DEVELOPING A GUIDELINE FOR RAINFED PRODUCTION OF UNDERUTILISED INDIGENOUS CROPS AND ESTIMATING GREEN WATER USE OF INDIGENOUS CROPS BASED ON AVAILABLE MODELS WITHIN SELECTED BIO-CLIMATIC REGIONS OF SOUTH AFRICA

Volume 1

Report to the
WATER RESEARCH COMMISSION

by

T Mabhaudhi, VGP Chimonyo, RP Kunz and AT Modi

School of Agricultural, Earth and Environmental Sciences
University of KwaZulu-Natal, Pietermaritzburg, South Africa

WRC Report No. 2717/1/23
ISBN 978-0-6392-0390-4

April 2023

Obtainable from
Water Research Commission
Bloukrans Building, 2nd Floor
Lynnwood Bridge Office Park
4 Daventry Road
Lynnwood Manor
PRETORIA

orders@wrc.org.za or download from www.wrc.org.za

This report forms part of a set of two reports. The other report is *Development of Production Guidelines and Green Water Use Estimation of Underutilised Indigenous Crops Using Available Models Within Selected Bio-Climatic Regions of South Africa. Volume 2: Climate change atlas for rainfed production of selected underutilised crops.* (WRC Report No. 2717/2/23)

EXECUTIVE SUMMARY

Neglected and underutilised crop species (NUS) have not been previously classified as major crops, are under-researched, occupy low utilisation levels, and are mainly confined to smallholder farming areas. They can tolerate adverse conditions and represent an important component of South Africa's agro-biodiversity with the potential to contribute to meaningful socio-economic development and transformation in poor rural areas. However, their importance in food systems and information describing their suitability across diverse agricultural landscapes remains limited. Over the years, the Water Research Commission (WRC) of South Africa has invested in developing knowledge in this critical area. Previous research showed that several underutilised indigenous crops were drought-tolerant, had good heat stress tolerance, and adapted to low water use levels. However, a lack of information describing their agronomy, water use, lack of production guidelines, and land suitability maps have previously been cited as the bottlenecks to their promotion.

This study builds on previous WRC-funded research on drought tolerance, water use, agronomy and modelling underutilised crops for South Africa. Specifically, the project builds on the crop modelling base and applies the existing knowledge to map and identify suitable areas for rainfed production of underutilised crops in South Africa. The specific objectives of the project were:

i. To conduct a state-of-the-art literature review focussing on identifying available information on the production, agronomy and water use of underutilised crops in South Africa. The review will focus on identifying locally available and international models that have been applied for modelling yield, water use and water productivity of underutilised crops and that can be adapted for South African conditions;

ii. To parameterise/calibrate and test/validate available crop models for selected underutilised crops under rainfed conditions in South Africa;

iii. To use available crop models to identify and map bio-climatic regions suitable for the rainfed production of selected underutilised crops in South Africa;

iv. To use available crop models and climate change data to map climate change impacts on yield, water use and water productivity of the selected underutilised crops for rainfed production under South African conditions; and

v. To use available crop models to develop production guidelines for selected underutilised crops based on best management recommendations for maximising yield, water use and water productivity under South African conditions.

State-of-the-art literature review focussing on identifying available information on modelling underutilised crops in South Africa

The literature review (***cf*** Chapter 2) provided the basis for selecting suitable crop models. It was noted that not all crop models had been calibrated and validated for underutilised crops. Water-driven models were shown to require fewer input parameters and were considered more robust and less complex to apply compared to radiation-driven models. Of the models reviewed, three (APSIM, AquaCrop and DSSAT) were mostly used for underutilised crops. However, AquaCrop has been used most extensively in South Africa for modelling underutilised crops. The APSIM and AquaCrop models were recommended for modelling the water use and yield of selected underutilised crops. To a limited extent, DSSAT was also considered together with emerging new crop models such as SIMPLE. However, AquaCrop was selected as the primary crop model used for the project based on its extensive application in South Africa and the availability of calibrated and validated crop files.

To calibrate and validate available crop models for selected underutilised crops

Model selection was followed by crop selection (see Volume 2 of the report). The selection of underutilised crops for the study was based on outputs of WRC Project Number K5/2603//4 "Developing an agenda for promoting underutilised crops in South Africa". The project proposed a list of 13 priority underutilised crops based on drought and heat stress tolerance and nutritional value. These were identified based on existing knowledge in the literature regarding drought and heat stress tolerance and nutritional value and categorised into four food groups (cereals, legumes, root and tuber, and leafy vegetable crops). Since there was no fieldwork budget for the current project, the project focused primarily on those crops that had already been modelled in South Africa and for which information already existed. Based on this criteria, four crops, sorghum (cereal), bambara groundnut (legume), taro (tuber) and amaranth (leafy vegetable), were selected from the priority list. These crops had all been calibrated and validated in previous WRC-funded research projects, and the crop files were available to the project team.

Mapping bio-climatic regions suitable for the rainfed production of selected underutilised crops

Introducing NUS into moderately to highly suitable regions could increase the crop choices available and contribute to biodiversity (***cf*** Chapter 3). This could be viewed as a climate change adaptation strategy and sustainable intensification of smallholder farming systems. Introducing NUS in the mapped zones could contribute to food and nutrition security, poverty alleviation and human health and wellbeing. However, the lack of consideration of key socio-economic indicators in current methods of developing suitability maps fails to consider the systemic nature and complexity of food systems. Holistic land suitability maps, which consider several socio-economic indices, could guide policymakers and decision-makers. Therefore, future studies should identify innovative ways to derive maximum value from integrating GIS and remote sensing with block-chain, big data, and Internet of Things (IoT) technologies to develop integrated factors for land suitability mapping.

Parameterisation and validation of crop models for selected underutilised crops

AquaCrop, DSSAT and SIMPLE were successfully applied to simulate yields, biomass, and WU for the selected crops under climate change and varying agricultural water management typologies (***cf.*** Chapter 4-7). This highlighted the suitability of these models for modelling underutilised crops under a range of conditions. With relatively comparable results (i.e. yields disagreement and yield variability) to DSSAT and SIMPLE model, AquaCrop was confirmed as the best-suited model for simulating yield, biomass and WU under climate change impacts and irrigation management. This may be attributed to the crop files used in this study being previously well calibrated and validated for AquaCrop in previous studies.

Crop models to develop production guidelines for selected underutilised crops

Developing guidelines for the production of NUS is important for optimising water productivity. There is a need for whole systems approaches that optimise water, soil nutrients and management for varying weather conditions. Results of the project reinforce the potential and promise of crop models for this purpose. The project was the first to model a range of African Leafy Vegetables in APSIM (***cf.*** Chapter 5). The observed model outcomes are somewhat consistent with results on land suitability mapping (***cf.*** Chapter 4). It was observed that the general wide suitability of amaranth was associated with the crop's growth requirements that allow for its production even under extremely marginal conditions.

Conclusions and Recommendations

Underutilised crops can be grown on marginal land, and they can complement major crops and contribute to cropping systems diversity hence climate change adaptation and sustainable intensification. Mapping NUS production potential zones is key to promoting their production by providing evidence to inform decision- and policymakers on crop choice. The results are useful to inform the Climate-Smart Agriculture Strategy, National Policy on Comprehensive Producer Development Support and Draft Indigenous Food Crops Strategy. The suitability maps are also helpful in informing decisions on climate change adaptation and sustainable intensification under climate change. Simple crop models (i.e. with fewer input requirements) can perform equally as complex models if well calibrated and validated. This is significant for underutilised crops whose modelling has been stifled by the lack of extensive data sets needed to parameterise complex models.

Innovation

The project developed new land suitability maps for four priority NUS. The maps can promote the selected NUS as alternative crop choices and inform site-specific crop diversification recommendations as part of climate-smart agriculture and sustainable intensification within smallholder farming systems. In planning for future sustainable crop production the interactions of biophysical and social-economic factors are critical for detecting areas threatened in terms of the NUS and zones with the potential to support the NUS.

Recommendations

There is a need for future studies to identify innovative ways to derive maximum value from the possible integration of GIS with block-chain, big data, and IoT technologies to mine updated data, especially on climatic data and social-economic factors.

ACKNOWLEDGEMENTS

The research reported here formed part of an unsolicited project initiated, funded and managed by the Water Research Commission (WRC) in Key Strategic Area 4 (Water Utilisation in Agriculture). The project team is sincerely grateful to the WRC for funding and managing the project. The project team also wishes to sincerely thank the following members of the Reference Group for their valuable contributions and guidance:

Prof. S Mpandeli	Water Research Commission (Chairman)
Dr L Nhamo	Water Research Commission
Prof. W van Averbeke	Tshwane University of Technology
Prof. K Ayisi	University of Limpopo
Dr G Ceronio	University of Free State
Dr C Mutengwa	University of Fort Hare
Dr S Hlophe-Ginindza	Water Research Commission
Dr K Tshikolomo	Department of Agriculture
Prof. S Walker	Agricultural Research Council

We would also like to thank the following individuals:

- The students who participated on the project: Hillary Mugiyo, Mendy Ndlovu, Thembelihle Nzimande and Thobeka Kunene
- Drs C Masemola, M Sibanda and Serge Kiala for supporting the development of maps.
- The administrative staff from the Centre for Transformative Agricultural and Food Systems (CTAFS) for supporting the project.
- The many communities whose contributions laid the groundwork for the data that is used in the report.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ACC	Australian Community Climate and Earth System Simulator
ACRU	Agricultural Catchments Research Unit
AHP	Analytic Hierarchy Process
ALV	African Leafy Vegetables
AMP	Annual amplitude in monthly temperature
APSIM	Agricultural Production Systems sIMulator
AR	Assessment Report
ARC	Agricultural Research Council
AVX	Advanced Vector Extensions
AZ	Altitude Zone
BIN	Binary
CABLE	CSIRO Atmosphere Biosphere Land Exchange model
CC	Canopy Cover
CCAM	Conformal-Cubic Atmospheric Model
CCS	Community Climate System Model
CDF	Cumulative Density Function
CHPC	High-Performance Computing
CI	Confidence Index
CMIP	Climate Model Inter-comparison Project
CNR	National Centre for Meteorological Research Coupled GCM
CORDEX	Coordinated Regional Climate Downscaling Experiment
CPU	Central Processing Unit
CRU	Climate Research Unit
CSAG	Climate System Analysis Group
CSIR	Council for Scientific and Industrial Research
CSIRO	Commonwealth Scientific and Industrial Research Organisation
CSMs	Crop simulation models
CSV	Comma Separated Value
CTAFS	Centre for Transformative Agricultural and Food Systems
CV	Coefficient of Variation
CWP	Crop Water Productivity
CWRR	Centre for Water Resources Research
DAFF	Department of Agriculture, Forestry and Fisheries (now DALRRD)

DALRRD	Department of Agriculture, Land Reform and Rural Development (former DAFF)
DALT	Altitude difference between rainfall and temperature station
DARD	Department of Agriculture and Rural Development (now DALRRD)
DF	Distant Future
DHSWS	Department of Human Settlements, Water and Sanitation (former DWS)
DPP	Directorate Plant Production
DSSAT	Decision Support System for Agrotechnology Transfer
DWS	Department of Water and Sanitation (now DHSWS)
ENSO	El Niño-Southern Oscillation
ET	Evapotranspiration
FACE	Free Air CO_2 Enrichment
FAO	Food and Agricultural Organisation of the United Nations
FAO	Food and Agriculture Organisation
FAO56	Food and Agriculture Organisation, Paper No. 56
GCM	Global Climate Model
GDD	Growing Degree-Day
GFD	Geophysical Fluid Dynamics Laboratory Coupled Model
GIS	Geographic Information System
HI	Harvest Index
IoT	Internet of Things
IPCC	Intergovernmental Panel on Climate Change
KZN	KwaZulu-Natal
LULC	Land use Land cover
MAP	Mean Annual Precipitation
MAPE	Mean Absolute Percentage Error
MCDA	Multi-criteria decision analysis
ME	Model Efficiency
MPI	Max Planck Institute Coupled Earth System Model
NetCDF	Network Common Data Form
NF	Near Future
NOR	Norwegian Earth System Model
NUS	Neglected and underutilised crop Species
NWP	Nutritional Water Productivity
OWA	Ordered weighted averaging
PC	Personal Computer

ppm	Parts Per Million
PR	PResent
QC	Quaternary Catchment
QDM	Quantile Delta Mapping
QM	Quantile Mapping
QnC	Quinary Catchment
QnCDB	Quinary Catchment Climate DataBase
RAM	Random Access Memory
RCM	Regional Climate Model
RCP	Representative Concentration Pathway
RMSE	Root Mean Square Error
RSR	RMSE Standard deviation Ratio
SA	South African
SASA	South African Sugar Association
SAWS	South African Weather Service
SDG	Sustainable Development Goals
SIMD	Single Instruction, Multiple Data
SOM	Self Organising Map
SSA	Sub Saharan Africa
SSE	Streaming SIMD Extensions
SST	Sea Surface Temperature
TAV	Average ambient temperature (TAV)
UCT	University of Cape Town
UKZN	University of KwaZulu-Natal
UWIN	Unix for WINdows
WMA	Water Management Area
WP	Water Productivity
WRC	Water Research Commission
WRO	Water Research Observatory
WSL	Windows Subsystem for Linux
WU	Water Use
WUE	Water Use Efficiency

