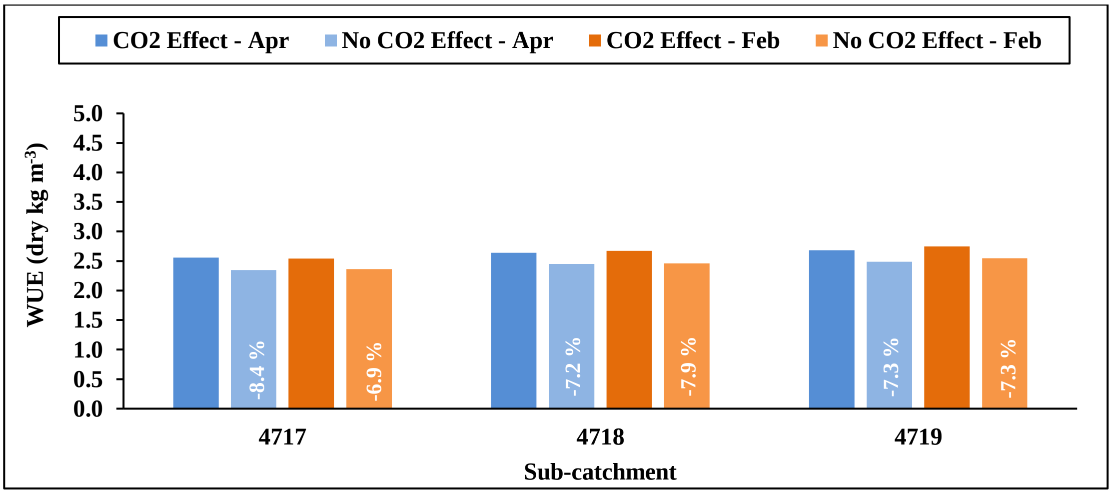

Figure 7-33 The effects of constant CO_2 on the WUE of sugarcane for April and February planting dates using the dynamically downscaled data for six GCMs

The results presented here indicate that the CO_2 fertilisation effect contributed to the increase in yields and WUE as presented in **subsections 7.4** and **7.5**. Singels *et al*. (2014) noted that the CO_2 fertilisation effect contributed to half of the projected increase in the sugarcane yields at La Mercy.

7.6.2 Sugarbeet

The results of the CO_2 impacts for sugarbeet are presented in **Figure 7-34** and **Figure 7-35**. Impacts vary across the different planting dates and quinary sub-catchments. The average reduction in yield is higher in the cooler planting season (i.e. May) compared to the warmer planting season (i.e. September), except in quinary 4696.

In general, there is a smaller reduction in WUE in the cooler season. This indicates that irrigation of the May planting had a greater influence in reducing the effects of constant CO_2 on the WUE and yield, particularly in the higher altitude (i.e. cooler) quinary (4696, 1024 m a.s.l). However, this is not the case in the mid (4697, 761 m a.s.l) and lower (4698, 566 m a.s.l) quinaries, which are affected by much lower rainfall and higher temperatures in the distant future (see **subsection 7.7.2.2**).

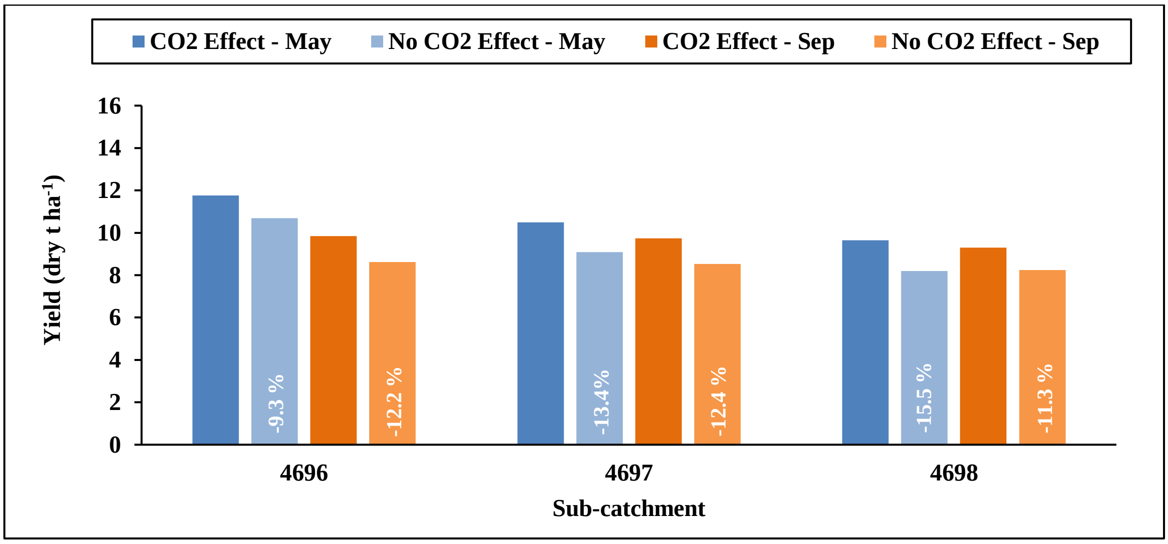

Figure 7-34 The effects of constant CO_2 on the yield of sugarbeet for May and September planting seasons using dynamically downscaled data for six GCMs

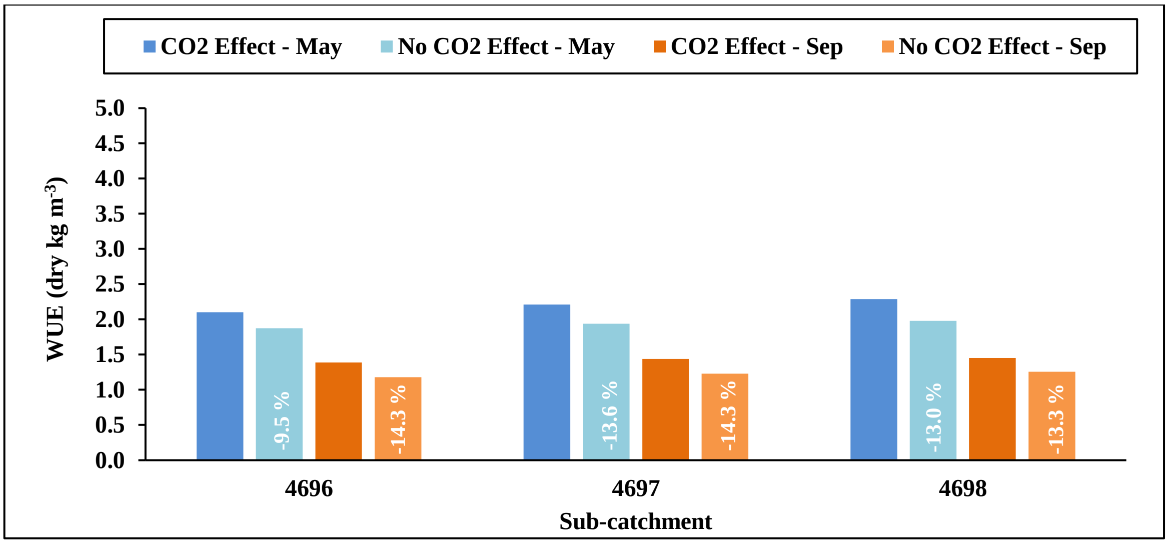

Figure 7-35 The effects of constant CO_2 on the WUE of sugarbeet for May and September planting seasons using dynamically downscaled for six GCMs

It is also worth noting that the average reductions in yield and WUE are higher for sugarbeet (C3 crop) than compared to sugarcane (C4 crop). The results show that sugarbeet is more sensitive to higher future temperatures than sugarcane. This is evident by the smallest reduction in yields experienced in the higher altitude (i.e. cooler) quinary.

7.6.3 Summary

To summarise, the year 2000 CO_2 value was held constant throughout the 139-year simulation for six dynamically downscaled climate scenarios. This nullified the CO_2 fertilisation effect in AquaCrop and thus, the yield reduction is purely the result of changes in climate as projected by the GCMs. Sugarcane (C4 crop) is less responsive to changes in CO_2 levels as it has lower average reductions in yield and WUE than compared to sugarbeet (C3 crop). C4 crops are "CO_2 saturated" and hence, are less affected by lower CO_2 levels (see **section 4.2**).

Therefore, higher temperatures may have resulted in photorespiration leading to lower photosynthetic activity, contributing to lower sugarbeet yields. The changes in rainfall and temperature projected by the downscaled GCMs are discussed in detail in the next section. The magnitude and direction of these changes in climate variables helps to explain the simulated changes in crop yield.

7.7 Future Changes in Climate

The quinary sub-catchment climate database was used to derive the baseline conditions. The MAP and MAT values were averaged for a 30-year period (1961-1990). The mean MAP and MAT from the four GCMs common to both downscaling techniques (i.e. statistical and dynamical) was calculated for the present climate and then compared to the baseline climate. This was undertaken to assess the GCMs' ability to predict the present-day climate.

7.7.1 Present climate

7.7.1.1 La Mercy - sugarcane

In quaternary catchment U30D representing the La Mercy area, the baseline MAP is highest in the middle quinary catchment (**Figure 7-36**). However, it was expected that the higher altitude quinary (4717, 206 m a.s.l) would receive more rainfall, with MAP decreasing towards the lower altitudes (i.e. quinary 4719, 50 m a.s.l). Lynch (2004) showed an increase in MAP from 1085 mm to 3199 mm over a distance of roughly 8.5 km in the Jonkershoek Mountains (Stellenbosch, Western Cape), as the altitude increased from 230 m to 1300 m.

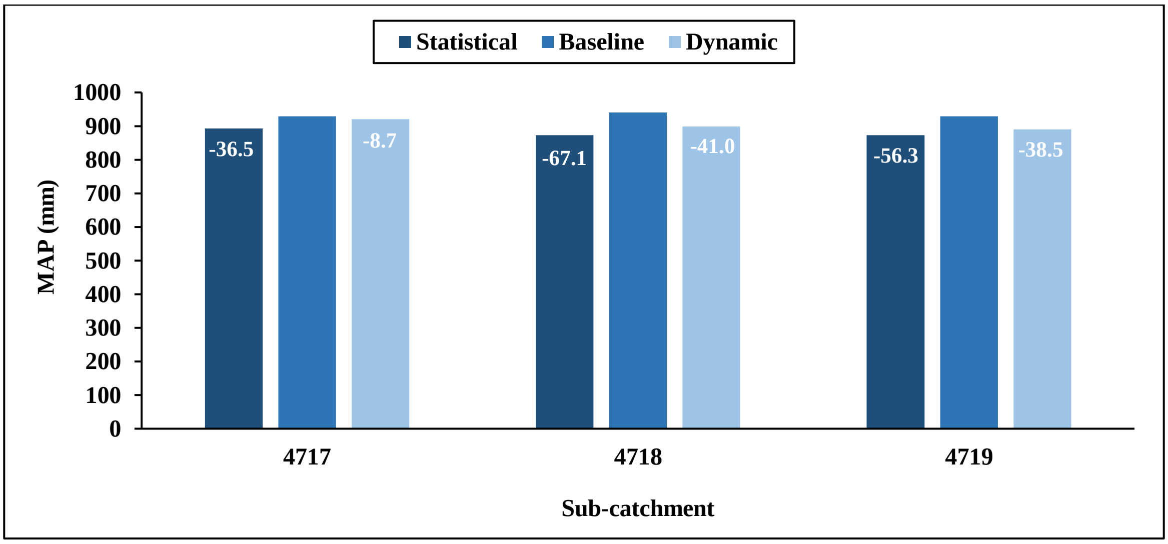

Figure 7-36 Comparison of the baseline MAP to the present MAP, derived from four statistical and dynamical downscaling climate scenarios for three quinary sub-catchments in quaternary catchment U30D

The MAPs simulated by both downscaling techniques under-estimate the baseline MAP in all quinaries, especially the statistically downscaled GCMs. Overall, there is no marked difference in MAP between the three quinary sub-catchments, which is expected since the same rainfall driver station is assigned to all three quinaries, with only slight adjustments made to the rainfall to make it more representative of each sub-catchment (see **subsection 6.7.2.1**).