LIST OF SYMBOLS

ALTD	Difference in altitude factor for temperature station selection (fraction)
B	Accumulated biomass (g m^{-2})
A-pan	A-pan equivalent evaporation (mm)
c	Coefficient of initial abstraction
CC	Canopy cover (%)
CC_O	Initial canopy cover at emergence (%)
CC_X	Maximum canopy cover reached (%)
CN	Curve number(integer)
CO_2	Atmospheric carbon dioxide concentration (ppm)
CV	Coefficient of variation (%)
d	Willmott's d Index
DALT	Altitude difference between rainfall and temperature station (m)
E	Soil water evaporation (mm)
ET_O	Reference crop evaporation (mm)
FC	Field capacity (volume%)
f_{CO2}	CO_2 factor for atmospheric CO_2 normalisation (fraction)
f_{WPS}	WP* adjustment factor (fraction)
f_{SINK}	Crop sink strength coefficient (fraction)
f_{TYPE}	Correction factor for crop type (fraction)
GDD	Growing degree-days accumulated for the month (°C d)
HI	Harvest Index (%)
I_a	Initial abstraction (% or fraction)
I_a	Infiltrated water (mm; $I_a = c \cdot S$)
K_S	Water stress index (fraction)
MAP	Mean annual precipitation (mm)
obs_rfl	Observed daily rainfall (mm)
PWP	Permanent wilting point (volume%)
R^2	Coefficient of determination (fraction)
rhmaxscr	Maximum screen relative humidity (%)
rhminscr	Minimum screen relative humidity (%)
rnd24	Daily precipitation (mm)
rnd24_BC	Bias corrected daily precipitation (mm)
S	Potential maximum storage (mm; S = 1000/CN – 10)

tmaxscr	Maximum screen temperature (°K or °C)
tminscr	Minimum screen temperature (°K or °C)
θ	Actual soil water content (mm)
θ_{FC}	Soil water content at field capacity/drained upper limit (mm m^{-1}; volume%)
θ_{PWP}	Soil water content at permanent wilting point (mm m^{-1}; volume%)
θ_{SAT}	Soil water content at saturation/porosity in (mm m^{-1} or %)
Tn	Daily minimum air temperature (ºC)
Tr	Transpiration (mm)
Tx	Daily maximum air temperature (ºC)
u10	Wind speed at height 10 meters (m s^{-1})
u2	Wind speed at height 2 meters (m s^{-1})
WP	Water productivity (kg m^{-3} or g m^{-2})
WP*	Normalised water productivity (kg m^{-2})
WUE	Water use efficiency of crop production (kg m^{-3})
Y	Dry crop yield (g m^{-2} or t ha^{-1})

REPOSITORY OF DATA

For details related to the project's data, please contact:

Prof Tafadzwa Mabhaudhi (Project Leader and Principal Researcher)
Centre for Transformative Agricultural and Food Systems
School of Agricultural, Earth and Environmental Sciences
University of KwaZulu-Natal
Private Bag X01, Scottsville 3209
Pietermaritzburg, South Africa

Email: mabhaudhi@ukzn.ac.za

1 INTRODUCTION

The increasingly low and variable rainfall patterns in South Africa threaten the viability and sustainability of food production in rural areas, threatening food security in poor rural households. The potential of underutilised indigenous crops to contribute under such conditions has been highlighted in several publications (Modi and Mabhaudhi, 2013; Chivenge et al., 2015; Mabhaudhi et al., 2016a; Mabhaudhi et al., 2016b). For South Africa, Modi and Mabhaudhi (2013) defined underutilised indigenous crops as either indigenous or have been “indigenised” in South Africa, still occupy low utilisation levels and are confined to their ecological niches. These crops were also characterised by low levels of research (Azam-Ali, 2010). Therefore, lack of information describing their agronomy, water use, lack of production guidelines, and land suitability maps have previously been cited as the bottlenecks to their promotion.

Underutilised indigenous crops represent an essential component of South Africa’s agro-biodiversity with the potential to contribute to meaningful socio-economic development and transformation in poor rural areas. Most of these underutilised indigenous crops possess attributes that make them ideal for production under low input agricultural systems and in marginal production areas, which typify South Africa’s rural landscape. Reports by Modi and Mabhaudhi (2013) showed that several underutilised indigenous crops were drought tolerant, had good heat stress tolerance, and adapted to low water use levels. These unique attributes suggest that underutilised indigenous crops would be ideal for promotion during periods of drought, such as the 2015/16 drought experienced across South Africa.

Over the years, the Water Research Commission of South Africa has invested in developing knowledge in this critical area. These efforts included screening for drought tolerance in several underutilised indigenous crops (Spreeth et al., 2004), describing the agronomy and determining drought tolerance and water use of selected underutilised indigenous crops (Modi and Mabhaudhi, 2013). Currently, there are other on-going projects focussing on determining water of indigenous cereal and legume food crops (WRC, 2014) and determining nutritional water productivity of underutilised crops (WRC, 2014; WRC, 2016). These efforts, coupled with others by the Department of Science and Technology (DST) and through other external partnerships, have led to an increase in the amount of information available on underutilised indigenous crops. There has also been progress in developing crop models for several of these crops such as amaranth (Walker et al., 2013), bambara groundnut (Mabhaudhi et al., 2014a), cowpea (Chimonyo et al., 2016), pearl millet (Modi and Mabhaudhi, 2013), sorghum (Hadebe, 2016), sweet potato (Beletse et al., 2009) and taro (Mabhaudhi et al., 2014b). Intercrops of featured underutilised crops (sorghum, cowpea and bottle gourd) have also been modelled (Chimonyo et al., 2016). Notably, most of the crop models that have been developed and are currently under development for underutilised crops have been done using the FAO's AquaCrop model. Most of this generated information is still current and highlights the progress that has been made on underutilised indigenous crops research. While the progress achieved to date is laudable, more still needs to be done if these crops are to feature more prominently in cropping systems. For instance, most of the studies to date have been in specific bio-climatic zones with limited extrapolation to other rainfed agro-ecologies. The use of developed models coupled with GIS could address this knowledge gap.

Whilst taking note of the existing gaps, there is a need to consolidate on gains already made and the momentum that has been built within the underutilised crops research community and articulate a way forward for underutilised crops in South Africa. In this regard, the WRC is already leading the way, having recently commissioned new research on "Developing a research agenda for underutilised crops in South Africa". This will go some way in guiding future investments in underutilised crops research. In addition, there is now a need to apply the information that has already been generated and make it useable. Here, available agronomic and water use information as well as crop models could be used to develop production guidelines as well as mapping suitable areas in South Africa for underutilised crop production. This would allow for the translation of existing research outputs into materials that can be disseminated to a wider audience and used practically to promote the inclusion of underutilised crops in cropping systems in South Africa.

In this regard, priority should be made to develop guidelines for rainfed agricultural systems since the majority of farmers (> 95%) still rely on rainfed production. In developing these guidelines, consideration should also be given to climate change. Current predictions suggest that South Africa will experience decreasing rainfall in some areas, increased rainfall variability and frequency of extremes such as drought and floods. This will have an effect on current production areas as there may be shifts in agro-ecological boundaries. Therefore, a study focussing on developing guidelines for underutilised indigenous crops for rainfed production in South Africa, which also accounts for climate change, would go a long way in promoting the sustainable inclusion and production of underutilised indigenous crops in rainfed rural cropping systems. To this end, the application of available crop models would aid in identifying suitable bio-climatic regions for rainfed production of underutilised indigenous crops in South Africa.

1.1 Objectives

The contractually specified objectives of the project were:

1.1.1 General Objective

To develop guidelines for rainfed production of underutilised indigenous crops and estimate water use of indigenous crops based on available models within selected bio-climatic regions of South Africa

1.1.2 Specific objective

i. To conduct a state-of-the-art literature review focussing on identifying available information on the production, agronomy and water use of underutilised crops in South Africa. The review will focus on identifying locally available and international models that have been applied for modelling yield, water use and water productivity of underutilised crops and that can be adopted for South African conditions
ii. To parameterise/calibrate and test/validate available crop models for selected underutilised crops under rainfed conditions in South Africa
iii. To use available crop models to identify and map bio-climatic regions suitable for the rainfed production of selected underutilised crops in South Africa

iv. To use available crop models and climate change data to map climate change impacts on yield, water use and water productivity of the selected underutilised crops for rainfed production under South African conditions

v. To use available crop models to develop production guidelines for selected underutilised crops based on best management recommendations for maximising yield, water use and water productivity under South African conditions

1.2 Crop selection

The selection of underutilised crops for the study was based on outputs of the recently completed WRC Project Number K5/2603//4 "Developing an agenda for promoting underutilised crops in South Africa". The project proposed a list of 13 priority underutilised crops based on drought and heat stress tolerance as well as nutritional value (**Table 1.1**)

Table 1.1: List of thirteen (13) priority drought tolerant and nutrient-dense underutilised crops for South Africa

	Common name	**Scientific Name**
Cereals	Sorghum	*Sorghum bicolor*
	Tef	*Eragrostis tef*
Legumes	Bambara groundnut	*Vigna subterranea* (L.)
	Lablab	*Lablab purpureus* (L.) Sweet
	Cowpea	*Vigna unguiculata* (L.) Walp
	Marama bean	*Tylosema esculentum*
Root and tubers	Taro	*Colocasia esculenta*
	Sweet potato	*Ipomoea batatas*
Leafy vegetables	Jews mallow	*Corchorus olitorius*
	Spider plant	*Cleome gynandra*
	Amaranth	*Amaranthus sp.*
	Nightshade	*Solanum nigrum*
	Wild watermelon	*Citrullus Lanatus* L.

The priority underutilised crops were identified based on existing knowledge in the literature with regards to drought and heat stress tolerance, and nutritional value, and further categorised into four food groups (cereals, legumes, root and tuber as well as leafy vegetable crops). Table 1 details the 13 crops that were identified. For the current project, since there was no budget for fieldwork, the project focused primarily on those crops that have already been modelled in South Africa and for which information already exists. These include sorghum, taro, amaranth, sweet potato and bambara groundnut. Other crops may also be considered in the future.

1.3 Scope of the report

The report is written in a series of self-contained chapters, with different authors. Each Chapter addresses at least one of the specific objectives of the project, as set out in the terms of reference. Due to the paper format that has been used, the report does not have a general methodology section; each Chapter has its own specific methodology. In some cases, this may have inadvertently created cases of minor repetition, especially in the methodology section.

The report is structured to address the project objectives of the study in a logical framework. Chapters 1 and 2 address the first objective related to conducting literature reviews. Chapters 3-7 report on the calibration and use of available crop models to develop production guidelines for selected underutilised crops based on best management recommendations for maximising yield, water use and water productivity under South African conditions.

A general overview of the report is provided below

Chapter 1: provides a general introduction, background and conceptualisation of the entire study. It provides a motivation for the broad study as set out in the terms of reference. It also sets out the project's aims and specific objects as defined in the contract.

Chapter 2: assessed progress, opportunities, and challenges for modelling NUS using a systematic review. The chapter reviews the usefulness of several models that have been calibrated for a range of NUS. The chapter addresses specific objective 1 of the project. It also addresses specific objectives 2, 4 and 5 related model calibration, validation and application.

Chapter 3: used a non-parametric machine learning algorithm to delineate bioclimatic regions with high rainfall variability for water-scarce environments. More specifically, Vegetation Drought Response Index (VegDRI), a hybrid drought index that integrates the Standardised Precipitation Index (SPI), Temperature Condition Index (TCI), and the Vegetation Condition Index (VCI) to delineate bioclimatic zones with both high rainfall variability and water scarcity for South Africa. This chapter was related to specific objectives 2 and 3.

Chapter 4: was aimed at developing land suitability maps for selected NUS [sorghum, (*Sorghum bicolor*), cowpea (*Vigna unguiculata*), amaranth and taro (*Colocasia esculenta*)] using Analytic Hierarchy Process (AHP) in ArcGIS. This chapter was also related to specific objectives 2 and 3.

Chapter 5: assessed the growth, productivity and water productivity of selected ALVs (amaranth (*Amaranth spp*), cowpea (*Vigna unguiculata*), sweet potato (*Ipomoea batatas*) and wild mustard (*Sinapis arvensis*)) under different management practices and addresses specific objective 4 and 5.

Chapter 6: compares the performance of three crop simulation models, namely, AquaCrop, DSSAT, and the SIMPLE model, in predicting yield, biomass, and water use of neglected and underutilized cereal crops and addresses specific objectives 4 and 5.

Chapter 7: reports on results of modelling yield and water use for the range of crops identified and addresses specific objective 4 and 5 of the study related to modelling yield and water use of the range of identified crops.

Chapter 8: provides a holistic discussion of the entire project and links all the separate studies to achieving the project objectives. The chapter also provides the conclusion and recommendations for future studies.

2 MODELING NEGLECTED AND UNDERUTILISED CROPS: A SYSTEMATIC REVIEW OF PROGRESS, CHALLENGES, AND OPPORTUNITIES

Mabhaudhi, T, Chimonyo, V.G.P., Chibarabada, T.P., Kunz, R.P., Walker, S., Massawe F and Modi, A.T.

Abstract

Developing and promoting neglected and underutilised crops (NUS) is essential to building resilience and strengthening food systems. The lack of robust, reliable and scalable evidence currently impedes their mainstreaming into policies and strategies to improve food and nutrition security. Well calibrated and validated crop models can be useful in closing the gap by generating evidence at multiple spatial and temporal scales needed to inform policy and practice. We, therefore, assessed progress, opportunities, and challenges for modelling NUS using a systematic review. While several models have been calibrated for a range of NUS, a few have been applied to evaluate growth, yield, and resource use efficiencies. The low progress in modelling NUS is due, in part, to the vast diversity found within NUS that available models cannot adequately capture. This is compounded by a general lack of research focus on modelling NUS, and more importantly, the lack of robust and reliable eco-physiological data needed to parameterise crop models. The use of Functional-structural plant models (FSPM) to generate eco-morphological and eco-physiological data for NUS can address this gap. There are also opportunities for advancing crop model databases and knowledge by tapping into big data and machine learning.