The largest difference in MAP between the statistical GCMs and the baseline climate is 67 mm in the mid-altitude quinary (mean altitude of 100 m a.s.l). For the dynamically downscaled GCMs, the highest difference with reference to the baseline is 41 mm in the mid-altitude quinary. Therefore, when comparing both downscaling techniques, the dynamically downscaled MAP data are higher than the MAPs simulated by the statistically downscaled GCMs. Hence, this explains why the yields derived from the dynamically downscaled GCMs were in general, higher than those predicted using statistically downscaled data (see **subsection 7.3.1**). However, the comparison of annual rainfall magnitudes does not provide any information about the seasonal distribution of rainfall, nor the amount of small and large rainfall events.

The MAT is higher at the lower altitude (50 m a.s.l) quinaries and decreases towards the higher altitude (206 m a.s.l) quinaries as expected (**Figure 7-37**). This is due to lower air pressures at higher altitudes (i.e. lapse rate), which result in cooler temperatures. However, both downscaling techniques over-estimate the baseline temperature, especially the dynamically downscaled GCMs. At most, this difference is up to 1°C which is relatively high. In addition, the dynamically downscaled GCMs are both wetter and hotter than the statistically downscaled GCMs.

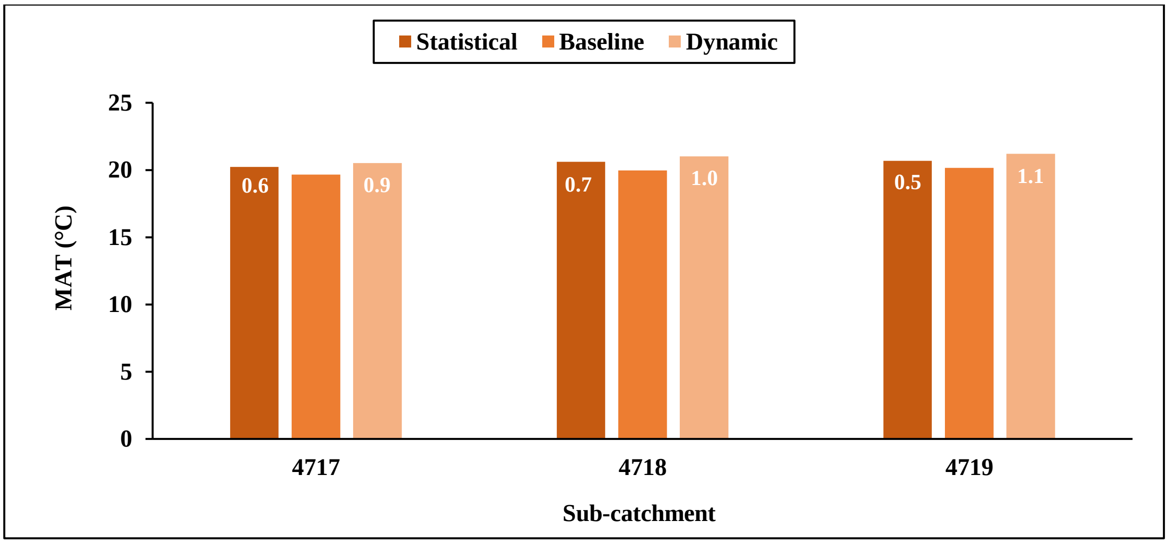

Figure 7-37 Comparison of the baseline MAT to the present MAT, derived from four statistical and dynamical downscaling climate scenarios for three quinary sub-catchments in quaternary catchment U30D

Overall, the ability of the downscaled GCMs to re-produce the baseline climate is considered adequate. It was expected that the statistically downscaled GCMs would better match the baseline climate considering the technique is calibrated using historically observed climate data.

7.7.1.2 Ukulinga - sugarbeet

The baseline MAP within quaternary catchment U20J (representing the Ukulinga area) follows the trend with altitude as expected (**Figure 7-38**). This was not the case in quaternary catchment U30D (see **subsection 7.7.1.1**). This could be due to the altitudinal effect being less prevalent in the coastal regions were the terrain is relatively flat. The altitude range across the quinaries in the coastal regions is 331 m, compared to the 1117 m range across the quinaries further inland. As expected, MAPs simulated by the two downscaling techniques show more rainfall at the higher altitude (1024 m a.s.l) quinary (4696). However, both downscaling techniques underestimate the baseline MAP, with the dynamically downscaled projections somewhat wetter than the statistical GCMs (as was the case in the La Mercy catchment). Because the altitudinal effect is evident in quaternary U20J, the MAPs in each sub-catchment are less similar, due to the different monthly adjustment factors that were applied (see **subsection 6.7.2.1**).

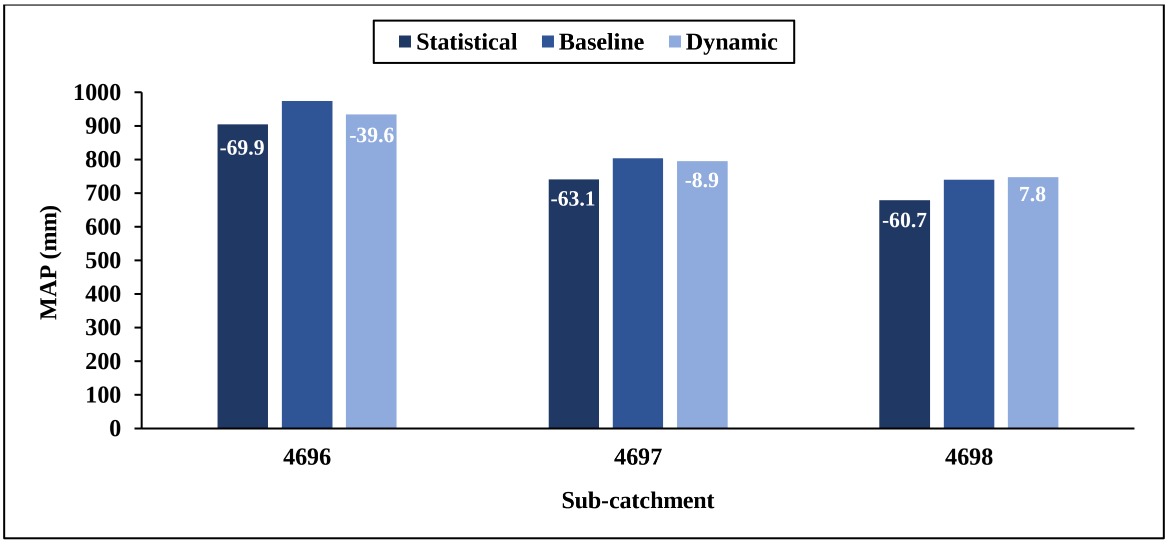

Figure 7-38 Comparison of the baseline MAP to the present MAP, derived from four statistical and dynamical downscaling climate scenarios for three quinary sub-catchments in quaternary catchment U20J

The trends in MAT for the Ukulinga catchment (**Figure 7-39**) are similar to those noted for the La Mercy catchment, where both downscaled techniques simulated warmer temperatures than the baseline. The largest difference in MAT between the baseline and the GCMs is 1.8°C projected in quinary 4698 by the dynamic downscaling technique. With the statistical approach, the biggest difference in MAT between the baseline and GCMs is 1.1°C in quinary 4697.

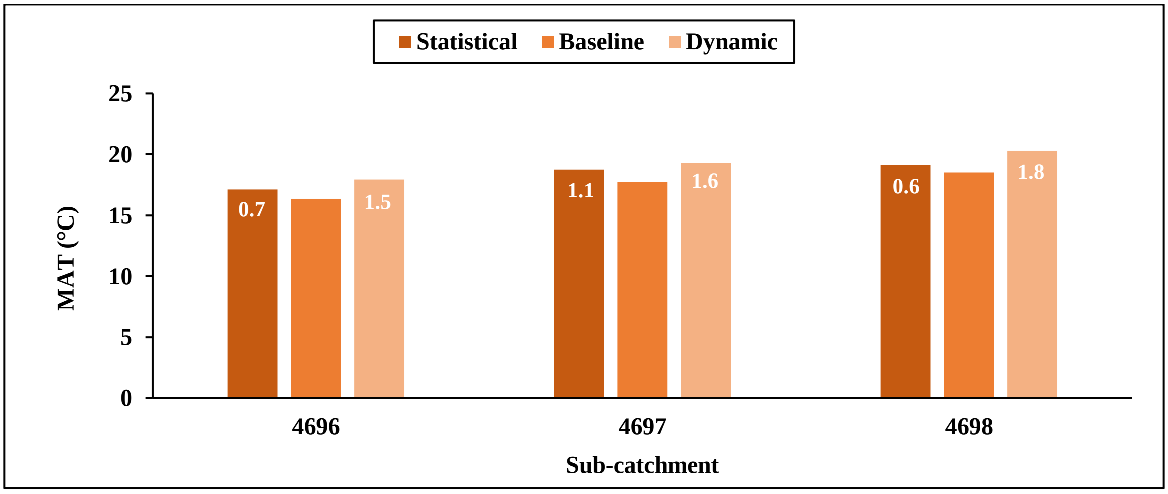

Figure 7-39 Comparison of the baseline MAT to the present MAT, derived from four statistical and dynamical downscaling climate scenarios for three quinary sub-catchments in quaternary catchment U20J

In general, the higher the rainfall, the higher the crop yield, assuming the crop is not temperature stressed (too cold or hot). The sugarbeet yields shown in **subsection 7.3.2** (**Figure 7-18**) are highest in the wetter quinary (4696), and decrease with altitude as expected. In general, the results indicate that the GCMs are biased towards higher MAT increases compared to MAP increases. It can be deduced that similar biases will be carried over in the future climate simulations (Zhang and Huang, 2013).

7.7.1.3 Summary

In summary, the MAP is underestimated, and the MAT is overestimated by both downscaling approaches when compared to the baseline. However, the difference in MAT estimates is considered more important than the difference in MAP. The biggest difference between the baseline and present MAT estimates is 1.8°C, which is larger than expected. It seems that the ensemble of GCM models are biased towards higher temperatures and lower rainfall. This bias is more evident in the quaternary catchment U20J for the sugarbeet simulations.

7.7.2 Future climate

This subsection presents and discusses the projected changes in MAP and MAT from the present to the future climate. The results help to better understand the response of sugarcane and sugarbeet to climate change. Changes in MAP and MAT were assessed as absolute differences between the present and projected future values. A 30-year present (1961-1990) and future (2071-2100) period was used for each dynamically downscaled GCM. Similarly, for the statistically downscaled GCMs, a 20-year period for the present (1971-1990) and future (2081-2100) periods was analysed.

7.7.2.1 La Mercy - sugarcane

<u>Dynamic downscaling</u>

The results in **Figure 7-40** and **Figure 7-41** shows both the projected MAP and MAT outputs of the six GCMs and the four GCMs that are common to both downscaling approaches. The MAP projected by the six GCMs will decrease in the future by an average of 30 mm. However, the four GCMs project a slight increase in rainfall of up to 12 mm. The graphs below highlight the importance of a GCM ensemble approach adopted in this study, as discussed in **Chapter 5.2.1**. This is evident from the different MAP projections, within the same quinary sub-catchments, between the six and four GCMs. Two of the six GCMs predict a much larger decrease in MAP in the future, which offsets the positive increase of the other four GCMs. However, analysing the results of each individual GCM is beyond the scope of this study.

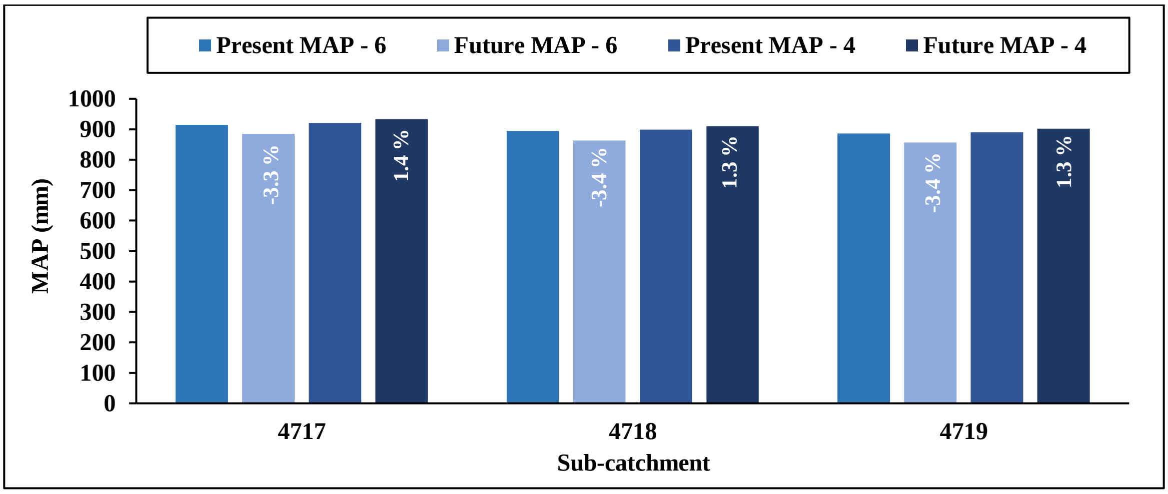

Figure 7-40 Absolute changes in MAP from present to future for three quinary sub-catchments in quaternary catchment U30D, derived using dynamically and statistically downscaled climate data available for six GCMs, four of which are common to both downscaling methods

The annual temperature in the future is similar to that projected by both ensembles (6 and 4 GCMs). The six GCMs project a 3.4°C temperature increase across all quinaries (**Figure 7-41)**. This MAT increase is within the range reported by the IPCC (2014b). Temperatures are expected to rise by 3°C to 6°C above the baseline period (1986 – 2005) by the end of the 21st century across the five African regions, i.e. east, north, west, central and southern Africa (IPCC, 2014b).

The results of both the MAP and MAT changes from the present to the future give a clearer understanding of the yield and WUE results discussed in **subsections 7.4.1** and **7.6.1**. The yield and WUE increases projected by AquaCrop are unlikely to be due to rainfall because the MAP is projected to be different in the future. Although the future MAP may be similar to the present MAP, the seasonal distribution or the frequency of wet and dry days may be significantly different.

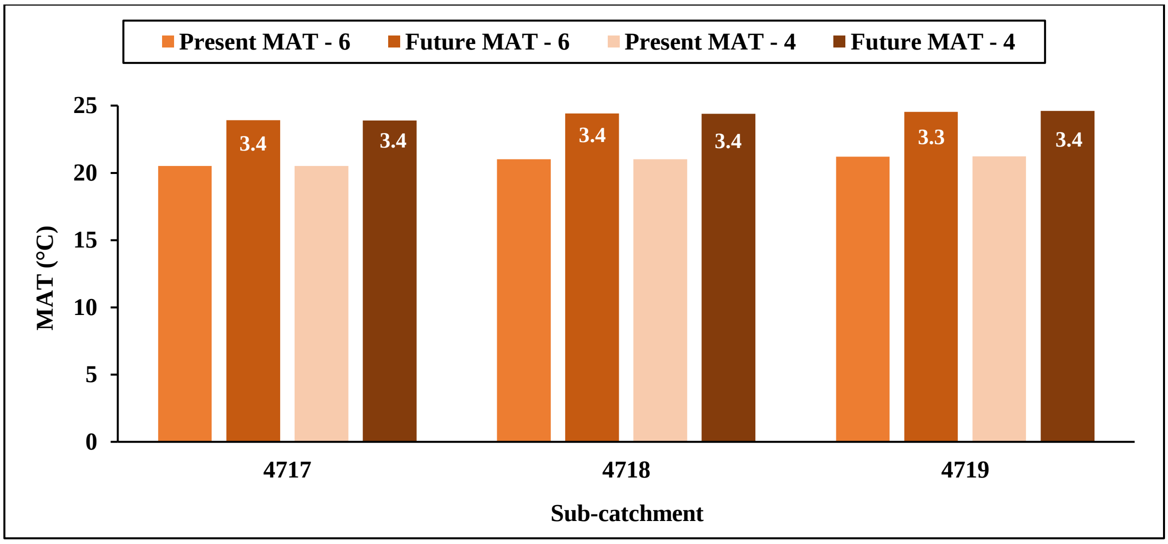

Figure 7-41 Absolute differences in MAT from present to future for three quinary sub-catchments in quaternary catchment U30D, derived using dynamically and statistically downscaled climate data available for six GCMs, four of which are common to both downscaling methods

GCMs also have a tendency to produce more events of low rainfall (i.e. drizzle) as opposed to fewer, larger events (i.e. thunderstorms), which may affect the growth of plants. Therefore, in order to assess the impacts of changes in rainfall only on crop yield and WUE, simulations using future rainfall would need be undertaken while keeping the future temperature the same as for the present period.

The yield increase is therefore mainly in response to the combined effect of higher temperatures and increased [CO_2] in the future. Higher temperatures improve canopy development which results in higher radiation interception and increased ET. The greater evaporative demand and a higher CC also increases ET (Singels *et al*., 2014). In **subsection 7.6.1**, where CO_2 was kept constant to nullify the CO_2 fertilisation effect, sugarcane yields and WUE decreased. This was probably due to the warmer temperatures resulting in increased temperature and water stress (due to greater evaporation loss). Singels *et al*. (2014) also noted that in a warmer climate, the canopy develops at a faster rate due to more growing degree days. This results in a shorter crop cycle or season length, which is likely to result in yield loss. Overall, the CO_2 fertilisation effect offsets the negative effects of the warmer climate which can potentially lead to water stress under low rainfall conditions.

<u>Statistical downscaling</u>

The statistically downscaled GCMs project a larger increase in MAP (**Figure 7-42**) relative to the dynamically downscaled GCMs. The MAP results highlight an average increase of 57 mm (i.e. 6.5%) across all sub-catchments. As noted previously, the projected decreases in yields are likely due to the impacts of a much warmer climate. The differences in MAT projections between the statistically and dynamically downscaled GCMs are relatively small (i.e. 0.2°C). Annual temperatures are predicted to be up to 3.6°C higher than the present (**Figure 7-43**). Similarly, this is within the predictions reported by the IPCC (2014b). As noted in **subsection 5.2.2**, the "business-as-usual" scenario to climate change will result in MAT rising above the 2°C target.

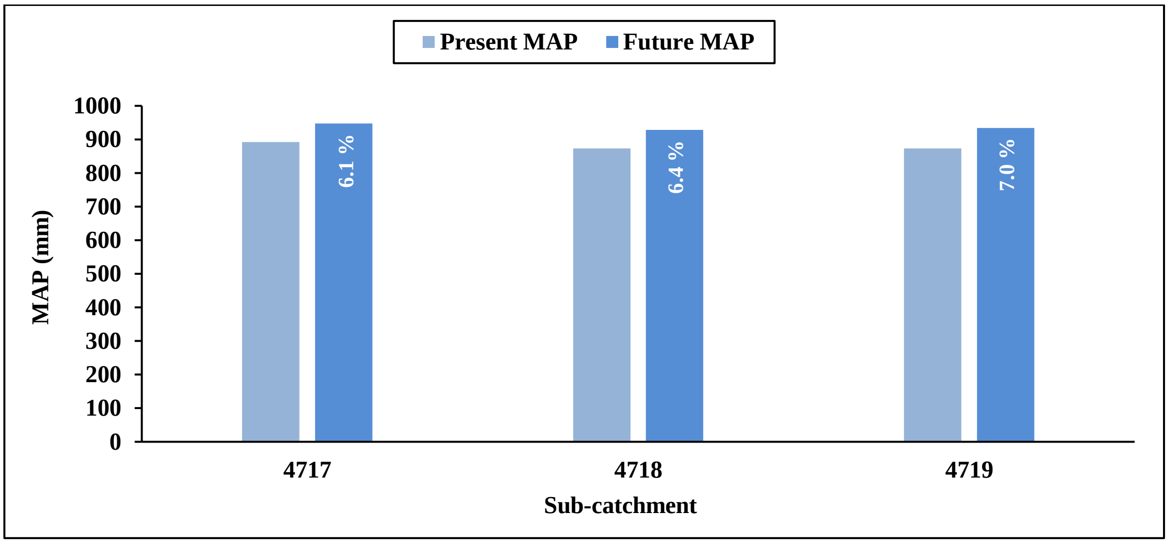

Figure 7-42 Absolute changes in MAP from present to future for three quinary sub-catchments in quaternary catchment U30D, derived using statistically downscaled climate data available for four GCMs

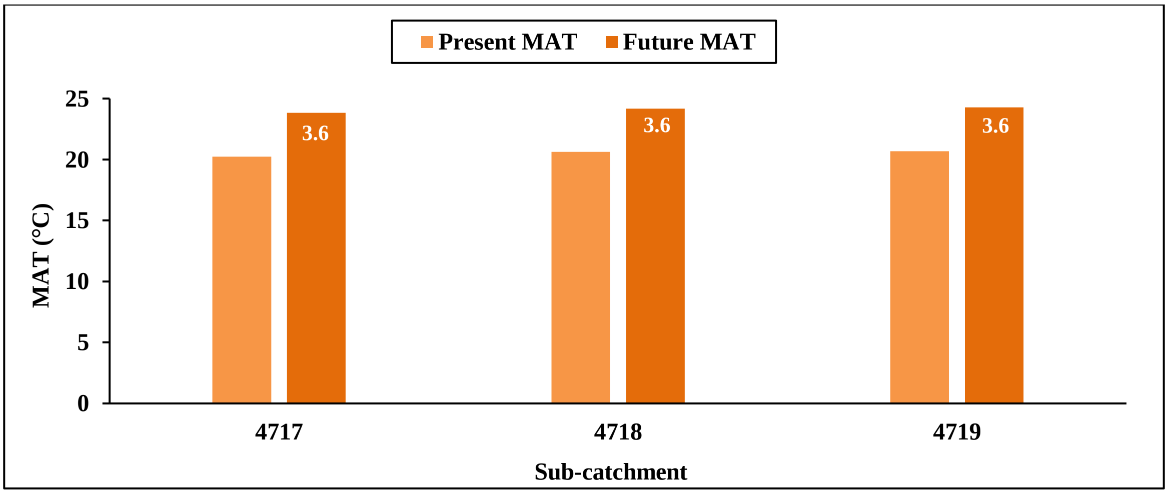

Figure 7-43 Absolute differences in MAT from present to future for three quinary sub-catchments in quaternary catchment U30D, derived using statistically downscaled climate data available for four GCMs

7.7.2.2 Ukulinga - sugarbeet

Dynamic downscaling

Similar to the results for sugarcane, the six GCMs predict a larger decrease of 33 mm (-4.0%) compared to the four GCMs (5.2 mm; ~0.5%) as shown in **Figure 7-44**. In addition, there are no marked differences in the percentages changes in MAP between the three quinaries. However, there is an altitudinal effect in that the upper quinary has higher rainfall than the lower quinary.