Keywords: Crop Simulation modelling; Climate resilience; Eco-physiology; Sustainability; NUS

2.1 Introduction

Dansi et al. (2012) defined (NUS) as plant species that are part of more substantial biodiversity, were once popular (in and out of their centres of diversity) are neglected by users and research but remain relevant in the regions of their diversity. Despite their status, NUS have gained attention as potential food and nutrition security crops (Malik and Chaudhary, 2019) poverty reduction (Chivenge et al., 2015) and climate change adaptation (Mabhaudhi et al., 2019b). Their adaptability, nutritional attributes and socio-economic potential make them suitable crops for promotion in marginal production areas where food and nutrition insecurity, poverty and unemployment are high (Chivenge et al., 2015). While NUS can contribute to transformative agriculture, their role in mainstay agriculture remains obscure (Massawe et al., 2015). Many proponents of modern agriculture highlight that they are low yielding, and there is insufficient spatial and temporal data detailing their response to different agro-ecologies and management options (Chivenge et al., 2015; Mabhaudhi et al., 2017a, 2019a). Additionally, information about their genomics, breeding, production, management, and performance in the broader agro ecosystem remain anecdotal and in poorly documented indigenous knowledge systems. By contrast, major crops are well-endowed with a coherent knowledge (scientific and indigenous) system, and this has contributed to their dominance and high yielding potentials (Mabhaudhi et al., 2017a). For NUS to fully partake in transformative agricultural and rural development, there is a need to consolidate and strengthen existing knowledge systems. Data to inform and design a knowledge base that is at par with their major crops' counterparts may need innovative tools to generate relevant data. It is in this regard that we suggest crop growth simulation models as useful tools in bridging the existing knowledge gap.

Crop growth simulation models ('crop models' hereafter) have proven to be useful tools for generating data to support decision making for sustainable resource management (Sinclair and Seligman, 1996; Singels et al., 2010; Liu et al., 2011; Dias et al., 2016). Crop models have been used widely in optimising management of major crops and in predicting the impact of environmental changes on crop eco-physiology and productivity. They have been used in ideotype-based plant breeding (e.g. Ramirez-Villegas et al. (2015) for wheat), to link physiology, genetics and phenomics

(Muller and Martre, 2019) and in assessing impacts of innovations on transformative adaptation to climate change (Carter et al., 2018; Larkin et al., 2019). However, most attention has been to further the understanding of major crops and in part, expand their dominance. At the same time, some progress has been made for NUS. For instance, quinoa (*Chenopodium quinoa*) (Pulvento et al., 2013), amaranth (*Amaranthus* spp.) (Nyathi et al., 2018), bambara groundnut (*Vigna subterranea*) (Karunaratne et al., 2010; Mabhaudhi et al., 2014), sorghum (*Sorghum bicolor*) (Hadebe et al., 2017; MacCarthy et al., 2017), cowpea (*Vigna unguiculata*) (Chimonyo et al., 2016a; Kanda et al., 2020), pearl millet (*Pennisetum glaucum*) (Bello and Walker, 2016), sweet potato (*Ipomoea batatas*) (Beletse et al., 2009) and taro (*Colocasia esculenta*) (Mabhaudhi et al., 2014b). However, these efforts are not nearly the same as those made for major crops.

The current study aimed to assess the current progress, gaps, and opportunities for modelling NUS. The scope of the study does not include the fundamentals of NUS and other well-established concepts on orphan and marginalised crops. These have been covered extensively (see Adhikari et al. (2017); Chivenge et al. (2015); Dansi et al. (2012); Gaisberger et al. (2016); Mabhaudhi et al., (2019a and 2019b) and Mayes et al. (2012)). The study also proposes solutions to addressing identified challenges in efforts to stimulate NUS modelling.

2.2 Methodology

The study was structured into two phases: (i) establishing progress on modelling NUS and identifying research gaps, and (ii) outlining challenges and opportunities for modelling NUS.

Phase 1 Progress: Literature search

A systematic review of the literature was conducted to determine the current progress in modelling NUS. Two databases (Scopus and Web of Science) were used to search for published peer-reviewed literature for the period 1996-2019. We framed the search according to the PRISMA statement (Liberati et al., 2009) (Table 1). To focus the review and provide an in-depth assessment of work on modelling NUS; we restricted the search on articles done on priority NUS for Africa identified by Williams and Haq

(2002). Williams and Haq (2002) defined 20 underutilised crops as a priority based on socio-economic and bio-physical importance, germplasm diversity and availability, and if sufficient innovation can be derived from them. Mabhaudhi et al. (2017) later amended this list of priority crops to give a total of 29 crops. As such, the terms included in the search string were “Sorghum” or “Finger Millet” or “Tef” or “Barnyard grass” or “Bambara groundnut” or “Lablab” or “Pigeon pea” or “Pigeon pea” or “Sword bean” or “Cowpea” or “Velvet bean” or “Marama bean” or “Taro” or “Sweet potato” or “Cassava” or “African yam bean” or “Cocoyam” or “Bottle gourd” or “Blackjack” or “African Eggplant” or “Jews Mallow” or “Roselle” or “Spider plant” or “Amaranth” or “Nightshade” or “Chinese Cabbage” or “Sunberry” or “Wild mustard” or “Wild Water Melon” AND “crop simulation model*” or “crop model*” or “crop growth model*”. Also, a second search was conducted on modelling initiatives on maize. The second search served to benchmark the type of advancements in crop modelling that has happened. Maize was used as it is considered a commercially important crop species. Like the NUS search string for maize we used “maize” or “corn” AND “crop simulation model*” or “crop model*” or “crop growth model*”.

The initial search retrieved a total of 595 and 2 911 articles for NUS and maize, respectively (**Table 2.1**). Thereafter, articles were screened for duplicates, and 386 and 1829 articles remained, respectively. For the NUS database, studies written in English were considered, and titles and abstracts from the remaining articles were examined to check whether studies mentioned the use of a crop simulation models to predict resource use, growth and productivity of the priority NUS. Following the screening, 145 abstracts remained, and research study details including crop simulation model used, model development (calibration, validation, and testing), application and improvements were extracted from the abstracts and if needed, full-length articles. We developed an excel spreadsheet to enter and later quantitatively assess the extracted data. The database for maize was not subjected to the same assessment since it only served to identify themes that show the advancements that have been made in crop simulation modelling.

Table 2.1: Search scope for NUS and maize database used in this study

Search scope	NUS Database	
	Web of science	Scopus
NUS – Title, abstract, keywords “Sorghum” OR “Finger Millet” OR “Tef” OR “Barnyard grass” OR “Bambara groundnut” OR “Lablab” OR “Pigeon pea” OR “Sword bean” OR “Cowpea” OR “Velvet bean” OR “Marama bean” OR “Taro” OR “Sweet potato” OR “Cassava” OR “African yam bean” OR “Cocoyam” OR “Bottle gourd” OR “Blackjack” OR “African Eggplant” OR “Jews Mallow” OR “Roselle” OR “Spider plant” OR “Amaranth” OR “Nightshade” OR “Chinese Cabbage” OR “Sunberry” OR “Wild mustard” OR “Wild Water Melon”	105 233	80 855
Maize – Title, abstract, keywords “Maize” OR “Corn	187 876	200 915
Crop simulation modelling – Title, abstract, keywords "crop simulation model*" OR "crop model*" OR "crop growth model"	5 266	5 572
Combined search NUS Modelling (#1 AND #3)	364	231
Combined search for maize Modelling (#2 AND #3)	1 701	1 211
Retained after removing duplicates in the combined search for NUS Modelling	386	
Retained after removing duplicates in the combined search for Maize Modelling	1829	
*Further screening of search by reading through titles, abstract, keywords for NUS Modelling	145	
Retained and available for final review NUS Modelling	145	

Phase 2 Research gaps and opportunities

The outcomes of the first phase were used to articulate existing research gaps in NUS modelling, and challenges and possible opportunities. We analysed the trends of key terms in NUS and maize modelling using bibliometric analysis. Bibliometric analysis is a quantitative method to assess published papers and has become helpful to evaluate peer-reviewed studies in a specific field of research (Rey-Martí et al., 2016; Small, 1973). The bibliometric analysis examines secondary data acquired on a digital database from a quantitative and objective perspective (Albort-Morant and Ribeiro-Soriano, 2016). Also, such analysis can help to structure the evolution of a focal research area (Cobo et al., 2011; Klavans and Boyack, 2006). In this study, we used VOSviewer software as a tool to perform the key term analysis and network visualisation of relevant literature for articles relating to the modelling of NUS and maize crops. We used titles and abstracts from145 and 1 807 articles from the Web of Science databases retained after screening exercise to do the analysis.

In addition to the information captured by the systematic review, this phase also used literature known and found relevant by the co-authors but not captured by the searches and covered both grey and academic literature. Therefore, this phase of the methodology also served as a sanity check of the outputs of the systematic review. Such a synthesis allowed the inclusion of other literature not picked up by the search. The identification of literature was made on the basis that authors are experts in both NUS eco-physiology and have contributed significantly to modelling NUS.

To adequately address the research objectives, we presented the review as two sections. The first section of the review explores the progress in modelling NUS and highlights gaps and opportunities in model initiatives. The objective of this section was to showcase the key attributes of models for NUS, which also best exemplify their potential to deliver on creating data to expand the current knowledge base. We also detailed the challenges and drawbacks in crop model development and simulation. The second section discusses possible opportunities and considerations that exist to advance crop modelling and knowledge creation for NUS.

2.3 Results and Discussion

2.3.1 Literature characteristics

Overall, when comparing the current body of knowledge on modelling NUS with that of maize, the results of the search showed that it was considerably small (**Table 2.2**). Articles on modelling maize (a single crop specie) constituted 0.7% of published maize articles while those for NUS (an ensemble of several crop species) represented 0.3% of published articles on NUS. The ensemble of NUS identified by the literature search covered a wide range of crop types, including cereals (sorghum, teff and millet), legumes (pigeon pea, bambara groundnut, cowpea, velvet bean and lablab), root and tuber crops (sweet potato, cassava, yam and taro) and African leafy vegetables (amaranth). These crop species represent 13 out of the 29 priority crops outlined by Mabhaudhi et al. (2017). Sorghum and millet had the largest share (44 and 20%, respectively) of articles on modelling. The geographical spread for the modelled NUS comprised 24 countries, most (14) of which were in Africa (South Africa and Ethiopia) (Table 2). Two studies presented multi-county experiences (Akinseye et al., 2017; B Sultan et al., 2019). The prominence of modelling work emerging out of South Africa and Ethiopia confirms reported efforts by these countries with regards to incorporating NUS into their agricultural strategies.

Results of literature search also showed that most of the modelling initiatives were done using generic crop models with well-established sub-models (**Table 2.2**). These sub-models consider the interdependency of physiological processes and responses to a range of management levers and growth factors. These generic crop models have evolved from a few landmark models such as CERES, EPIC and SUCROS (Muller and Martre, 2019). AquaCrop was the most versatile crop model as it has been used for most crop types (cereals, legumes, root and tuber, and leafy vegetables) (**Table 2.2**). ASPIM and CERES have also been used widely (20% of the identified articles) but mainly on a handful of underutilised cereals (sorghum and millet) and legumes (pigeon pea, cowpea and lablab). It is also worth noting that among the modelled NUS, sorghum has received the most attention having been calibrated and applied for models such as ALMANAC, APSIM, AquaCrop, CROPSYST, DSSAT, EPIC, SORKAM and STICS. The reviewed articles show that specific simulation models have been developed for crops such as sorghum (SORKAM), bambara groundnut (BamGRO).

From the survey of 232 papers published on modelling NUS, researchers considered a wide range of issues (**Figure 2.1**). These included the effects of planting date (Ahmad et al., 2016), water-use efficiency (Chimonyo et al., 2016b, 2016c; Steduto and Albrizio, 2005), nitrogen-use efficiency (Amouzou et al., 2019), phosphorus-uptake (Adam et al., 2018), solar radiation (Albrizio and Steduto, 2005; Mithra et al., 2013), yield gaps (Steinbuch et al., 2016; Van Loon et al., 2018; Visses et al., 2018) planting densities (Karunaratne et al., 2010; Knezevic et al., 1999; Mauget et al., 2020), soil carbon dynamics (De Vries et al., 2012; Meki et al., 2013; Srinivas et al., 2020), growing crops in marginal environments (El-Sharkawy et al., 2014; Mabhaudhi et al., 2014; Nanaiah and Rakshit, 2020; Perkins et al., 2011), cultivar responses (Akinseye et al., 2019; Alagarswamy et al., 1998; El-Sharkawy et al., 2014; Rankine et al., 2015) and impacts of and adaptation to climate change (Nuttall et al. 2012; Phelan et al. 2014). Sorghum had most of the themes identified, followed by millet and cowpea (**Figure 2.1**). The observed large number of themes is consistent with the number of articles on modelling sorghum. The geographic importance of sorghum makes it underutilised as it has a high economic value in northern and western Africa but remains a minor crop in central and southern Africa (Leff et al., 2004). Also, the advancements in sorghum modelling are attributed to its inclusion in global research initiatives as an alternative biofuel and fodder crop for maize, especially under climate risk (Sinnathamby et al., 2017). Sorghum is also one of ICRISAT's mandate crops (Upadhyaya et al., 2017b, 2017a).