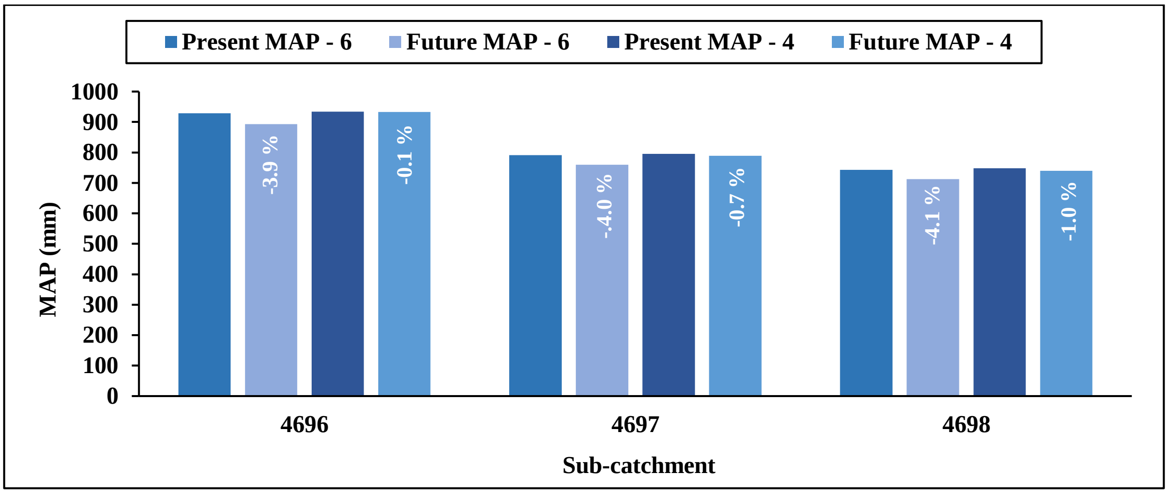

Figure 7-44 Absolute changes in MAP from present to future for three quinary sub-catchments in quaternary catchment U20J, derived using dynamically and statistically downscaled climate data available for six GCMs, four of which are common to both downscaling methods

Temperature increases incrementally more in the distant future as indicated in **Figure 7-45**. The six and four GCMs project similar increases in MAT in the distant future, i.e. annual temperatures are forecast to be 3.5°C higher than the present. In addition, the altitudinal effect is evident in that the upper quinary is cooler than the lower quinary.

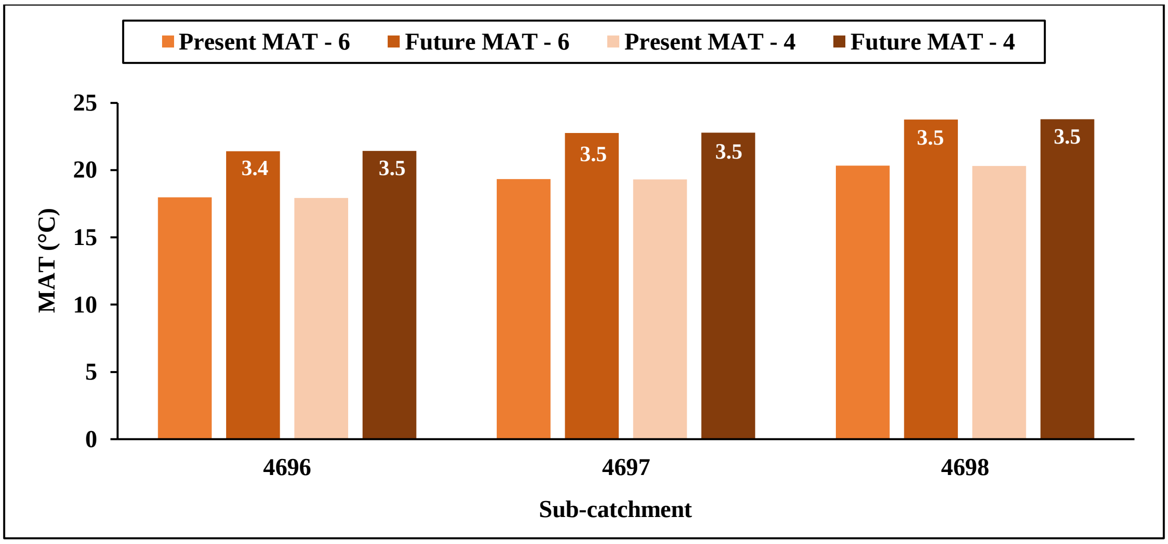

Figure 7-45 Absolute differences in MAT from present to future for three quinary sub-catchments in quaternary catchment U20J, derived using dynamically and statistically downscaled climate data available for six GCMs, four of which are common to both downscaling methods

As for sugarcane, the effects of the larger temperature increase "outweighs" the slight decrease in rainfall with regard to crop production. This helps to explain the projected decreases in sugarbeet yield and WUE when the CO_2 fertilisation effect was nullified. In the future, quinary 4698 (lower altitude, 566 m a.s.l) is hotter and drier than the other two quinaries and thus, experiences the largest yield and WUE decrease (see **subsection 7.6.2**). This further indicates that sugarbeet is sensitive to higher temperatures, which is exacerbated by lower rainfall conditions.

Statistical downscaling

Compared to the four dynamically downscaled GCMs, the statistical GCMs forecast a positive outlook for MAP, with an increase of approximately 11% (**Figure 7-46**). Overall, the MAT is projected to increase on average by 3.8°C in quaternary catchment U20J, which is 0.3°C higher than the dynamically downscaled simulations (**Figure 7-47**). The largest projected increase in MAP occurs in the higher altitude quinary (4696, 1024 m a.s.l). However, the annual temperature in quinary 4696 is lower when compared to the other two quinaries due to the altitudinal effect. The combination of wetter conditions in the future at the higher altitude (lower evaporative demand) may result in a significantly higher yield (+50.3%) as simulated by the statistical GCMs in quinary 4696 (see **Figure 7-26**). Hence, sugarbeet productivity appears to thrive when lower temperatures and sufficient rainfall exist throughout its growing season.

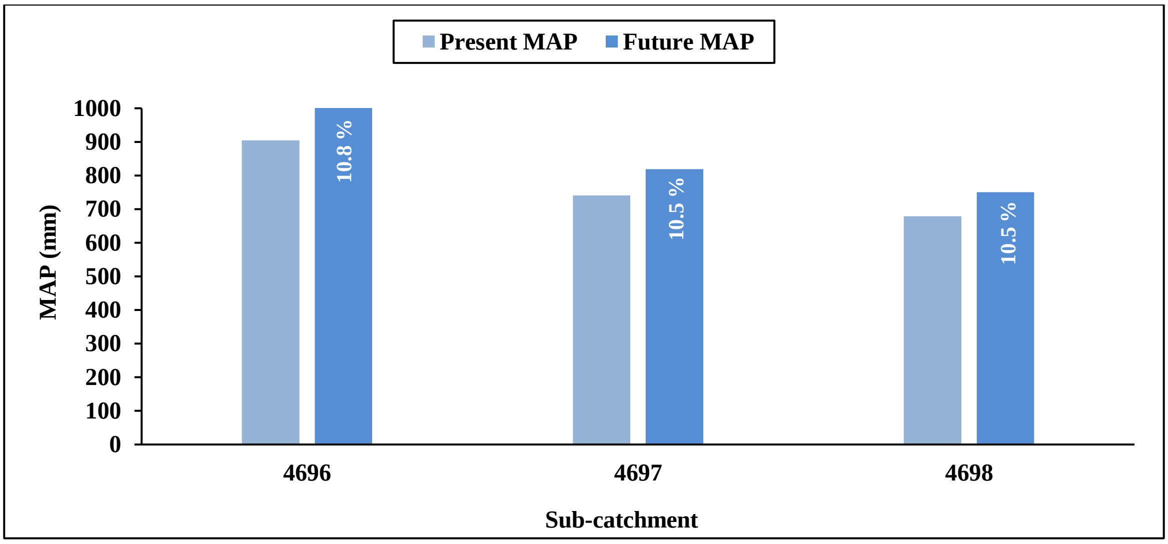

Figure 7-46 Absolute changes in MAP from present to future for three quinary sub-catchments in quaternary catchment U20J, derived using statistically downscaled climate data available for four GCMs

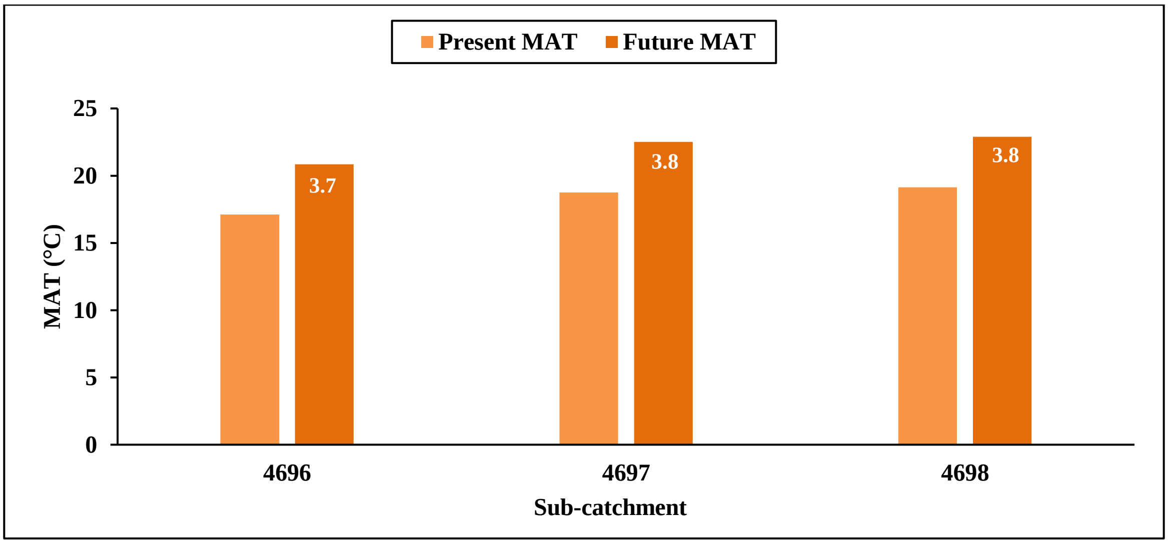

Figure 7-47 Absolute differences in MAT from present to future for three quinary sub-catchments in quaternary catchment U20J, derived using statistically downscaled climate data available for four GCMs

7.7.2.3 Summary

The results presented in this section help to explain the effects of climate change on yield and WUE of sugarcane and sugarbeet as discussed in previous chapters. The yield and WUE increases are more likely attributed to higher temperatures and the CO_2 fertilisation effect, as opposed to slight changes in future rainfall. When the CO_2 fertilisation effect is nullified, yields and WUE decreased (more so for sugarbeet than sugarcane). This was probably due to higher temperatures, increased water stress (due to greater evaporation loss) and the shortened growing season (due to increased growing degree days). Hence, the CO_2 fertilisation effect offsets the negative effects of the future warmer climate.

To conclude, the increase in annual temperature projected for the distant future ranges between 3.4°C to 3.8°C, with the statistically downscaled GCMs showing higher increases. This is evident in both quaternary catchments and the MAT increases are similar to those reported by the IPCC (2014a; 2014b). Of more importance is the slight decrease in rainfall projected by the dynamically downscaled GCMs, compared to the statistically downscaled scenarios which suggest a more significant increase in rainfall. As noted in **subsection 7.3.3**, studies have recommended that both statistically and dynamically downscaled climate scenarios should be used in climate change studies.

7.8 Final Thoughts

In this study, calibrated crop parameters for both sugarcane and sugarbeet were developed. The adjusted parameters were then validated using independent datasets and thus, are deemed more representative of South Africa’s growing conditions. In order to demonstrate a useful application of the calibrated crop parameter files, they were used to assess the impacts of climate change on crop response.

This study produced a wide range of results that emanated from the different climate change simulations. The results visually illustrate how the number of GCMs, downscaling techniques, planting dates, altitudinal effect s and consideration of the CO_2 fertilisation effect can influence the outcome of climate change impact assessments on agricultural response. The purpose of this study was not to show if one GCM is “better” than another, or one downscaling technique is “better” than another, nor to provide climate change mitigation or adaptation strategies to climate change. The following subsections provide final thoughts on five issues that can influence climate change studies.

7.8.1 Number of GCMs

The different ensemble sizes (i.e. 4 vs. 6 GCMs) produced relatively similar percentage changes in yield and WUE. This may indicate that increasing the number of GCMs in the ensemble may not always add more value or significance to the predictions. However, increasing the number of ensemble size has a direct impact on the computational expense.

In terms of relevance, more emphasis should be placed on which GCMs are selected for the ensemble, than on the number of GCMs to be included. Although this study did not consider the influence of GCM selection, **APPENDIX F** illustrates the wide range in yield and WUE increases that were simulated by the six dynamically downscaled GCMs. For sugarcane planted in April, MIR and GF1 produced the smallest and largest percentage changes in yield and WUE, respectively. Hence, the exclusion of these two GCMs would produce a smaller (i.e. more conservative) range in projected impacts.

7.8.2 Downscaling techniques

In this study, the statistically downscaled simulations matched the baseline simulations fairly well than compared to the dynamically downscaled simulations, which generally overestimated crop productivity. It is important to note that no bias correction was applied to the dynamically downscaled scenarios. However, it is recommended that using both downscaling techniques is a better approach in climate change studies.

7.8.3 Planting date

Based on the results for sugarcane, the February planting date produced the best yield and WUE projections than compared to the April planting date. However, the difference in projected yields for the two planting dates, as simulated by the dynamically and statistically downscaled GCMs are marginal. For sugarbeet, the best possible yields would be achieved when planted in May. However, the results showed that supplemental irrigation s required to improve crop establishment and growth. In addition, there are larger improvements in WUE for sugarbeet planted in May than compared to September.

However, the planting dates that produced the highest yield and WUE for the baseline climate also exhibit greater inter-seasonal variability (**APPENDIX E**). For sugarcane, the February planting has a greater coefficient of variation (CV) compared to April. Similarly, the May planting of sugarbeet (for dryland conditions) has a higher CV compared to September. When the May planting of sugarbeet is irrigated, there is less variability in both yield and WUE. These results show that changing the crop's planting date may be a possible climate change mitigation strategy. Furthermore, irrigation is beneficial for autumn plantings of sugarbeet.

7.8.4 Altitudinal effects

The difference in altitude across the six quinaries (4717-4718 and 4696-4698) in the two quaternary catchments largely account for the variation in temperature and rainfall. Overall, the altitudinal effect was more visible in the statistically downscaled projections, than compared to the dynamically downscaled scenarios. In addition, the inland catchment (Ukulinga) was more affected by altitudinal differences than the coastal catchment (La Mercy). This is due to the altitudinal range being less in the flatter, coastal region. Hence, the altitudinal effect influenced the yield and WUE results of sugarbeet more so than compared sugarcane.

However, performing the analysis at quinary level increased computational complexity by increasing the number of model runs by three. The variable that was most affected by the altitudinal effect was yield. Overall, the results given for three sub-catchments, as opposed to a single catchment, provided a wider range of possible impacts.

7.8.5 CO_2 fertilisation effect

Sugarbeet (C3 crop) benefitted more from elevated [CO_2] in the distant future, compared to sugarcane (C4 crop). This finding has been reflected in several studies. For example, Vanuytrecht *et al*. (2012) showed that the yield of C3 crops increased by 18%, whereas C4 crops did not benefit as much (+7% on average) from CO_2 fertilisation. Regarding biomass production, Vanuytrecht *et al*. (2012) also noted that rainfed crops responded equally well to elevated [CO_2] and that stomatal closure diminished the adverse effect of limited water resources. However, the way in which crops respond to elevated [CO_2] is dependent on water availability (Vanuytrecht *et al*., 2012). When there is no water stress, photosynthesis is the main driver for crop production. During conditions of water stress, crops decrease evapotranspiration and increase water productivity to drive production.

In this study, it evident that the above mechanisms contributed to the differences in yields for rainfed sugarcane and sugarbeet and as well as for irrigated sugarbeet. Irrigation of the May planting alleviated water stress and hence, the increase in photosynthesis (in response to higher [CO_2] and temperature) resulted in higher projected yields. Conversely, during periods of water stress experienced by the rainfed crops, an increase in WUE was simulated. This is evident since sugarcane (C4) showed a higher WUE compared to sugarbeet (C3).

Although the f_{sink} values (which determines how crops respond to [CO_2] increases) have been previously determined for sugarbeet (Vanuytrecht *et al*., 2011), they were not adjusted and hence, left as default in this study. No FACE experiments have been undertaken for sugarcane to determine its f_{sink} range. Therefore, it is unknown how the results would differ if the f_{sink} parameters for sugarbeet (or sugarcane) were adjusted. However, Vanuytrecht *et al*. (2014) indicated that such adjustments may not be necessary. Owing to the uncertainty around crop response to elevated [CO_2], future climate change studies should perform simulations both with and without the CO_2 effect. This approach will allow the full range of climate change impacts on crop response to be determined.

8 CONCLUSION

This chapter is separated into three sections, *viz*. 1) the approach taken in the study to answer the research questions and achieve the objectives, 2) a synthesis of important findings, and 3) recommendations for future research. For more detail on a particular topic, the reader is referred to the summaries given at the end of each subsection (i.e. labelled "Summary") in the previous chapter.

8.1 Summary of Approach

One of the main aims of the study was to calibrate the AquaCrop model for two biofuel feedstocks, *viz*. sugarcane and sugarbeet. These two crops were the preferred feedstocks for bioethanol production in South Africa as stated by the NBIS (DME, 2007a). However, previous studies (i.e. Jewitt *et al*., 2009) have noted that a better understanding regarding the potential yields, water use efficiencies and potential impacts of climate change on these crops is required. With reference to the above, the following research questions were addressed:

- What are the attainable yield and WUE of sugarbeet and sugarcane?
- What are the potential impacts of climate change on yield and WUE of these biofuel feedstocks?

In order to address the above research questions, the following objectives were met:

- Calibrate and validate AquaCrop for sugarcane and sugarbeet.
- Undertake a comparison between using 30 years and 50 years of data for long-term assessments of yield and WUE.
- Assess the influence of using two downscaling techniques on the yield and WUE of both crops.
- Assess the impacts of changes in CO_2, temperature and rainfall on feedstock yield and WUE.

Various methodologies were adopted to meet these objectives, which included collecting primary data from field and laboratory experiments involving sugarbeet for the calibration of AquaCrop. In addition, secondary (AgMIP) datasets were obtained from SASRI and used for the calibration and validation of AquaCrop for both feedstocks. Thereafter, the crop parameters files were used to simulate mean dry yield and mean WUE of sugarcane and sugarbeet. This was done using 30 and 50 years of historical climate data, as well as present and future climate projections derived from multiple GCMs and downscaled using two well-known techniques. Institutions such as the CSIR and CSAG provided the data for the present and future climate scenarios.

The utilisation of a mechanistic crop model (AquaCrop) to estimate the attainable yield and WUE of two bioethanol feedstocks has proven useful. Preliminary versions of the calibrated parameter files for sugarcane and sugarbeet were used by Kunz *et al*. (2015c) to develop maps of crop yield and WUE at a national scale. In addition, the majority of previous climate change studies used empirical models that only consider climate (rainfall and temperature) effects on crop productivity and not the effects of rising [CO_2].

The graphs produced in this study depict the simulated dry yield and WUE under the present climate and future climate. Values were derived for multiple GCMs, then averaged and presented at a quinary sub-catchment level. At a smaller (i.e. more local) scale within each quinary, there may be no potential for crop production due to other factors (e.g. micro climate or soils related).

The study did not consider the impact of climate change on biomass production. Although above-ground plant biomass is important for bioenergy production, the utilisable portion of the crop (containing sugar, starch or vegetable oil) is important for biofuel production. This study focussed on the impacts of climate change on biofuel feedstock production (not bioenergy production).

8.2 Summary of Findings

The AquaCrop model was calibrated for two feedstocks, *viz*. sugarcane and sugarbeet. An AgMIP dataset for La Mercy, which contained LAI measurements for different planting dates, was used to calibrate the model for sugarcane. Even though a limited number of LAI measurements were available, the model performed better using the calibrated parameter file than compared to the default crop parameter file. With respect to sugarbeet, a much more detailed calibration dataset was used to calibrate the model. The dataset contained weekly and bi-weekly measurements of LAI undertaken in a field trial conducted at Ukulinga during 2013. AquaCrop closely simulated the canopy cover, yields and WUE of sugarbeet, although there were slight over-estimations. AquaCrop was then validated for both feedstocks using AgMIP datasets for two different regions (Pongola and Komatipoort). The model's ability to simulate soil water content at Ukulinga was less satisfactory, with little variability simulated over the growing season at the lower soil depths.

The calibrated model was then used for long-term assessments of yield and WUE. The baseline simulations were performed using the 50-year quinary sub-catchment climate database. When compared to the 50-year model runs, results showed that 30 years of climate data adequately estimated the long-term attainable productivity of sugarcane and sugarbeet. Thus, running the model with 30 years of data (as opposed to 50 years) provides considerable saving in computational expense, with little impact on the accuracy of the long-term attainable yield. This confirmed similar findings reported in the available literature.

In order to establish confidence in projections of future climate, the baseline mean yields and WUE results were compared to those simulated for the present climate. Two downscaling techniques, which had four GCMs in common, were used to obtain climate scenarios representing the present period (1961-1990). For the present climate, the GCMs displayed a bias towards a lower MAP and a higher MAT when compared to baseline (i.e. observed) conditions. Consequently, this was also noticed in the future climate simulations (i.e. high MAT increases). It is therefore acknowledged that bias correction of GCM output is important in climate change studies, although it was not done in this study.

Future MAT is projected to be between 3.4°C to 3.8°C higher than the present climate. A smaller temperature increase may only be realised when moving away from the "business-as-usual" (i.e. A2 CO_2 emission) scenario. The dynamically downscaled GCMs projected a decrease in MAP in both quaternary catchments, whereas the statistically downscaled GCMs indicate a higher increase in annual rainfall. This highlights the need to consider both downscaling techniques to be considered in climate change studies.

A comparison of both downscaling techniques showed that statistically downscaled scenarios for the present climate better match the baseline climate. This implies that the statistical downscaling technique is better suited at replicating historical (i.e. observed) conditions. This may imply greater confidence in future projections derived using statistically downscaled techniques.