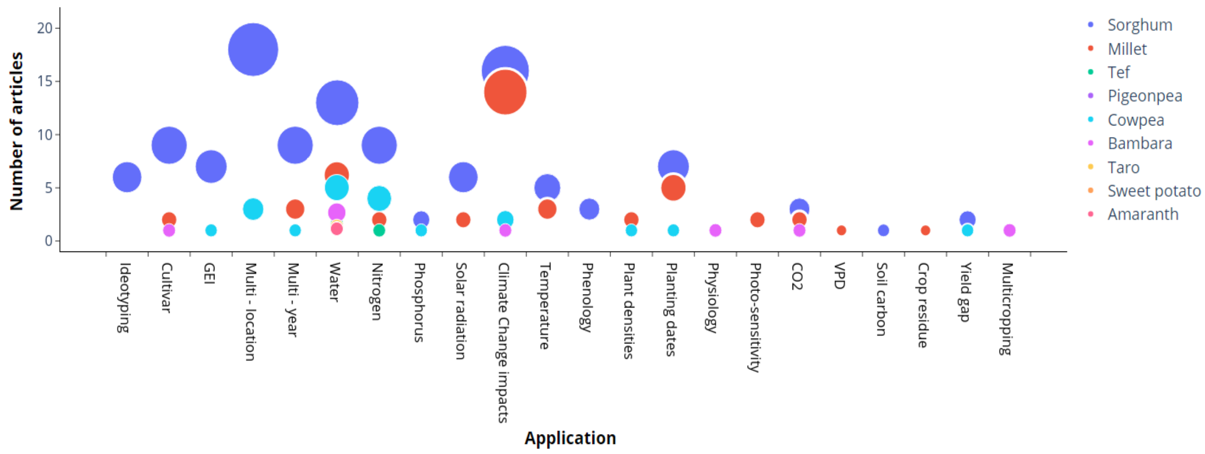


Figure 2.1: Overview of model application across the identified neglected and underutilised crop species. The size of the bubble corresponds with the number of articles identified. VPD = vapour pressure deficit; GEI = genotype-environment interactions.

2.3.2 Progress in modelling NUS: challenges and opportunities

Out of the 75 crop and plant growth models identified by Di Paola et al. (2016), we identified 25 crop models that have been calibrated and/or validated for NUS (Table 2). This number is low considering that the spread is across 13 crop species, and when compared with major crops, e.g. maize (Kogo et al., 2019), potato (Raymundo et al., 2014) and soybean (Di Paola et al., 2016), that have more than 20 crop models each that simulate growth, resource use and yield. The limited number of NUS models restricts the applicability of the models for spatial and temporal impact assessment studies. For instance, Asseng et al. (2015) noted that simulated climate change impacts vary across models owing to differences in model structures and parameter values. The authors concluded that the uncertainties in impact modelling could be better quantified and minimised using multi-model ensembles. This notion was also supported by Hao et al. (2020) who stated that combined predictions from an ensemble of models can produce a more reliable mean forecast and reduces the risk of reporting a false-negative finding (Type II error). The limited number of capable models for NUS reflects a limited investment in NUS R&D more generally and specifically apathy towards their model.

Di Paola et al. (2016) and Raymundo et al. (2014) showed how crop model and module improvements have often resulted in the development of new models. For models used for NUS, the number of publications on improvements is relatively small. For instance, a canopy algorithm improvement of the MADHURAM model for sweet potato has led to the SPOTCOMS model (Somasundaram and Mithra, 2008). For bambara groundnut, the PARCH (Predicting Arable Resource Capture in Hostile Environment) model (Bradley and Crout, 1993) initiated the concepts of modelling bambara groundnut from an adaptation of CROPGRO and BAMnut (Bannayan, 2001) and BAMFOOD project models (Cornelissen, 2005). Consequently, many sorghum models share a similar structure with some changes (**Table 2.2**). In some cases, researchers modified the code to create versions of crop models. Still, such efforts are often complicated by the design of the models themselves and the lack of adequate documentation in some cases.

According to Jones et al. (2017), model development and use, after that, has been driven or motivated by the need to increase scientific understanding and to support or inform decision/policy formulation. Model development to advance scientific knowledge often occurs to address research questions regarding the quality, quantity, magnitude, and interactions. Such endeavours are evident in **Figure 2.2** where themes within maize modelling speak to an array of research areas of interest such as scale (spatial and temporal), resource use (water, nitrogen, phosphorus and solar radiation) and use efficiencies (water use efficiency), system optimisation, climate change impacts, scenario analysis, data and model performance, and decision making. Then again, the focus across NUS modelling articles (Figure 3) is limited to a few key research themes that are mostly related to agronomy. What seems to be lacking are thematic areas relating to environment and policy dimensions, and 'big picture issues' such as crop system optimisation, spatial and temporal assessments on climate impacts, and genotype by environment by management interactions. The limited research scope confirms previous reports that identify the lack of an articulated research agenda (Mabhaudhi et al., 2017a) and low research incentives (Mayes et al., 2012) possibly emanating from misalignments with international, regional and national policies. Conversely, models are useful in generating data for evidence-based policy formulation. If model development is motivated primarily by academic and research outcomes, crop models might remain only loosely connected to user needs.

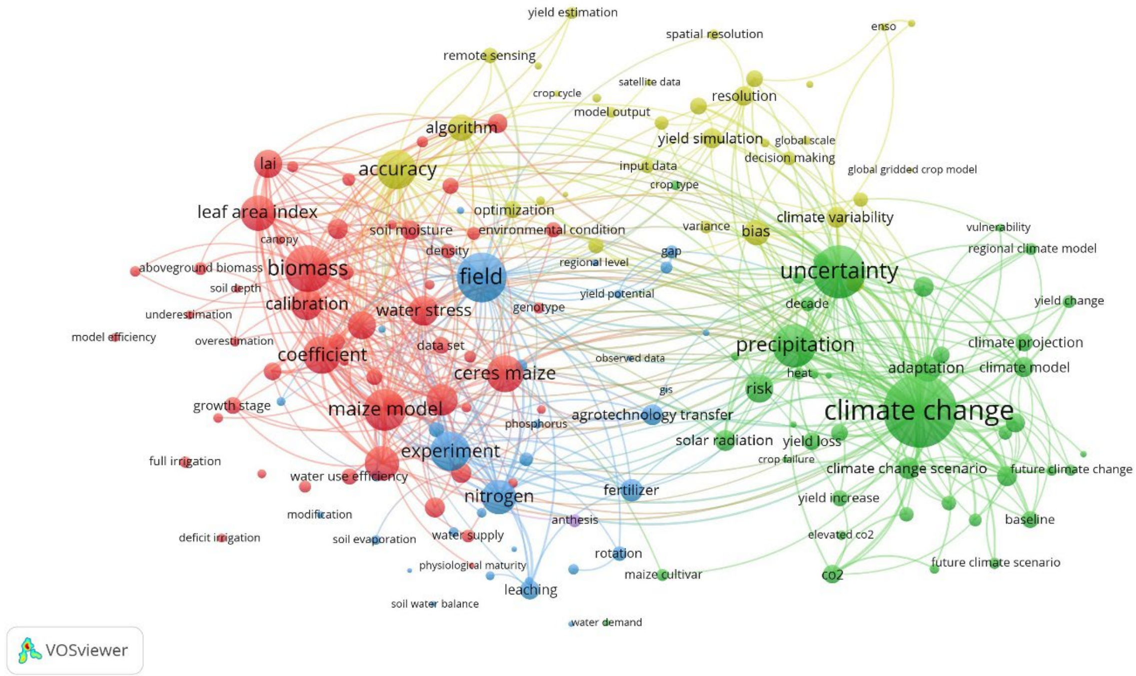


Figure 2.2: Visualization of thematic areas assessed across 1829 research articles on modelling activities for maize (Zea mays L.) using VOSviewer. The network map designated NUS modelling studies into three thematic areas namely climate change impact modelling (green), model development (red), model performance (blue), model optimisation and hybridisation (yellow).

Beyond the efforts highlighted in **Table 2.2**, there is little evidence of uptake and application of models for NUS. An example is AquaCrop, where the calibration of several NUS has occurred, but there has been limited follow-up research on the application of the calibrated models. In the case of bambara groundnut, Mabhaudhi et al. (2018) applied a previously calibrated and validated AquaCrop model to evaluate the impacts of climate change on yield and water productivity. The lack of follow-through is also evident in that the model still does not include NUS crop files in its data folder. This could be due to inadequate knowledge sharing amongst crop model developers, modellers and policymakers. When we say policymakers, we are not just referring to government agencies but a broader network of actors that formulate a course or principle of action for agriculture innovation. Another bottleneck to modelling

NUS may be related to the lack of validated empirical information and data sets for NUS (Chivenge et al., 2015). For most of the major crops, modellers have been able to tap into existing global databases from spatial and temporal trials (**Figure 2.3**). Experimentation on NUS continues to be descriptive and not nomothetic, limiting the ability of crop modellers to develop well calibrated models (Chivenge et al., 2015).

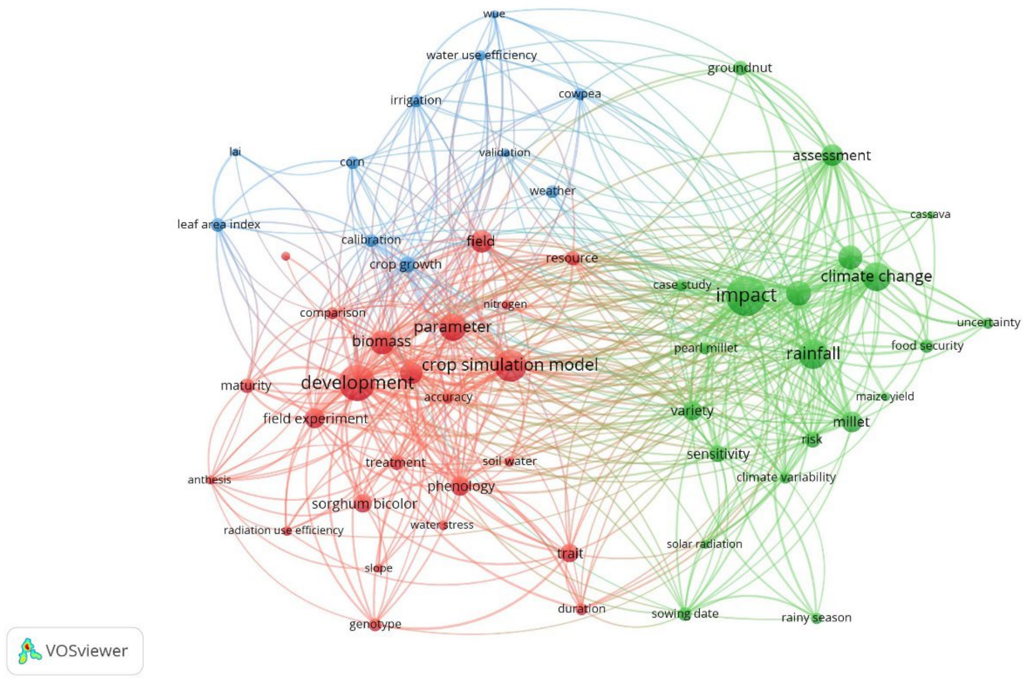


Figure 2.3: Visualization of thematic areas assessed across 231 research articles on modelling activities for neglected and underutilised crop species (NUS) using VOSviewer. The network map designated NUS modelling studies into three thematic areas, namely climate change (green), model development (red) and model performance (blue).

Table 2.2: Overview of selected neglected and underutilised crop species, models used to simulate crop growth and productivity, level of application, and the region where the simulations were performed.

Crop	Model	Level	Country/region	Reference
Sorghum	ALMANAC	Application	USA	(Xie et al., 2003a) (Xie et al., 2003b)
	APSIM	Calibration and application	India	(Dimes and Revanuru, 2004)
		Application	Zimbabwe	(Ncube et al., 2009)
		Application	USA	(Truong et al., 2017)
		Calibration and application	South Africa	(Chimonyo et al., 2016a)
		Application	Ghana	(McCarthy and Vlek, 2012)
	AquaCrop	Calibration	-	Steduto and Raes, 2012
		Calibration	South Africa	(Hadebe et al., 2017)
		Calibration	USA	Araya et al., 2016
		Calibration	USA	(Kahsay et al., 2018)
	CROPSYST	Calibration and application	Kenya	(Muli, 2015)
	SORKAM	Calibration	Cameroon	(Tingem and Rivington, 2009)
	EPIC	Calibration and application	USA	(Niu et al., 2009)
	STICS	Calibration and application	France	(Constantin et al., 2015)
	DSSAT	Application	Italy	(Castrignanò et al., 1997)

		Calibration and application	Mali and Burkina Faso	(Akinseye et al., 2017)
		Calibration	USA	Lopez et al. 2017
		Calibration and application	Benin	(Amouzou et al., 2019)
		Calibration and application	Brazil	(Amaral et al., 2014)
Tef	AquaCrop	Calibration	Ethiopia	(Van Gaelen et al., 2015)
		Calibration	Ethiopia	(Tsegay et al., 2015)
		Calibration	Ethiopia	(Araya et al., 2010)
	DSSAT	Calibration and Application	Ethiopia	(Paff and Asseng, 2019a, 2019b)
Pearl Millet	AquaCrop	Calibration	South Africa	(Bello and Walker, 2016)
	APSIM	Application	Sahel	(Akponikpè et al., 2010; Boubou Diallo et al., 2019)
	DSSAT-CERES	Application	Pakistan	(S Ahmad et al., 2016; Santos et al., 2017; Ullah et al., 2019)
	SARRA-H	Calibration and application	Senegal, Mali, Burkina Faso and Niger	(Guan et al., 2015; Sultan et al., 2019)
	EPIC	Calibration and application	Nigeria	(Adejuwon, 2006)
	CYGMA	Calibration and application	West Africa	(Sultan et al., 2019)
Pigeon pea	APSIM	Application	Zimbabwe	(Ncube et al., 2009)