The climate change simulations projected increases in mean yield and WUE for both sugarcane and sugarbeet in the distant future (up to 2100). The statistically downscaled GCMs projected higher increases in mean yield and WUE when compared to the dynamically downscaled GCMs. In addition, the percentage increases in WUE were up to three times higher than those for yield increases. Hence, the response of WUE to climate change is amplified, not only by the yield increase, but also by the reduced transpiration caused by the CO_2 fertilisation effect. It is evident that the CO_2 fertilisation effect benefits sugarbeet (C3 crop) more so than sugarcane (C4 crop), which concurs with findings from the literature. Hence, climate change is expected to have a more positive impact on sugarbeet productivity than for sugarcane. A relatively wide range in crop response to climate change was noted due to the two different planting dates considered for both crops as well as the altitudinal effects introduced by using the three quinary sub-catchments. The results showed that sugarcane and sugarbeet would benefit favourably from climate change when planted in February and May, respectively. This infers that altering the planting date may ameliorate some of the negative impacts of climate change on crop response.

As noted previously, climate change may lead to higher feedstock productivity compared to present day simulations. However, the magnitude of crop response is strongly influenced by the CO_2 fertilisation effect. Projected changes in future MAP and MAT (with no CO_2 fertilisation effect) resulted in a reduction in yield and WUE, particularly for sugarbeet. Higher temperatures result in a faster accumulation of GDDs and therefore, the crop matures quicker that results in a shorter crop cycle and lower yields. Warmer temperatures further contribute to the reduction of yields due to increased soil water stress, particularly if there is not enough rainfall in the future to compensate for increases in crop water demands. Therefore, the CO_2 fertilisation effect offsets the negative impacts of higher temperatures and greater evaporation demands, particularly under water stressed conditions. When there is sufficient rainfall to meet the crop’s water demand, the higher evaporative demands can increase yields.

When undertaking climate change studies, it is important to consider impacts of future climate scenarios, both with and without the CO_2 fertilisation effect. The results of CO_2

effects highlighted the sensitivity of sugarbeet to higher temperatures in the future. However, this sensitivity may not be present at other sites which have much higher rainfall than the Ukulinga quinaries.

The GCM ensemble approach proved useful in this study because the comparison between using four and six GCMs produced different results. This highlights the importance of carefully selecting ensemble members from the available GCMs. The ensemble of four GCMs (which were common to both downscaling techniques) projected higher future yield and WUE for both feedstocks. This occurred because one of the two remaining GCMs projected smaller crop responses (due to lower future rainfall), thus reducing the mean yield calculation.

The water use efficiency of biofuel feedstocks is an important consideration in a water stressed country such as South Africa. With this in mind, sugarcane (C4 crop) has an advantage over sugarbeet (C3 crop) because of higher WUE. C4 crops can survive in hotter climates and lose less water than compared to C3 crops. Nevertheless, sugarbeet showed large improvements in WUE in the future, especially when planted in May (irrigated conditions) compared to September. The autumn planting is preferable since it avoids the higher temperatures starting in September, which the crop appears to be sensitive to. However, it worth noting that the May simulations were also undertaken with supplemental irrigation, and irrigation of biofuel feedstocks is not supported by the Department of Water and Sanitation.

In conclusion, numerous findings emanated from this research, but it is important to note that AquaCrop was run at one site for each feedstock. Therefore, it is not recommended that results from this study are extrapolated and deemed applicable to other sites. The most beneficial outcome of this study was it showed how the outcome of any assessment of climate change on crop response can be strongly influenced by the approach taken. The study considered two crops (C3 vs C4), each with two planting dates, two GCM downscaling techniques and simulations both with and without the CO_2 effect as well as an altitudinal effect (i.e. at each site respectively). For example, the "with and without CO_2 effect" simulations cannot be considered when an empirical crop model is used in climate change studies, since such models do not account for the effects of [CO_2] on plant response. Hence, an empirical crop model may likely simulate a yield reduction, compared to a mechanistic model which may simulate a yield increase.

8.3 Recommendations for Future Research

From this study, the following recommendations are made regarding future research:

- The calibration process for sugarcane lacked sufficient experimental data. Additional field work would need to be carried out to fine-tune AquaCrop for local growing conditions for sugarcane. Additionally, it is recommended that initiatives such as AgMIP should aim to improve the quality of data collected, especially when the datasets are used for model calibration.

- Only one simulation model was used in this study. Hence, a different crop model should be calibrated and validated using the same procedures outlined in this study. An analysis could then be undertaken to compare the output from both models in order to determine if the additional results improve the confidence of projections in crop response to climate change.

- Canopy cover (CC) values can be calculated using a simpler equation which only requires the diffuse non-interceptance (DIFN) value, which is an output of the LAI-2200 plant canopy analyser used in this study. DIFN may be more indicative of CC than LAI. In the future, this method of determining CC would need to be compared against the two other methods used in this study.

- Given that the majority of sugarbeet may be grown near or around Cradock in the Eastern Cape, it would be beneficial to test or validate AquaCrop using suitable growth and yield information obtained from that region.

- Future work on climate change studies using AquaCrop should include adjusting the f_{sink} parameters for sugarcane and sugarbeet in order to better understand the influence on this parameter on crop response under a changing climate (i.e. a sensitivity study).

- Future studies should consider using the CO_2 values from Cape Point for southern African climate change studies instead of the Hawaii (i.e. Mauna Loa) values.

- Sugarcane simulations were undertaken for two transplanting months, *viz*. February and April. These dates were chosen as they produced the highest observed yields at La Mercy. However, the milling season in South Africa is from April to December. Therefore, a February transplanting is not representative of the sugarcane industry and thus, future research should consider other transplanting dates such as October.

- The soil water content simulations of AquaCrop were not satisfactory, whilst other studies have shown the opposite. Hence, it would be useful to undertake a study that compares soil water content simulations using a single (i.e. one) soil profile and comparing it to a two- or three-layered soil. As noted, either the PWP values were incorrectly determined using the pressure outflow method or the TDR probes at the lower soil depths were faulty.

- AquaCrop does not consider canopy interception and consequently, it will under-estimate ET when compared to measurements which include the evaporation of intercepted water (eddy covariance or surface renewal techniques). Therefore, future updates to the model should include interception loss, which should improve ET simulations when compared to observations.

- As noted, the GCMs were biased towards a lower MAP and higher MAT. Therefore, bias correction should be considered in future studies in order to improve confidence in the ability of climate models to predict the future climate.

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10 APPENDIX A

Figure 10-1 Pit dug to insert TDR probes and the transparent access tubes for the rhizotron camera

Figure 10-2 A view of where the pit was dug showing the transparent access tubes and the Campbell Scientific instrumentation for measurements of soil water content

Figure 10-3 A spade was used to carefully dig up several sugarbeet plants to measure the maximum root lengths

11 APPENDIX B

Table 11-1 Irrigation schedule for the 2013 sugarbeet trial

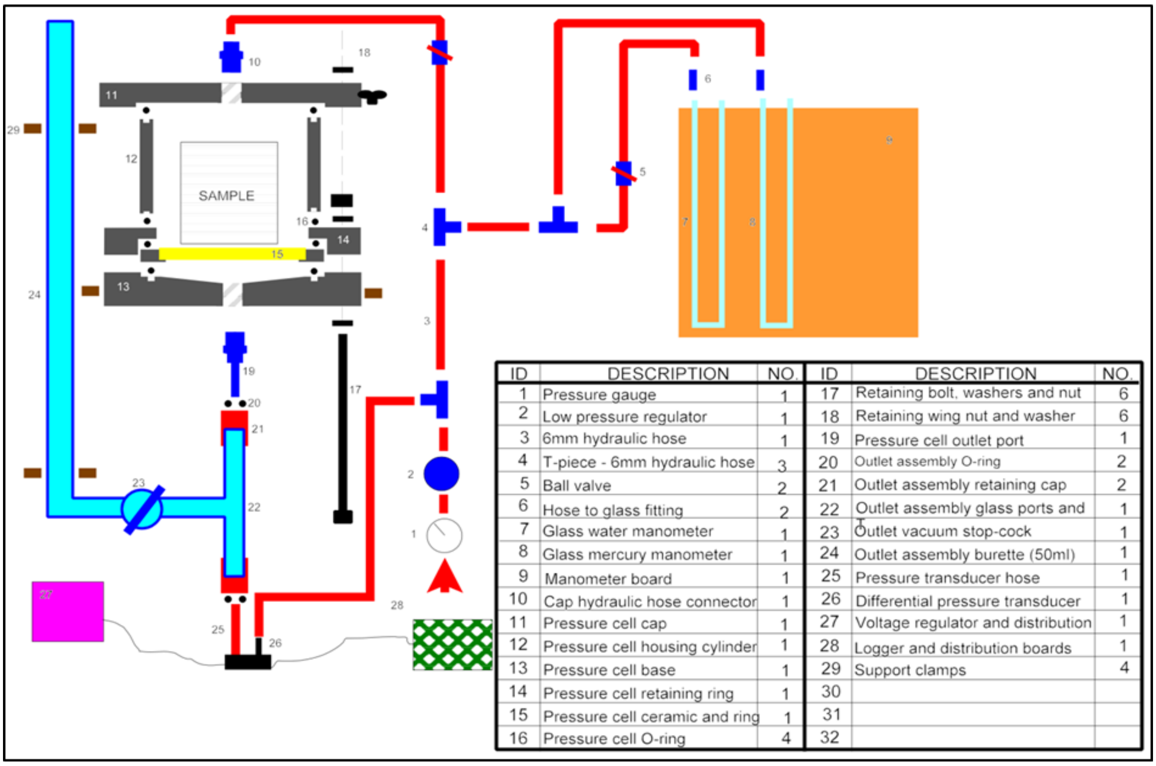
Date	Depth (mm)	Field notes
2013/05/22	0	Transplanting of 2013 sugarbeet
2013/05/24	8.3	Transplanting continued
2013/05/25	6.6	Saturday
2013/05/31	12.7	End of transplanting
2013/06/01	3.3	Before hot day
2013/06/07	3.0	Repaired leaking connectors
2013/06/10	2.8	Approximately 1 hour of irrigation
2013/06/12	6.9	Over 2 hours of irrigation
2013/06/14	5.3	Before long weekend
2013/06/27	19.5	14-27 June
2013/07/15	15.8	8-15 July
2013/07/20	2.0	Saturday
2013/07/22	2.2	Monday
2013/07/24	3.9	Wednesday
2013/07/26	4.1	Friday
2013/07/29	1.9	Monday
2013/07/31	5.8	Wednesday
2013/08/02	3.8	Friday
2013/08/05	2.2	Monday
2013/08/07	4.7	Wednesday after fertilisation
2013/08/08	1.1	Thursday before rain (12 mm)
2013/08/14	3.0	Wednesday
2013/08/19	9.4	Watered twice
2013/08/23	7.0	Friday
2013/08/26	7.2	Monday
2013/08/28	6.6	Wed
2013/08/30	8.3	Friday
2013/09/02	6.1	Monday
2013/09/04	10.2	Wednesday after fertiliser spray
2013/09/13	0.0	Off for the week
2013/09/18	8.9	Wednesday after fertiliser spray
2013/09/20	7.7	Friday
2013/09/25	7.7	Wednesday
2013/09/27	7.7	Friday
2013/10/03	8.9	Thursday after fertiliser spray - Hot day
2013/10/04	7.3	Friday - Hot day
2013/10/11	9.7	Friday - Hot day
*2013/10/14	8.4	Monday
2013/10/17	0	Sufficient rainfall, no irrigation
2013/10/20	0	Sufficient rainfall, no irrigation
2013/10/25	0	Sufficient rainfall, no irrigation

*The crop was not irrigated after the 2013/10/14 until harvest to decrease chances of root diseases, considering the rainy season had begun.