		Calibration and Application	Malawi	(Smith et al., 2016)
Bambara groundnut	AquaCrop	Calibration	UK	(Karunaratne et al., 2010)
		Calibration	South Africa	(Mabhaudhi et al., 2018)
	BAMGRO	Calibration	UK	(Karunaratne et al., 2010)
	CROPSYST	Application	Cameroon	(Tingem et al., 2008)
Cowpea	APSIM	Calibration and application	South Africa	(Chimonyo, 2016)
	DSSAT – CROPGRO	Calibration and application	Malawi	(Ngwira et al., 2014)
		Calibration	Brazil	(Lima Filho et al., 2013)
	AquaCrop	Calibration and application	-	(Nunes et al., 2019)
	INTERCOM	Calibration	-	(Wang et al., 2007)
Velvet bean	DSSAT – CROPGRO	Parameterization	Mexico	(Hartkamp et al., 2002)
Lablab	APSIM	Calibration and application	Australia	(Hill et al., 2006)
Taro	AquaCrop	Parameterization	South Africa	(Mabhaudhi et al., 2014a)
	AquaCrop	Calibration and application	South Africa	(Walker et al., 2013)
Sweet potato	AquaCrop	Parameterization	Caribbean	(Rankine et al., 2015)
		Calibration and application	South Africa	(Beletse et al., 2012)
	MADHURAM	Calibration		(Somasundaram and Mithra, 2008)
	STOPCOMS			(Somasundaram and Mithra, 2008)
Amaranthus	AquaCrop	Calibration and application	South Africa	(Bello and Walker, 2017)

		Calibration and application	South Africa	(Nyathi et al., 2018)
	SALTMED	Calibration and application	Italy	(Pulvento et al., 2015)
	LINTUL	Calibration and application	Austria	(Gimplinger and Kaul, 2012)
Cassava	EPIC	Application	Cambodia	(Le et al., 2018)
		Calibration	Nigeria	(Adejuwon, 2006)
	CROPSIM Cassava	Calibration and Application	Thailand	(Kumsueb and Jintrawet, 2020)
	DSSAT CROPSIM Cassava	Calibration and Application	Thailand	(Kumsueb and Jintrawet, 2020)
	SIMCAS	Calibration and Application	Indonesia	(Masithoh and Yuliyanda, 2019)
		Calibration and Application	Brazil	(Araujo et al., 2018)
	DSSAT-MANIHOT	Application	Colombia	(Moreno-Cadena et al., 2020)
	LINTUL	Calibration and Application	Togo	(Ezui et al., 2018)
Yam	CROPSYSTVBYam	Application	United States of America	(Raymundo et al., 2014)
		Calibration and Application	France	(Marcos et al., 2011)
	EPIC-Yam	Calibration and Application	Germany	(Srivastava et al., 2012, 2016; Srivastava and Gaiser, 2010)

2.4 Way forward

Current food systems have contributed to observed environmental and socio-economic challenges, especially in marginalized communities (Rosegrant et al., 2014). The emphasis on a few economically important crop species has resulted in increased risk from climate variability and change, and economic volatility (Bedoussac et al., 2015) as well as an increase in vulnerability of marginalised communities. According to Jones et al. (2017) and the Royal Society (2014), policy shifts and operationalisation of research agendas on NUS (e.g. Mabhaudhi et al., 2017a) can only occur after a need presents itself. In the wake of the challenges mentioned above, the current need to transform agricultural systems has created a window of opportunity for advancing NUS modelling. Thus, there is a need to tap into available tools to promote the development of models with the capability to simulate growth, yield and resource use for a broader range of NUS. Numerous crop models have been developed, with different levels of detail, sophistication, scale and representativeness. Crop modelling requires reliable experimental data to describe plant processes accurately. For most of the major crops, crop modellers have been able to tap into existing global data sets from long term trials. Hence, another bottleneck to modelling NUS may be related to the lack of empirical information and available long-term data sets for NUS hence limiting the ability of crop modellers to develop well calibrated models for NUS. Furthermore, in most cases, there are no bred varieties of NUS, but rather a wide range of landraces with different characteristics, which presence a challenge when developing conservative crop coefficients needed to drive crop models. The incomplete and scattered nature of information on NUS has been cited as an obstacle to their modelling (Modi and Mabhaudhi, 2017).

The history of model development indicates that many existing models are a result of questions formulated based on scenarios and then adapted to address user needs. As reiterated by Jones et al. (2017), having one “perfect” model cannot capture the level of diversity within the full suite of crops used in agriculture. Instead, the aim should be to develop component/modular models that can be used alone or in tandem to answer specific questions (such as when to apply a climate change response or management option). The fundamental structure of models – climate, soil and management modular structures – are easily transferable; however, the integration of biophysical and economic models (i.e. bioeconomic models) is required to address socio-economic issues.

2.4.1 Closing the gap in NUS modelling

Cropping systems are characterised by complexity and variability (Keating and Thorburn, 2018; Thornton et al., 2018). This complexity comes from the inherent multifaceted processes that drive the interactions within the plant, soil and atmosphere continuum (Keating et al., 2010). The combined interactions produce an infinite set of outcomes that are inherently dynamic in both space and time (Keating and Thorburn, 2018). This complexity tends to be more pronounced in NUS, as most of them exhibit wide within-species genetic variability compared to well-developed major crops (Mabhaudhi et al., 2016).

Crop models often require a significant amount of input data (Adam et al., 2011; Brown et al., 2014; Wang et al., 2013). Besides the management levers, which vary based on the model objectives, crop models require soil and weather data to drive phasic development. Modellers need these input parameters in a range of temporal (hourly, daily, weekly or monthly) and spatial (point, field, catchment, regional) scales. In addition to biophysical data, models also require information on crop physiology and morphology. The number of parameters and rigour used to obtain data for parameterisation often limits model usefulness for research. The biggest challenge met by many researchers working on NUS has been the absence of detailed description of these interactions and hypotheses such that it has been challenging to adapt the current suite of crops in existing many crop models. This gap in understanding is due to the lack of data to construct the biophysical processes governing the plants within the models. According to Jones et al. (2017), most crop models have been established using relatively narrow ranges of data. The limited data could be because most modellers, in the absence of crop physiologist and ecologists, have collected their own data sets to develop a model. To address the challenges of data availability and quality for NUS, the subsections below describe several opportunities to improve data availability.

2.4.2 Mapping NUS genomics

The advances in genomics, phenomics (phenotyping), and computational technologies within the last century have allowed plant scientist to understand the constructs of a given crop phenotype (Blancon et al., 2019). These insights have seen the unpacking of complex interactions among crop types, crop varieties, biophysical environment, and management (Cooper et al., 2014). Genomic studies of many NUS are still in their infancy with a limited number of known improved cultivars. The lack of data has resulted in gaps in the knowledge base regarding eco-physiology, resource use and yield potential of NUS. Then again, Washburn et al. (2020) suggested that the integration of molecular phenotypes, machine learning, and physiological crop models could enable accelerated progress in predictive breeding for maize. Chapman (2008) used crop models to understand genotype by environment expressions for drought in real-world and simulated maize breeding trials. Also, Chenu et al. (2009) applied a gene-to-phenotype modelling approach to understand yield Impacts of organ-level quantitative trait loci associated with drought response in maize. In this regard, crop models may well offer a solution to consolidating available information on NUS genomics and addressing some of the knowledge gaps. Then again, genetics and genomics offer avenues to reduce model uncertainty by improving descriptions of cultivar differences and of individual plant processes (White, 2009). As such, some information of NUS genetics and genomics is required to advance their modelling.

There are two schools of thought about advancing information on NUS genomics for modelling. One side of the discussion suggests it is instructive to look back at historic genomic studies of related crops and use these as a framework to construct crop modules in generic models (see for example Chivenge et al., 2015 and Mabhaudhi et al., 2017b). On the other hand, some researchers believe there is a need to promote genetic studies of NUS to understand better gene expression and responses. The latter has been met with a considerable amount of resistance from researchers owing to the wide genetic diversity within a single collection or population of most NUS species. Then again, during the last 30 years, the progress in mapping genomes of major crops has been impressive. Taking maize as an example, Washburn et al. (2020) noted that since 1998 the U.S.A. National Science Foundation's Plant Genome

Research Program has invested sequence the maize genome. The results of these investments culminated in the development and use of a novel clone-by-clone approach to sequence the genome of the maize inbred B73 (Washburn et al., 2020). Such technological advances in performing genomic analyses on plants have also led to rapid and inexpensive genotyping that resulted in significant changes in breeding and understanding the underlying response of specific genes to crop physiology and morphological responses to the environments. The potential value of this molecular genetics information includes the enhancement of the ability of crop model to predict the performance of crop varieties under specific climate and management conditions.

2.4.3 Mapping the underlying eco-physiology in NUS

The principles of system dynamics have been around for decades, and the empirical nature of most crop models represent this. Building on the experience in designing the model GECROS, Yin et al. (2010) suggested that model developers could make models less empirical if they employed existing physiological understanding and mathematical tools. This rhetoric is continuing from research that believes that the genetic fundamentals of NUS genomics can be studied with greater ease by using existing examples. On the other hand, to address gaps in knowledge on function-ecophysiology, resource use and crop responses to climate extremes for NUS the use of Functional-structural plant models (FSPM), or virtual plant models can be employed (Liu et al., 2017). Functional-structural plant models are models that explicitly describe the development of the 3D structure of plants over time as influenced by physiological processes (Sievänen et al., 2014). As such, it allows for a hierarchical and systematic representation of a plant in response to environmental factors (Cartenì et al., 2014; Chelle, 2005; Sievänen et al., 2014)). Therefore, FSPM framework considers that plant response to the environment is a function of eco-physiological adaptation (e.g. photosynthesis, transpiration, N allocation) but often also their structure (e.g. breaking buds or keeping buds dormant, shape and orientation of organs), which, in turn, modifies the condition (e.g. light) in which functions operate (Sievänen et al., 2014). Thus, feedbacks within and between components are expressed at the level of an individual organ (the ‘local level’), and the functioning of the plant or plant stand as a whole (the ‘global level’) (Cartenì et al., 2014). Therefore, FSPM explicitly allows the feedbacks between the structure and function of complex NUS species to be captured with much ease.

2.4.4 NUS phenology

There is considerable pressure to increase the yield potential of NUS because the current yields in farmers' fields are far below that of their counterparts, which are already approaching the ceiling of existing cultivars (Cassman, 1999; Fischer, 2007). In the face of water scarcity and pressure to reduce environmental pollution arising from extensive homogenous production systems, improving use efficiencies of various resources through sustainable intensification has been receiving attention in agriculture (see for example Lipper et al. (2014)). There is a need to assess relevant traits within NUS that are related to agricultural production. However, many of these traits are quantitative and complex. For instance, phenotypes at the crop level, irrespective of yield per se or resource use efficiencies, are regulated by multiplicative interactions of genes and final expression is often dependent on environmental conditions, stress factors and stage of development. Also, multiple intermediate component processes and coordinated feedback mechanisms and intra- and interplant competition affect the outcome. Because of this interaction, a change of one component may result in an often-unexpected consequence on other parts and finally yield of a crop. As for cereal yield, crop physiologists and agronomists have used the simple equation that considers yield components to analyse limitations to yield formation (Van Ittersum et al., 2016). Similar equations were derived for other crops and traits; however, in the case of NUS, applying such a simple equation might be difficult because of the broad diversity present within and across crop species. Also, the equation assumes that the series of interactions and feedbacks occur along a crop developmental cascade. Because NUS generally have a poorly developed research agenda, breeding out of indeterminacy has not yet happened meaning many of them may have several phenological processes occurring at a given time. It thus follows that; a significant increase of one component may not necessarily increase crop yield ha^{-1}. The results of Yin et al. (2000a) indicate that analysing genotype-phenotype relationships requires more robust crop models than make conventional agricultural applications.

2.4.5 The role of Information and Computer Technologies and data management

The history of crop science shows that when different disciplines join forces, significant advances can occur. For instance, when crop modelling and remote sensing scientists collaborated to create models for predicting global wheat yield in the 1970s (Kasampalis et al., 2018) or to advance sustainable intensification through precision agriculture (Kasampalis et al., 2018). There is a need to broaden and strengthen the collaboration among biophysical modellers, engineers and agricultural practitioners and policymakers to come up with dynamic strategies to modelling NUS. Many of the collaborative initiatives such as the Agricultural Model Intercomparison and Improvement Project (AgMIP), the CGIAR Platform for Big Data in Agriculture (launched in 2017), as well as other initiatives for dataset standardization have emerged from the need to address global challenges. Such initiatives understand the need to increase agrobiodiversity for sustainable food systems. Researchers working on modelling NUS can leverage on these collaborative initiatives; however, additional investments are needed to improve the collection of open access, easy to use data for NUS modelling purposes.

How agriculture is contributing to rural development is undergoing a new and rapid change due to the need for transformative technologies, awareness of globalization and advancements in ICT. Information and Computer Technology can address the challenge of generating new and relevant data on NUS for crop modelling. Techniques such as the Internet of Things, Cloud Computing and large-scale phenotyping methods such as using remote sensing with drones (unmanned aerial vehicles), nanosatellites and planned satellite missions), can leverage this development and introduce artificial intelligence in NUS data value chain (Basse et al., 2014). The main advantages from incorporating remote sensing data into crop models are the representation of the missing spatial information of the latter and the more accurate description of the crop’s actual condition along various stages of the growing season (Kasampalis et al., 2018). This, while being moderated by Big Data, can ensure that massive volumes of data with a wide variety are captured analysed and used to build and simulate NUS in existing or new crop models.

Crop models require parameters that contribute to mechanistic and functional components within the framework. While these parameters may differ based on the needs of the model and modeller, there are generic parameters that speak to the technical attributes of most models. Several databases have been generated, and these are somewhat accessible for use. In many cases, direct access of yield data for many commercially important crops is available through national statistics bureaus websites, FAO/IFPRI/SAGRE agro-maps (FAO/IFPRI/SAGRE, 2006; http://kids.fao.org/agromaps/) or retrieved by agronomists from their local statistical bureaus or institutions. Unfortunately, yield data for most NUS is available in grey literature and is not readily accessible. This gives a false sense of confidence about data quality, especially for many developing countries where reporting of yields, in general, is not well developed. There is a need to create and harmonise standards and protocols for data collection for NUS. This harmonisation ensures there is access and use from the same sources of data "in the cloud" from multiple sources and to operate various models, knowledge products, and decision support systems. It is essential to have different models and approaches, but we need to develop standards and protocols to gain the benefits from these developments fully.

2.5 Considerations for informing the modelling of NUS

There are several crop models in existence, and these differ in the level of complexity which ranges from relatively simple empirical relationships (i.e. rule-based yield equations using climate and soils data) to complex mechanistic models. Several reviews have summarised crop model capabilities and use. For instance, Jones et al. (2017) and Antle et al. (2017) discussed a possible option for designing next-generation by assessing capabilities and limitations of existing models relative to "Use Cases". Chimonyo et al. (2015) and Gaudio et al. (2019) reviewed opportunities for modelling annual crop mixtures. Holzworth et al. (2015) discussed status and prospects in software capabilities, and applications of crop models for overtime to inform climate change adaptation and mitigation. Jin et al. (2019) provided a detailed overview of the latest developments and applications of crop models, and data assimilation remote sensing techniques. While these reviews and others have offered sufficient critic on capabilities and uses, very few have provided an in-depth assessment of the considerations made during model selection. Such information is essential if this is to guide the use of current models on NUS. Although many factors have motivated the development of crop models, three characteristics stand out among them: 1) intended use of models, 2) approaches taken to develop the models, and 3) their target scales. In this section, we provide a systematic overview of factors to consider when selecting a crop simulation model. To overcome the challenges established by the literature review, **Table 2.3** provides an overview of considerations that need to be made to increase the use of models for NUS.

2.6 Conclusion

The use of crop models for understanding growth, productivity and resource use in NUS is still in its infancy with a limited number of articles published. There is an urgent need for more significant investments in NUS research and development to increase their knowledge base. This should also be accompanied by the development and or improvement of crop models capable of modelling NUS. This calls for a paradigm shift with regards to how research is currently prioritised and funded, a system that has favoured the major crops that are aligned to industrial agriculture. As such, policymakers need to transform policy-making processes that support research and promotes more collaborations across different fields in crop modelling. This ensures that modelling research on NUS can also inform policy and that there are co-creation and co-development of crop models for NUS.

The review highlighted significant challenges to advancing modelling NUS, and this included data availability and accessibility. Other challenges included the large agrobiodiversity present within NUS. The limited data availability and the large ensemble of NUS make it challenging to develop conservative crop coefficients needed to parameterise crop models as well as, to an extent, misalignment in research priorities. To bridge the gaps in data availability and accessibility, the use of pre-existing crop databases, the use of Functional-structural plant type models, data value chains and ICT, and promoting research collaborations should be used for NUS. Also, GIS and remote sensing can be integrated into crop models to collate high-resolution data.

Table 2.3: Considerations for crop model selection

Consideration	Description	Key feature/requirements	Comment
Modelling and model goals	The first criterion when choosing a crop model should be the main purpose of applying it.	Simulate plant growth and development, biophysical processes, resource use and management, inter-plant competition and climate change impacts	For NUS, one of the primary research objectives is to develop production guidelines for mainstreaming them into the existing cropping system. Hence, the selected crop model should be able to simulate various management levers and more importantly, climate variability and change scenarios to address some of the existing knowledge gaps on NUS
	A model's goal should inform on what function the model is to perform and what degree of accuracy is required in the model outputs	Simulate plant growth and development, biophysical processes, resource use and management, inter-plant competition and climate change impacts	For NUS, crop models should consider the multiple aspects of climate change drivers (including rainfall, atmospheric CO2, temperature and ozone) while capturing the main crop physiological processes as well as biophysical aspects of the crop-soil-atmosphere

			systems to address production and natural resource management issues.
Model availability	The essential aspect to consider is whether the selected model is freely available for use. Not all crop models are freely available. Based on 70 models reviewed by Di Paola et al. (2016), only 29 are freely available	Most established models can be downloaded free of charge	The use of generic crop models can allow for several NUS to be calibrated for specific cultivars under specific environments
Mode type	The complexity, degree of detail, level of comprehensiveness and the scale of application (specific cultivar, field, catchment, region) of crop models differ.	Models can be described as either simple empirical type or complex mechanistic models.	Mechanistic crop models exhibit increased robustness
	Most models are "source-driven", thus assume growth is limited by factors that drive the production and partitioning of assimilates	Growth engine can be either carbon-driven (WOFOST), solar radiation-driven (APSIM) and water-driven (AquaCrop)	Across sub-Saharan Africa, current projections of climate change indicate an increase in atmospheric CO_2 concentration and weather extremes such as heatwaves, droughts and floods. It is in this context of expected

			climate change impacts and climate change adaptation that carbon-, solar radiation and water-driven models should be considered
System boundaries	Predictive capabilities are generally most robust within the boundaries of the data used to develop a model	To rely on a model's output for decision-making purposes, it is vital to use a model that is not "built on oversimplified and unrealistic assumptions about natural processes."	
Model input	Model complexity increases with the number of input parameters required by the model	A model's descriptive or predictive ability depends on the quality of the data used to populate it.	As shown by Asseng et al. (2013), the number of cultivar-specific parameters ranged from 2 (e.g. AquaCrop) to 22 (GLAM)
Spatialisation	The Impacts of climate variability and change on the agricultural system are interrelated, with cascading and interchanging biophysical layers of air, water,	To run the models non-stop and at a regional and national level	NUS have been produced and studied in a few agro-ecologies, where the temporal drivers for their growth and production operate at much smaller

	soil and crops at spatial and temporal scales		resolutions than courser scale at which most crop models are presented
Model output	Outputs generated by the model allow the user to fully answer and analyse the questions or objectives of the modelling exercise		
Intersectionality	Intersectionality refers to how different processes within the model interact to create a distinct outcome based on different management levers	The model needs to include the representation of several physiological processes to describe or predict outcomes	

There are several crop models in existence; however, not all of them can be used to advance the knowledge base for NUS. Several factors must be considered, notably, the model and modelling objectives, model input and outs, and spatialization. The use of current crop models requires an understanding of their strengths and weaknesses and knowing when to apply them for maximum benefit. Therefore, future progress in modelling NUS should be achieved by consulting experts and key stakeholders for developing and improving more robust and versatile models.

2.7 References

Adam, M., Dzotsi, K.A., Hoogenboom, G., Traoré, P.C.S., Porter, C.H., Rattunde, H.F.W., Nebie, B., Leiser, W.L., Weltzien, E. and Jones, J.W., 2018. Modelling varietal differences in response to phosphorus in West African sorghum. European Journal of Agronomy, 100, pp.35-43. doi:10.1016/j.eja.2018.04.001

Adejuwon, J.O., 2006. Food crop production in Nigeria. II. Potential effects of climate change. Climate Research, 32(3), pp.229-245. https://doi.org/10.1071/CP15226

Adejuwon, J.O., 2006. Food crop production in Nigeria. II. Potential effects of climate change. Climate Research, 32(3), pp.229-245. doi:10.3354/cr032229

Adhikari, L., Hussain, A. and Rasul, G., 2017. Tapping the potential of neglected and underutilized food crops for sustainable nutrition security in the mountains of Pakistan and Nepal. Sustainability, 9(2), p.291. doi:10.3390/su9020291

Ahmad, S., Hussain, S., Fatima, Z., Abbas, G., Khan, M.R., Younis, H., Naz, S., Sohail, M., Ajmal, M., Abbas, N. and Akhtar, M., 2016. Application of DSSAT Model for Sowing Date Management of C 4 Summer Cereals for Fodder and Grain Crops under Irrigated Arid Environment. Pakistan Journal of Life & Social Sciences, 14(2).

Akinseye, F.M., Adam, M., Agele, S.O., Hoffmann, M.P., Traore, P.C.S. and Whitbread, A.M., 2017. Assessing crop model improvements through comparison of sorghum (sorghum bicolor L. moench) simulation models: a case study of West African varieties. Field Crops Research, 201, pp.19-31. doi:10.1016/j.fcr.2016.10.015

Akinseye, F.M., Folorunsho, A.H., Hakeem, A. and Agele, S.O., 2019. Impacts of rainfall and temperature on photoperiod insensitive sorghum cultivar: model evaluation and sensitivity analysis. Journal of Agrometeorology, 21(3), pp.262-269.

Akponikpè, P.I., Gérard, B., Michels, K. and Bielders, C., 2010. Use of the APSIM model in long term simulation to support decision making regarding nitrogen management for pearl millet in the Sahel. European Journal of Agronomy, 32(2), pp.144-154. doi:10.1016/j.eja.2009.09.005

Alagarswamy, G., Reddy, D.M. and Swaminathan, G., 1998. Durations of the photoperiod-sensitive and-insensitive phases of time to panicle initiation in sorghum. Field Crops Research, 55(1-2), pp.1-10. doi:10.1016/S0378-4290(97)00039-7

Albort-Morant, G. and Ribeiro-Soriano, D., 2016. A bibliometric analysis of international impact of business incubators. Journal of Business Research, 69(5), pp.1775-1779.

Albrizio, R. and Steduto, P., 2005. Resource use efficiency of field-grown sunflower, sorghum, wheat and chickpea: I. Radiation use efficiency. Agricultural and Forest Meteorology, 130(3-4), pp.254-268. doi:10.1016/j.agrformet.2005.03.009

Amaral, T.A., Andrade, C.L.T., Hoogenboom, G., Silva, D.F., Garcia, G.Y. and Noce, M.A., 2015. Nitrogen management strategies for maize production systems: Experimental data and crop modeling. International Journal of Plant Production, 9(1), pp.51-74.

Amouzou, K.A., Lamers, J.P., Naab, J.B., Borgemeister, C., Vlek, P.L. and Becker, M., 2019. Climate change impact on water-and nitrogen-use efficiencies and yields of maize and sorghum in the northern Benin dry savanna, West Africa. Field Crops Research, 235, pp.104-117. doi:10.1016/j.fcr.2019.02.02

Araújo, A., Marinho, W. and De Araújo Gomes, A., 2018. A fast and inexpensive chemometric-assisted method to identify adulteration in acai (Euterpe oleracea) using digital images. Food Analytical Methods, 11(7), pp.1920-1926.

Araya, A., Keesstra, S.D. and Stroosnijder, L., 2010. Simulating yield response to water of Teff (Eragrostis tef) with FAO's AquaCrop model [Erratum: 2010 June 3, v. 117, no. 2-3, p. 265]. Field crops research. doi:10.1016/j.fcr.2010.03.009

Asseng, S., Zhu, Y., Wang, E. and Zhang, W., 2015. Crop modeling for climate change impact and adaptation. In Crop physiology (pp. 505-546). Academic Press. doi:10.1016/B978-0-12-417104-6.00020-0

Basse, R.M., Omrani, H., Charif, O., Gerber, P. and Bódis, K., 2014. Land use changes modelling using advanced methods: Cellular automata and artificial neural networks. The spatial and explicit representation of land cover dynamics at the cross-border region scale. Applied Geography, 53, pp.160-171. doi:10.1016/j.apgeog.2014.06.016

Bedoussac, L., Journet, E.P., Hauggaard-Nielsen, H., Naudin, C., Corre-Hellou, G., Jensen, E.S., Prieur, L. and Justes, E., 2015. Ecological principles underlying the increase of productivity achieved by cereal-grain legume intercrops in organic farming. A review. Agronomy for sustainable development, 35(3), pp.911-935. doi:10.1007/s13593-014-0277-7

Beletse, Y.G., Laurie, R., Du Plooy, C.P., Laurie, S.M. and Van den Berg, A., 2012, January. Simulating the yield response of orange fleshed sweet potato 'Isondlo' to water stress using the FAO AquaCrop model. In II All Africa Horticulture Congress 1007 (pp. 935-941).

Bello, Z.A. and Walker, S., 2016. Calibration and validation of AquaCrop for pearl millet (Pennisetum glaucum). Crop and Pasture Science, 67(9), pp.948-960. doi:10.1071/CP15226

Bello, Z.A. and Walker, S., 2017. Evaluating AquaCrop model for simulating production of amaranthus (Amaranthus cruentus) a leafy vegetable, under irrigation and rainfed conditions. Agricultural and Forest Meteorology, 247, pp.300-310. doi:10.1016/j.agrformet.2017.08.003

Blancon, J., Dutartre, D., Tixier, M.H., Weiss, M., Comar, A., Praud, S. and Baret, F., 2019. A high-throughput model-assisted method for phenotyping maize green leaf area index dynamics using unmanned aerial vehicle imagery. Frontiers in plant science, p.685. doi:10.3389/fpls.2019.00685

Boubou Diallo, M., Akponikpè, P.I., Abasse, T., Fatondji, D. and Agbossou, E.K., 2019. Why is the spatial variability of millet yield high at farm level in the Sahel? Implications for research and development. Arid Land Research and Management, 33(4), pp.351-374. doi:10.1080/15324982.2019.1625984

Caicedo-Ortiz, J.G., De-la-Hoz-Franco, E., Ortega, R.M., Piñeres-Espitia, G., Combita-Niño, H., Estévez, F. and Cama-Pinto, A., 2018. Monitoring system for agronomic variables based in WSN technology on cassava crops. Computers and Electronics in Agriculture, 145, pp.275-281.