12 APPENDIX C

Conventional methods for determining soil water retention parameters are dependent on monitoring the equilibration of the volumetric water content. However, in this method, they are determined by monitoring the time to equilibration of the matric potential (Lorentz *et al.*, 2001). The advantage of this is it allows for the water outflow to be controlled rather than just letting it flow until equilibration is reached (i.e. no water outflow), thus saving time for the observer.

The bottom of the soil cores were first sealed with permeable ceramic discs (label 15 in **Figure 12-1**) to ensure no soil fell out. After that, a glass container was half-filled with water, in which the soil cores were placed for at least 24 hours, making sure that the samples were not fully submerged in water. Following that, an electric pump was used to remove as much air as possible, thus creating a vacuum. This facilitated the saturation of each soil core and the removal of air bubbles that could potentially disrupt the flow of water during measurements.



ID	DESCRIPTION	NO.	ID	DESCRIPTION	NO.
1	Pressure gauge	1	17	Retaining bolt, washers and nut	6
2	Low pressure regulator	1	18	Retaining wing nut and washer	6
3	6mm hydraulic hose	1	19	Pressure cell outlet port	1
4	T-piece - 6mm hydraulic hose	3	20	Outlet assembly O-ring	2
5	Ball valve	2	21	Outlet assembly retaining cap	2
6	Hose to glass fitting	2	22	Outlet assembly glass ports and	1
7	Glass water manometer	1	23	Outlet vacuum stop-cock	1
8	Glass mercury manometer	1	24	Outlet assembly burette (50ml)	1
9	Manometer board	1	25	Pressure transducer hose	1
10	Cap hydraulic hose connector	1	26	Differential pressure transducer	1
11	Pressure cell cap	1	27	Voltage regulator and distribution	1
12	Pressure cell housing cylinder	1	28	Logger and distribution boards	1
13	Pressure cell base	1	29	Support clamps	4
14	Pressure cell retaining ring	1	30		
15	Pressure cell ceramic and ring	1	31		
16	Pressure cell O-ring	4	32		

Figure 12-1 Diagram of the outflow pressure apparatus for measuring soil water parameters of undisturbed soil cores (Lorentz *et al.*, 2001)

After the saturation process, the following procedure was used for all three samples:

- The soils samples were weighed on a sensitive balance with an accuracy of up to 0.001 g.
- The pressure cell base (label 13 in **Figure 12-1**) was filled with water to displace all air bubbles.
- The stop-cock (23) of the burette (24) was opened to allow water and air bubbles to flow into the outflow burette.
- The soil sample was placed into the pressure cell housing (12).
- The pressure cell ring was then used to retain the sample (14).
- Finally, the soil sample was enclosed (11).

Air pressure (2) was then applied to the samples so water (e.g. 5 mm) could drain into the burette (known as the drainage phase). When no more water drained out, the stopcock was closed until equilibration was reached between the applied air pressure and the liquid in the soil sample. This is known as the equilibration phase (or steady state) and at this point, the matric potential remained constant. The pressure transducer (26) measured the difference in pressure between the pores of the sample and the air pressure applied. This was monitored by observing the changes in matric potential values displayed on the computer monitor. Air pressure was applied at different levels throughout this experiment to vary the matric potential. The amount of water that is available for plant use is retained at matric potentials of -10 to -1500 kPa. The low matric potential (0 kPa) applied in the beginning (i.e. water easily drained out) and a higher matric potential (33 kPa) correspond to porosity and field capacity, respectively. For lower matric potentials, the water manometer (7) was used for observations. However, the mercury manometer (8) was used for higher matric potentials.

At a matric potential of -1500 kPa, most crops wilt because the soil water is not available for plant uptake (Schulze *et al.*, 1985). The three soil cores were carefully removed from the low-pressure cells and weighed again, then transferred to a high-pressure pot that was operated at 15 bars (-1500 kPa) of pressure to determine the wilting point. Before using this technique (similar to **Figure 12-1**), a ceramic disc that could withstand these pressures was saturated with water for over 24 hours. A similar approach of free drainage phase and equilibrium state was used but in this instance, the water was allowed to drain out of the samples until an equilibration state was reached. At equilibrium (i.e. no more water dripped out into the burette), the soil cores were weighed and oven dried for 48 hours and then weighed again. Measurements were used to calculate the bulk density of the soil, which was also used to calculate the porosity of the soil (see **Equation 12-1** and **Equation 12-2**).

$$Bulk\ density = \frac{dry\ mass\ of\ soil\ core}{volume\ of\ soil\ core}$$ **Equation 12-1**

$$Porosity = 1 - \frac{Bulk\ density}{2.65}$$ **Equation 12-2**

The units of bulk density are g cm^{-3}, dry soil mass in g, volume of soil cores in cm^3 and the constant 2.65 represents the particle density in g cm^{-3}. Using a Microsoft Excel spreadsheet, calculations were done using porosity, bulk density and readings recorded from the burette in order to obtain the soil water content at the different applied pressures. These values corresponded to the soil moisture content at saturation (i.e. porosity), field capacity and permanent wilting point.

13 APPENDIX D

Table 13-1 AquaCrop input parameters that were changed in this study

Parameters	Type of Parameter	Model Inputs			
		Sugarcane		Sugarbeet	
		Calibrated*	Parameterised+	Calibrated*	Parameterised+
Reference Harvest Index (%)	Cultivar specific	65	50	70	70
Max Canopy (%)	Influenced by the environment and/or management	90	90	84	98
Time to maximum canopy (GDD)	Influenced by the environment and/or management	1643	268	1625	916
Canopy size transplanted seedling (cm^2/plant)	Can be a conservative parameter for a given specie or may be cultivar specific	10.0	10.0	5.0	15.0
Canopy growth coefficient (%/GDD)	Conservative	0.420	2.880	0.510	0.751
Canopy declining coefficient (%/GDD)	Conservative	0.226	0.321	0.354	0.386
Time to canopy senescence (GDD)	Cultivar specific	3072	2910	1861	1704
Time to maturity (GDD)	Cultivar specific	3141	3134	2381	2203
Initial canopy cover (%)	Can be a conservative parameter for	1.33	1.33	0.33	1.50

Parameters	Type of Parameter	Model Inputs			
		Sugarcane		Sugarbeet	
		Calibrated*	Parameterised+	Calibrated*	Parameterised+
	a given specie or may be cultivar specific				
Start of yield formation (GDD)	Cultivar specific	667	540	811	867
Length of harvest index build up (GDD)	Cultivar specific	1279	2253	1569	1472
Time to maximum root depth (GDD)	Influenced by the environment and/or management	1040	1148	825	420
Minimum effective rooting depth (m)	Influenced by the environment and/or management	0.3	0.3	0.2	0.3
Maximum effective rooting depth (m)	Influenced by the environment and/or management	1.8	1.8	1.0	1.0
Shape factor for root expansion	Conservative	1.3	1.3	1.5	1.5
Root expansion rate (cm/day)	Conservative	0.8	0.9	1.1	1.1
Base temperature (°C)	Conservative	13	13	5	5
Upper temperature (°C)	Conservative	30	30	30	30
Normalised water productivity (g/m^2)	Conservative	30	30	17	17
Sink Strength	Influenced by the environment	0.5	0.5	0.5	0.5

Parameters	Type of Parameter	Model Inputs			
		Sugarcane		Sugarbeet	
		Calibrated*	**Parameterised+**	**Calibrated***	**Parameterised+**
	and/or management / Parameter is cultivar specific				
Soil water depletion factor canopy expansion (p-leaf) Upper Limit	Conservative	0.25	0.25	0.10	0.20
Soil water depletion factor canopy expansion (p-leaf) Lower Limit	Conservative	0.55	0.60	0.45	0.60
Shape factor for water stress coefficient leaf expansion	Conservative	3	3	3	3
Soil water depletion for stomatal control (p-stomatal) Upper Limit	Conservative	0.50	0.50	0.65	0.65
Shape factor for water stress coefficient stomatal control	Conservative	3	3	3	3
Soil water depletion for canopy senescence (p-senescence) Upper Limit	Conservative	0.60	0.60	0.75	0.75
Shape factor for water stress canopy senescence	Conservative	3	3	3	3
Crop transpiration Kc_{tr}	Conservative	1.15	1.15	1.1	1.10
Effect of canopy shelter in late season Kex (%)	Conservative	60	60	60	60
Aeration stress	Conservative	Moderate tolerance		Moderate tolerance	
Salinity stress	Conservative	Tolerant		Moderate tolerance	

+default parameters obtained from the model's crop files (Raes *et al.*, 2011)
*parameters that were changed in this study during the calibration of AquaCrop
Type of parameter:
Conservative parameter - is not usually changed for the same crop.

14 APPENDIX E

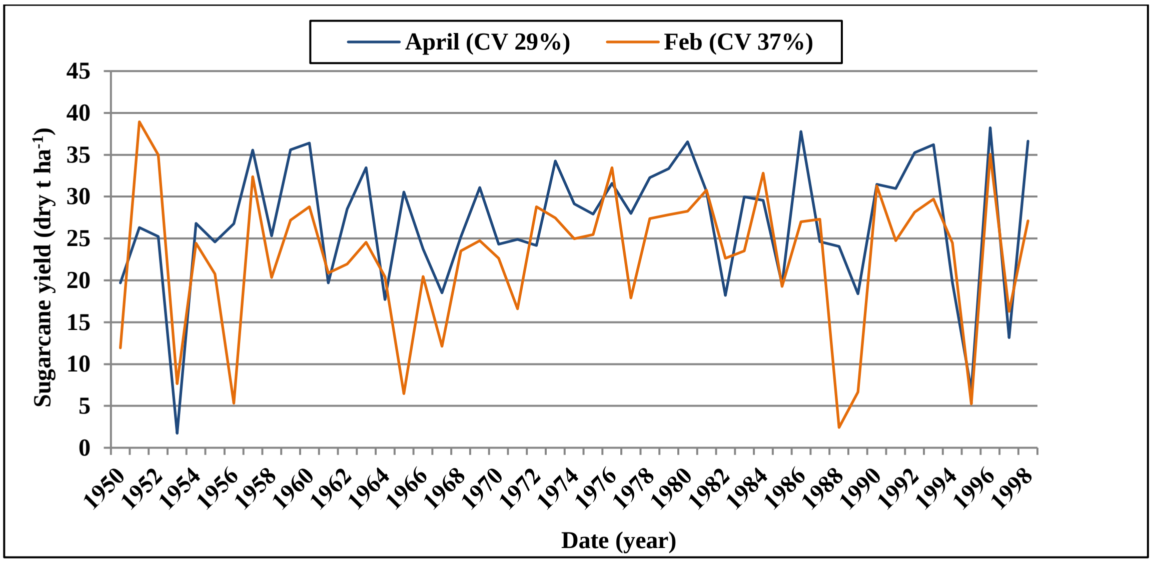


Figure 14-1 Inter-seasonal variability of sugarcane yield over 50 years in quinary 4719 (La Mercy)

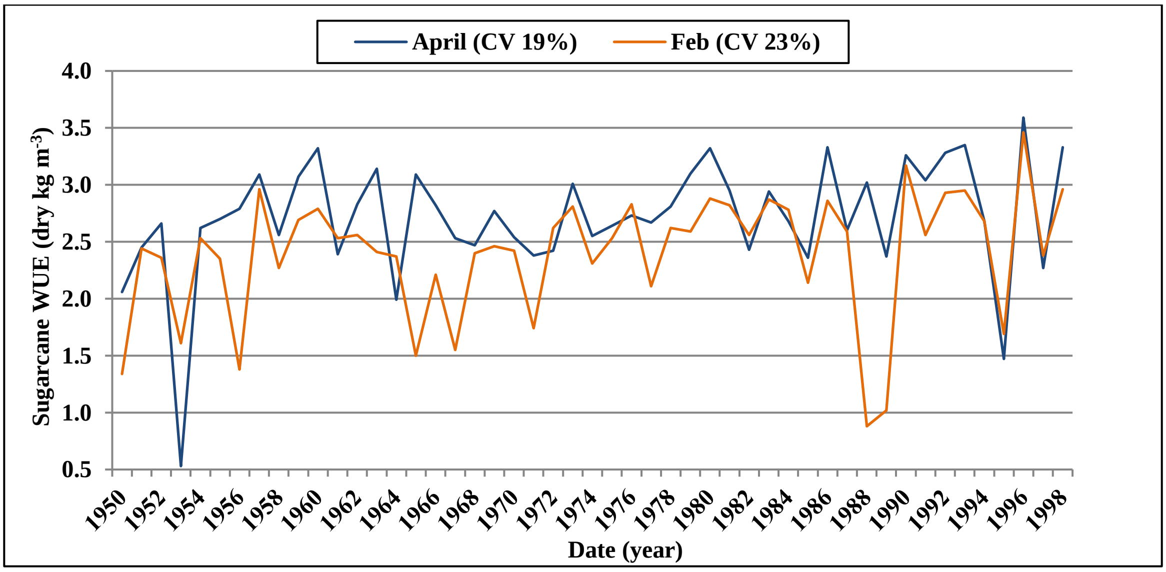


Figure 14-2 Inter-seasonal variability of sugarcane WUE over 50 years in quinary 4719 (La Mercy)

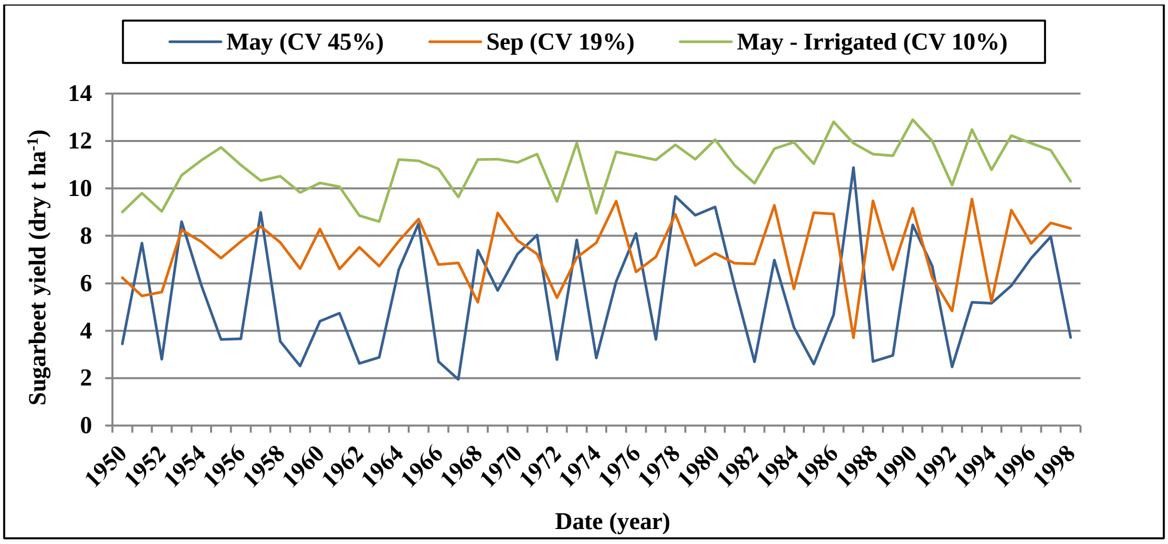


Figure 14-3 Inter-seasonal variability of sugarbeet yield over 50 years in quinary 4697 (Ukulinga)

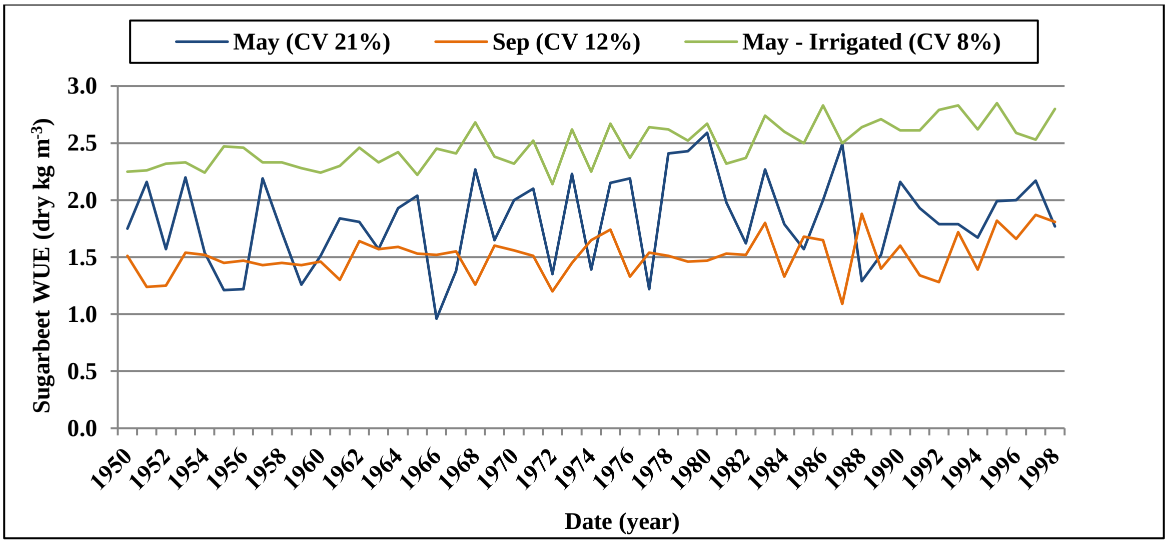


Figure 14-4 Inter-seasonal variability of sugarbeet WUE over 50 years in quinary 4697 (Ukulinga)

15 APPENDIX F

Table 15-1 Percentage changes in yield and WUE of sugarcane for April and February (grey) plantings, derived using dynamically downscaled climate data available for six GCMs

GCM	4717				4718				4719			
	Yield	**%DIF**	**WUE**	**%DIF**	**Yield**	**%DIF**	**WUE**	**%DIF**	**Yield**	**%DIF**	**WUE**	**%DIF**
CSI	33.18	14.85	2.18	47.71	33.07	13.68	2.30	45.87	32.48	15.83	2.35	45.63
GF0	33.87	7.34	2.18	40.83	33.08	6.74	2.33	35.70	32.71	7.17	2.40	32.50
GF1	33.07	22.85	2.22	48.53	31.85	25.90	2.32	48.71	31.93	25.10	2.35	49.25
MIR	32.01	2.80	2.19	33.11	31.17	3.80	2.32	31.68	31.05	3.97	2.35	32.77
MPI	34.79	12.34	2.22	44.47	35.27	10.08	2.41	36.93	35.08	10.40	2.46	36.86
UKM	33.16	16.19	2.20	40.09	33.55	13.16	2.35	34.54	33.26	13.25	2.39	34.17
Mean (6)	33.35	**12.73**	2.20	**42.46**	33.00	**12.23**	2.34	**38.90**	32.75	**12.62**	2.38	**38.53**
Mean (4)	33.73	**14.35**	2.20	**45.39**	33.32	**14.10**	2.34	**41.80**	33.05	**14.63**	2.39	**41.06**
CSI	32.82	18.88	2.15	62.24	32.64	19.98	2.22	64.86	33.10	20.35	2.28	65.93
GF0	32.18	18.12	2.15	53.95	31.84	18.71	2.24	55.36	31.81	19.87	2.29	56.46
GF1	31.82	25.79	2.16	57.18	31.62	26.29	2.25	59.02	31.73	27.21	2.30	59.69
MIR	30.86	10.07	2.08	54.81	30.42	8.79	2.18	54.71	30.41	9.26	2.22	50.68
MPI	32.61	19.03	2.17	59.12	32.30	17.70	2.26	58.54	32.34	18.08	2.32	58.53
UKM	31.89	18.57	2.17	51.38	31.82	19.58	2.26	53.44	32.46	18.32	2.31	55.63
Mean (6)	32.03	**18.41**	2.15	**56.45**	31.77	**18.51**	2.23	**57.65**	31.98	**18.85**	2.28	**57.82**
Mean (4)	32.36	**20.46**	2.16	**58.12**	32.10	**20.67**	2.24	**59.45**	32.25	**21.38**	2.30	**60.15**

Note: Yield in dry t ha^{-1}; WUE in kg m^{-3}

Table 15-2 Percentage changes in yield and WUE of sugarbeet for May and September (grey) plantings, derived using the dynamically downscaled GCMs

GCM	4696				4697				4698			
	Yield	**%DIF**	**WUE**	**%DIF**	**Yield**	**%DIF**	**WUE**	**%DIF**	**Yield**	**%DIF**	**WUE**	**%DIF**
CSI	10.22	50.46	1.59	106.62	9.19	47.43	1.71	94.13	8.33	47.30	1.86	78.44
GF0	10.12	34.96	1.62	82.35	9.58	18.90	1.77	70.82	8.98	10.01	1.88	61.87
GF1	9.79	58.85	1.58	106.65	7.96	75.62	1.62	108.05	6.97	85.97	1.64	108.56
MIR	9.73	34.85	1.62	90.40	8.52	26.74	1.61	93.48	7.59	29.16	1.69	86.65
MPI	10.44	44.03	1.66	97.89	10.39	15.93	1.81	78.45	9.23	15.77	1.90	70.00
UKM	10.09	43.89	1.60	84.33	9.59	27.99	1.74	79.83	8.69	31.76	1.79	81.28
Mean (6)	10.06	**44.51**	1.61	94.71	9.20	**35.43**	1.71	87.46	8.30	**36.66**	1.79	**81.13**
Mean (4)	10.14	**47.08**	1.61	98.38	9.28	**39.47**	1.73	87.86	8.38	**39.76**	1.82	**79.72**
CSI	7.92	43.33	1.08	59.26	8.08	42.71	1.12	61.88	7.93	37.30	1.15	55.22
GF0	8.07	46.04	1.08	60.65	7.96	47.19	1.12	63.68	7.87	46.08	1.14	62.72
GF1	8.05	44.52	1.08	61.86	8.18	43.81	1.14	58.15	7.92	45.34	1.17	55.98
MIR	8.01	40.22	1.08	58.33	7.89	33.35	1.13	52.65	7.78	30.39	1.14	51.75
MPI	8.37	41.03	1.10	58.90	8.13	44.09	1.15	57.39	8.02	39.92	1.17	58.12
UKM	8.18	41.47	1.09	58.26	8.09	42.37	1.13	56.89	7.78	42.28	1.16	56.28
Mean (6)	8.10	**42.77**	1.08	**59.54**	8.06	**42.25**	1.13	**58.44**	7.88	**40.22**	1.15	**56.68**
Mean (4)	8.10	**43.73**	1.09	**60.17**	8.09	**44.45**	1.13	**60.28**	7.94	**42.16**	1.16	**58.01**

Note: Yield in dry t ha^{-1}; WUE in kg m^{-3}