Cartenì, F., Giannino, F., Schweingruber, F.H. and Mazzoleni, S., 2014. Modelling the development and arrangement of the primary vascular structure in plants. Annals of botany, 114(4), pp.619-627. doi:10.1093/aob/mcu074

Carter, R., Ferdinand, T. and Chan, C., 2018. Transforming agriculture for climate resilience: A framework for systemic change.

Castrignano, A., Di Bari, V. and Stelluti, M., 1997. Evapotranspiration predictions of CERES-Sorghum model in Southern Italy. European journal of agronomy, 6(3-4), pp.265-274. doi:10.1016/S1161-0301(97)00002-6

Chapman, S.C., 2008. Use of crop models to understand genotype by environment interactions for drought in real-world and simulated plant breeding trials. Euphytica, 161(1), pp.195-208. doi:10.1007/s10681-007-9623-z

Chelle, M., 2005. Phylloclimate or the climate perceived by individual plant organs: what is it? How to model it? What for?. New Phytologist, 166(3), pp.781-790. doi:10.1111/j.1469-8137.2005.01350.x

Chenu, K., Chapman, S.C., Tardieu, F., McLean, G., Welcker, C. and Hammer, G.L., 2009. Simulating the yield impacts of organ-level quantitative trait loci associated with drought response in maize: a "gene-to-phenotype" modeling approach. Genetics, 183(4), pp.1507-1523. doi:10.1534/genetics.109.105429

Chimonyo, V.G.P., 2015. Quantifying productivity and water use of sorghum intercrop systems (Doctoral dissertation).

Chimonyo, V.G.P., Modi, A.T. and Mabhaudhi, T., 2016. Simulating yield and water use of a sorghum-cowpea intercrop using APSIM. Agricultural Water Management, 177, pp.317-328. doi:10.1016/j.agwat.2016.08.021

Chimonyo, V.G.P., Modi, A.T. and Mabhaudhi, T., 2016. Simulating yield and water use of a sorghum-cowpea intercrop using APSIM. Agricultural Water Management, 177, pp.317-328. doi:10.1016/j.agwat.2016.08.021

Chimonyo, V.G.P., Modi, A.T. and Mabhaudhi, T., 2016. Assessment of sorghum-cowpea intercrop system under waterlimited conditions using a decision support tool. Water SA, 42(2), pp.316-327. . doi:10.4314/wsa.v42i2.15

Chivenge, P., Mabhaudhi, T., Modi, A.T. and Mafongoya, P., 2015. The potential role of neglected and underutilised crop species as future crops under water scarce conditions in Sub-Saharan Africa. International journal of environmental research and public health, 12(6), pp.5685-5711. doi:10.3390/ijerph120605685

Cobo, M.J., López-Herrera, A.G., Herrera-Viedma, E. and Herrera, F., 2011. Science mapping software tools: Review, analysis, and cooperative study among tools. Journal of the American Society for information Science and Technology, 62(7), pp.1382-1402.

Constantin, J., Willaume, M., Murgue, C., Lacroix, B. and Therond, O., 2015. The soil-crop models STICS and AqYield predict yield and soil water content for irrigated crops equally well with limited data. Agricultural and Forest Meteorology, 206, pp.55-68. doi:10.1016/j.agrformet.2015.02.011

Cooper, M., Messina, C.D., Podlich, D., Totir, L.R., Baumgarten, A., Hausmann, N.J., Wright, D. and Graham, G., 2014. Predicting the future of plant breeding: complementing empirical evaluation with genetic prediction. Crop and Pasture Science, 65(4), pp.311-336. doi:10.1071/CP14007

Dansi, A., Vodouhè, R., Azokpota, P., Yedomonhan, H., Assogba, P., Adjatin, A., Loko, Y.L., Dossou-Aminon, I. and Akpagana, K.J.T.S.W.J., 2012. Diversity of the neglected and underutilized crop species of importance in Benin. The scientific world journal, 2012. doi:10.1100/2012/932947

de Sousa Lobato, K.B., Alamar, P.D., dos Santos Caramês, E.T. and Pallone, J.A.L., 2018. Authenticity of freeze-dried açai pulp by near-infrared spectroscopy. Journal of Food Engineering, 224, pp.105-111.

de Vries, S.C., Van de Ven, G.W., Van Ittersum, M.K. and Giller, K.E., 2012. The production-ecological sustainability of cassava, sugarcane and sweet sorghum cultivation for bioethanol in Mozambique. GCB Bioenergy, 4(1), pp.20-35. doi:10.1111/j.1757-1707.2011.01103.x

Di Paola, A., Valentini, R. and Santini, M., 2016. An overview of available crop growth and yield models for studies and assessments in agriculture. Journal of the Science of Food and Agriculture, 96(3), pp.709-714. doi:10.1002/jsfa.7359

Dimes, J.P. and Revanuru, S., 2004. Evaluation of APSIM to simulate plant growth response to applications of organic and inorganic N and P on an Alfisol and Vertisol in India. In Aciar Proceedings (pp. 118-125). ACIAR; 1998.

El-Sharkawy, M.A., De Tafur, S.M. and Lopez, Y., 2012. Eco-physiological research for breeding improved cassava cultivars in favorable and stressful environments in tropical/subtropical bio-systems. Environmental Research Journal, 6, pp.143-211.

Ezui, K.S., Leffelaar, P.A., Franke, A.C., Mando, A. and Giller, K.E., 2018. Simulating drought impact and mitigation in cassava using the LINTUL model. Field Crops Research, 219, pp.256-272. https://doi.org/10.1016/j.fcr.2018.01.033

Ezui, K.S., Leffelaar, P.A., Franke, A.C., Mando, A. and Giller, K.E., 2018. Decision Support System for Site-Specific Fertilizer Recommendations in Cassava Production in Southern Togo. In Improving the Profitability, Sustainability and Efficiency of Nutrients Through Site Specific Fertilizer Recommendations in West Africa Agro-Ecosystems (pp. 125-138). Springer, Cham.

Gaisberger, H., Deletre, M., Gaiji, S., Bordoni, P., Padulosi, S., Hermann, M. and Arnaud, E., 2014. Diversity of neglected and underutilized plant species (NUS) in perspective. Biodiversity International, Rome, Italy doi:10.13140/2.1.3692.6722

Gaudio, N., Escobar-Gutiérrez, A.J., Casadebaig, P., Evers, J.B., Gérard, F., Louarn, G., Colbach, N., Munz, S., Launay, M., Marrou, H. and Barillot, R., 2019. Current knowledge and future research opportunities for modeling annual crop mixtures. A review. Agronomy for Sustainable Development, 39(2), pp.1-20. doi:10.1007/s13593-019-0562-6

Gimplinger, D.M. and Kaul, H.P., 2012. Calibration and validation of the crop growth model LINTUL for grain amaranth (Amaranthus sp.). Journal of applied botany and food quality, 82(2), pp.183-192.

Guan, K., Sultan, B., Biasutti, M., Baron, C. and Lobell, D.B., 2015. What aspects of future rainfall changes matter for crop yields in West Africa?. Geophysical Research Letters, 42(19), pp.8001-8010. doi:10.1002/2015GL063877

Hadebe, S.T., Modi, A.T. and Mabhaudhi, T., 2017. Calibration and testing of AquaCrop for selected sorghum genotypes. Water SA, 43(2), pp.209-221. doi:10.4314/wsa.v43i2.05

Hao, T., Elith, J., Lahoz-Monfort, J.J. and Guillera-Arroita, G., 2020. Testing whether ensemble modelling is advantageous for maximising predictive performance of species distribution models. Ecography, 43(4), pp.549-558. doi:10.1111/ecog.04890

Hartkamp, A.D., Hoogenboom, G. and White, J.W., 2002. Adaptation of the CROPGRO growth model to velvet bean (Mucuna pruriens): I. Model development. Field Crops Research, 78(1), pp.9-25. doi:10.1016/S0378-4290(02)00091-6

Hill, J.O., Robertson, M.J., Pengelly, B.C., Whitbread, A.M. and Hall, C.A., 2006. Simulation modelling of lablab (Lablab purpureus) pastures in northern Australia. Australian Journal of Agricultural Research, 57(4), pp.389-401. https://doi.org/10.1016/j.agwat.2018.06.012

Jones, J.W., Antle, J.M., Basso, B., Boote, K.J., Conant, R.T., Foster, I., Godfray, H.C.J., Herrero, M., Howitt, R.E., Janssen, S. and Keating, B.A., 2017. Brief history of agricultural systems modeling. Agricultural systems, 155, pp.240-254. . doi:10.1016/j.agsy.2016.05.014

Kahsay, A., Haile, M., Gebresamuel, G. and Mohammed, M., 2018. Land suitability analysis for sorghum crop production in northern semi-arid Ethiopia: Application of GIS-based fuzzy AHP approach. Cogent food & agriculture, 4(1), p.1507184. doi:10.1080/23311932.2018.1507184

Kanda, E.K., Senzanje, A. and Mabhaudhi, T., 2020. Modelling soil water distribution under Moistube irrigation for cowpea (VIGNA unguiculata (L.) Walp.) crop. Irrigation and Drainage, 69(5), pp.1116-1132. doi:10.1002/ird.2505

Karunaratne, A.S., Azam-Ali, S.N., Al-Shareef, I., Sesay, A., Jørgensen, S.T. and Crout, N.M.J., 2010. Modelling the canopy development of bambara groundnut. Agricultural and Forest Meteorology, 150(7-8), pp.1007-1015. doi:10.1016/j.agrformet.2010.03.006

Kasampalis, D.A., Alexandridis, T.K., Deva, C., Challinor, A., Moshou, D. and Zalidis, G., 2018. Contribution of remote sensing on crop models: a review. Journal of Imaging, 4(4), p.52.

Ke, Q., Wang, Z., Ji, C.Y., Jeong, J.C., Lee, H.S., Li, H., Xu, B., Deng, X. and Kwak, S.S., 2015. Transgenic poplar expressing Arabidopsis YUCCA6 exhibits auxin-overproduction phenotypes and increased tolerance to abiotic stress. Plant Physiology and Biochemistry, 94, pp.19-27. doi:10.1016/j.plaphy.2015.05.003

Klavans, R. and Boyack, K.W., 2006. Identifying a better measure of relatedness for mapping science. Journal of the American Society for Information Science and Technology, 57(2), pp.251-263.

Knezevic, S.Z., Horak, M.J. and Vanderlip, R.L., 1999. Estimates of physiological determinants for Amaranthus retroflexus. weed Science, 47(3), pp.291-296. doi:10.1017/s0043174500091797

Kogo, B.K., Kumar, L., Koech, R. and Langat, P., 2019. Modelling impacts of climate change on maize (Zea mays L.) Growth and productivity: A review of models, outputs and limitations. Journal of Geoscience and Environment Protection. doi:10.4236/gep.2019.78006

Kumsueb, B. and Jintrawet, A., 2020. Development of DSSAT CROPSIM-cassava model in Thailand: A review current development. Current Applied Science and Technology, 20(1).

Kuyyamudi Nanaiah, G. and Rakshit, S., 2020. Genomic designing for climate smart sorghum. In Genomic Designing of Climate-Smart Cereal Crops (pp. 171-219). Springer, Cham. doi:10.1007/978-3-319-93381-8_5

Larkin, D.L., Lozada, D.N. and Mason, R.E., 2019. Genomic selection – considerations for successful implementation in wheat breeding programs. Agronomy, 9(9), p.479. doi:10.3390/agronomy9090479

Le, K.N., Jha, M.K., Reyes, M.R., Jeong, J., Doro, L., Gassman, P.W., Hok, L., De Moraes Sá, J.C. and Boulakia, S., 2018. Evaluating carbon sequestration for conservation agriculture and tillage systems in Cambodia using the EPIC model. Agriculture, Ecosystems & Environment, 251, pp.37-47

Le, K.N., Jeong, J., Reyes, M.R., Jha, M.K., Gassman, P.W., Doro, L., Hok, L. and Boulakia, S., 2018. Evaluation of the performance of the EPIC model for yield and biomass simulation under conservation systems in Cambodia. Agricultural systems, 166, pp.90-100. https://doi.org/10.1016/j.agsy.2018.08.003

Le, K.N., Jha, M.K., Jeong, J., Gassman, P.W., Reyes, M.R., Doro, L., Tran, D.Q. and Hok, L., 2018. Evaluation of long-term SOC and crop productivity within conservation systems using GFDL CM2. 1 and EPIC. Sustainability, 10(8), p.2665. https://doi.org/10.3390/su10082665

Le, K.N., Jha, M.K., Reyes, M.R., Jeong, J., Doro, L., Gassman, P.W., Hok, L., De Moraes Sá, J.C. and Boulakia, S., 2018. Evaluating carbon sequestration for conservation agriculture and tillage systems in Cambodia using the EPIC model. Agriculture, Ecosystems & Environment, 251, pp.37-47. https://doi.org/10.1016/j.agee.2017.09.009

Leff, B., RamankuttyN., and FoleyJ. A., 2004: Geographic distribution of major crops across the world. Global Biogeochem. Cycles, 18. doi:10.1029/2003GB002108

Li, H. and Zhang, X., 2017. A spatial explicit assessment of food security in Africa based on simulated crop production and distribution. Journal of Cleaner Production, 147, pp.628-636.

Liberati, A., Altman, D.G., Tetzlaff, J., Mulrow, C., Gøtzsche, P.C., Ioannidis, J.P., Clarke, M., Devereaux, P.J., Kleijnen, J. and Moher, D., 2009. The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: explanation and elaboration. Journal of clinical epidemiology, 62(10), pp.e1-e34. doi:10.1371/journal.pmed.1000100

Lima Filho, A.F., Coelho Filho, M.A. and Heinemann, A.B., 2013. Calibration and evaluation of CROPGRO model for cowpea in Reconcavo of Bahia--Brazil/Calibracao e avaliacao do modelo CROPGRO para a cultura do feijao caupi no Reconcavo Baiano. Revista Brasileira de Engenharia Agrícola e Ambiental, 17(12), pp.1286-1294. doi:10.1590/S1415-43662013001200006

Lipper, L., Thornton, P., Campbell, B.M., Baedeker, T., Braimoh, A., Bwalya, M., Caron, P., Cattaneo, A., Garrity, D., Henry, K. and Hottle, R., 2014. Climate-smart agriculture for food security. Nature climate change, 4(12), pp.1068-1072. doi:10.1038/nclimate2437

Liu, X., Rahman, T., Yang, F., Song, C., Yong, T., Liu, J., Zhang, C. and Yang, W., 2017. PAR interception and utilization in different maize and soybean intercropping patterns. PloS one, 12(1), p.e0169218. doi:10.1371/journal.pone.0169218

Mabhaudhi, T., Chibarabada, T.P., Chimonyo, V.G.P., Murugani, V.G., Pereira, L.M., Sobratee, N., Govender, L., Slotow, R. and Modi, A.T., 2018. Mainstreaming underutilized indigenous and traditional crops into food systems: A South African perspective. Sustainability, 11(1), p.172. doi:10.3390/su11010172

Mabhaudhi, T., Chibarabada, T.P., Chimonyo, V.G.P. and Modi, A.T., 2018. Modelling climate change impact: a case of bambara groundnut (Vigna subterranea). Physics and Chemistry of the Earth, Parts A/B/C, 105, pp.25-31. doi:10.1016/j.pce.2018.01.003

Mabhaudhi, T., Chimonyo, V.G., Chibarabada, T.P. and Modi, A.T., 2017. Developing a roadmap for improving neglected and underutilized crops: A case study of South Africa. Frontiers in plant science, 8, p.2143. doi:10.3389/fpls.2017.02143

Mabhaudhi, T., Chimonyo, V.G.P., Hlahla, S., Massawe, F., Mayes, S., Nhamo, L. and Modi, A.T., 2019. Prospects of orphan crops in climate change. Planta, 250(3), pp.695-708. doi:10.1007/s00425-019-03129-y

Mabhaudhi, T., Chimonyo, V.G. and Modi, A.T., 2017. Status of underutilised crops in South Africa: Opportunities for developing research capacity. Sustainability, 9(9), p.1569. doi:10.3390/su9091569

Mabhaudhi, T., Modi, A.T. and Beletse, Y.G., 2014. Parameterization and testing of AquaCrop for a South African bambara groundnut landrace. Agronomy journal, 106(1), pp.243-251. doi:10.2134/agronj2013.0355

Mabhaudhi, T., Modi, A.T. and Beletse, Y.G., 2014. Parameterisation and evaluation of the FAO-AquaCrop model for a South African taro (Colocasia esculenta L. Schott) landrace. Agricultural and Forest Meteorology, 192, pp.132-139. doi:10.1016/j.agrformet.2014.03.013

Mabhaudhi, T., Modi, A.T. and Beletse, Y.G., 2014. Parameterization and testing of AquaCrop for a South African bambara groundnut landrace. Agronomy journal, 106(1), pp.243-251. doi:10.2134/agronj2013.0355

MacCarthy, D.S., Adiku, S.G., Freduah, B.S., Gbefo, F. and Kamara, A.Y., 2017. Using CERES-Maize and ENSO as decision support tools to evaluate climate-sensitive farm management practices for maize production in the northern regions of Ghana. Frontiers in Plant Science, 8, p.31. doi:10.3389/fpls.2017.00031

Malik, A.A. and Chaudhary, G., 2019. Global food security: a truncated yield of underutilized and orphan crops. In Biotechnology Products in Everyday Life (pp. 161-171). Springer, Cham. doi:10.1007/978-3-319-92399-4_11

Marcos, J., Cornet, D., Bussière, F. and Sierra, J., 2011. Water yam (Dioscorea alata L.) growth and yield as affected by the planting date: Experiment and modelling. European Journal of Agronomy, 34(4), pp.247-256.

Masithoh, R.E. and Yuliyanda, I., 2019, November. NIR reflectance spectroscopy and SIMCA for classification of crops flour. In IOP Conference Series: Earth and Environmental Science (Vol. 355, No. 1, p. 012004). IOP Publishing. https://doi.org/10.1088/1755-1315/355/1/012004

Massawe, F.J., Mayes, S., Cheng, A., Chai, H.H., Cleasby, P., Symonds, R., Ho, W.K., Siise, A., Wong, Q.N., Kendabie, P. and Yanusa, Y., 2015. The potential for underutilised crops to improve food security in the face of climate change. Procedia Environmental Sciences, 29, pp.140-141.

Mauget, S., Kothari, K., Leiker, G., Emendack, Y., Xin, Z., Hayes, C., Ale, S. and Louis Baumhardt, R., 2020. Optimizing dryland crop management to regional climate. Part II: US southern high plains grain sorghum production. Frontiers in Sustainable Food Systems, p.119. doi:10.3389/fsufs.2019.00119

Mayes, S., Massawe, P.G., Alderson, J.A. and Roberts, S.N., Azam-Ali and Hermann, M. 2011. The potential for underutilized crops to improve security of food production. Journal of Experimental Botany.pp.1-5. doi:10.1093/jxb/err396

McCarthy, D.S. and Vlek, P.L., 2012. Impact of climate change on sorghum production under different nutrient and crop residue management in semi-arid region of Ghana: a modeling perspective. African Crop Science Journal, 20, pp.243-259.

Meki, M.N., Snider, J.L., Kiniry, J.R., Raper, R.L. and Rocateli, A.C., 2013. Energy sorghum biomass harvest thresholds and tillage effects on soil organic carbon and bulk density. Industrial Crops and Products, 43, pp.172-182. doi:10.1016/j.indcrop.2012.07.033

Mithra, V.S., Sreekumar, J. and Ravindran, C.S., 2013. Computer simulation of cassava growth: a tool for realizing the potential yield. Archives of Agronomy and Soil Science, 59(4), pp.603-623. doi:10.1080/03650340.2011.653681

Moreno-Cadena, L.P., Hoogenboom, G., Fisher, M.J., Ramirez-Villegas, J., Prager, S.D., Lopez-Lavalle, L.A.B., Pypers, P., De Tafur, M.S.M., Wallach, D., Muñoz-Carpena, R. and Asseng, S., 2020. Importance of genetic parameters and uncertainty of MANIHOT, a new mechanistic cassava simulation model. European Journal of Agronomy, 115, p.126031. https://doi.org/10.1016/j.eja.2020.126031

Mirriam, N., 2015. Simulation of Soil Moisture, Sorghum (Sorghum bicolor L.) and Sweet potato (Ipomea batatas L. lam) Yields using CropSyst Model in Matuu Sub-County, Kenya (Doctoral dissertation). Kenya. University of Nairobi.

Muller, B. and Martre, P., 2019. Plant and crop simulation models: powerful tools to link physiology, genetics, and phenomics. Journal of Experimental Botany, 70(9), pp.2339-2344. doi:10.1093/jxb/erz175

Ncube, B., Dimes, J.P., Van Wijk, M.T., Twomlow, S.J. and Giller, K.E., 2009. Productivity and residual benefits of grain legumes to sorghum under semi-arid conditions in south-western Zimbabwe: Unravelling the effects of water and nitrogen using a simulation model. Field Crops Research, 110(2), pp.173-184. doi:10.1016/j.fcr.2008.08.001

Ngwira, A.R., Aune, J.B. and Thierfelder, C., 2014. DSSAT modelling of conservation agriculture maize response to climate change in Malawi. Soil and Tillage Research, 143, pp.85-94. doi:10.1016/j.still.2014.05.003

Niu, X., Easterling, W., Hays, C.J., Jacobs, A. and Mearns, L., 2009. Reliability and input-data induced uncertainty of the EPIC model to estimate climate change impact on sorghum yields in the US Great Plains. Agriculture, ecosystems & environment, 129(1-3), pp.268-276. doi:10.1016/j.agee.2008.09.012

Nunes, H.G.G.C., De Pinho Sousa, D., Moura, V.B., Ferreira, D.P., De Nóvoa Pinto, J.V., De Oliveira Vieira, I.C., Da Silva Farias, V.D., De Oliveira, E.C. and De Oliveira Ponte de Souza, P.J., 2019. Performance of the AquaCrop model in the climate risk analysis and yield prediction of cowpea ('Vigna Unguiculatta'L. Walp). Australian Journal of Crop Science, 13(7), pp.1105-1112. doi:10.21475/ajcs.19.13.07.p1590

Nyathi, M.K., Van Halsema, G.E., Annandale, J.G. and Struik, P.C., 2018. Calibration and validation of the AquaCrop model for repeatedly harvested leafy vegetables grown under different irrigation regimes. Agricultural water management, 208, pp.107-119. doi:10.1016/j.agwat.2018.06.012

Paff, K. and Asseng, S., 2019. A crop simulation model for tef (Eragrostis tef (Zucc.) Trotter). Agronomy, 9(12), p.817. doi:10.3390/agronomy9120817

Paff, K. and Asseng, S., 2019. Comparing the effects of growing conditions on simulated Ethiopian tef and wheat yields. Agricultural and forest meteorology, 266, pp.208-220. doi:10.1016/j.agrformet.2018.12.010

Perkins, S.A., Douglas-Mankin, K., Nelson, R. and Staggenborg, S., 2011. Modeling the Economic Feasibility of Sweet Sorghum in Western Kansas and the Panhandles of Texas and Oklahoma. In 2011 Louisville, Kentucky, August 7-10, 2011 (p. 1). American Society of Agricultural and Biological Engineers. ASABE 2011. pp. 3632-3639.

Pulvento, C., Riccardi, M., Lavini, A., d'Andria, R. and Ragab, R., 2015. Parameterization and field validation of SALTMED Model for grain amaranth tested in South Italy. Irrigation and drainage, 64(1), pp.59-68.

Pulvento, C., Riccardi, M., Lavini, A., D'andria, R. and Ragab, R., 2013. SALTMED model to simulate yield and dry matter for quinoa crop and soil moisture content under different irrigation strategies in south Italy. Irrigation and Drainage, 62(2), pp.229-238. doi:10.1002/ird.1727

Ramirez-Villegas, J., Watson, J. and Challinor, A.J., 2015. Identifying traits for genotypic adaptation using crop models. Journal of Experimental Botany, 66(12), pp.3451-3462. doi:10.1093/jxb/erv014

Rankine, D.R., Cohen, J.E., Taylor, M.A., Coy, A.D., Simpson, L.A., Stephenson, T. and Lawrence, J.L., 2015. Parameterizing the FAO AquaCrop Model for Rainfed and Irrigated Field-Grown Sweet Potato. Agronomy Journal, 107(1), pp.375-387. doi:10.2134/agronj14.0287

Rankine, D.R., Cohen, J.E., Taylor, M.A., Coy, A.D., Simpson, L.A., Stephenson, T. and Lawrence, J.L., 2015. Parameterizing the FAO AquaCrop Model for Rainfed and Irrigated Field-Grown Sweet Potato. Agronomy Journal, 107(1), pp.375-387. doi:10.2134/agronj14.0287

Raymundo, R., Asseng, S., Cammarano, D. and Quiroz, R., 2014. Potato, sweet potato, and yam models for climate change: A review. Field Crops Research, 166, pp.173-185. https://doi.org/10.1016/j.fcr.2014.06.017
Raymundo, R., Asseng, S., Cammarano, D. and Quiroz, R., 2014. Potato, sweet potato, and yam models for climate change: A review. Field Crops Research, 166, pp.173-185. doi:10.1016/j.fcr.2014.06.017
Rey-Martí, A., Ribeiro-Soriano, D. and Palacios-Marqués, D., 2016. A bibliometric analysis of social entrepreneurship. Journal of Business Research, 69(5), pp.1651-1655.
Rosegrant, M.W., Koo, J., Cenacchi, N., Ringler, C., Robertson, R.D., Fisher, M., Cox, C.M., Garrett, K., Perez, N.D. and Sabbagh, P., 2014. Food security in a world of natural resource scarcity: The role of agricultural technologies. International Food Policy Research Institute. doi:10.2499/9780896298477
Santhosh Mithra, V.S., Abhinand, C.S. and Sreekumar, J., 2014. Horoscope algorithm to predict potential yield of cassava. World Applied Sciences Journal, 30(3), 341-344.
Santos, R.D., Boote, K.J., Sollenberger, L.E., Neves, A.L., Pereira, L.G., Scherer, C.B. and Gonçalves, L.C., 2017. Simulated optimum sowing date for forage pearl millet cultivars in multilocation trials in Brazilian semi-arid region. Frontiers in Plant Science, 8, p.2074. doi:10.3389/fpls.2017.02074
Semenov, M.A., Martre, P. and Jamieson, P.D., 2009. Quantifying effects of simple wheat traits on yield in water-limited environments using a modelling approach. Agricultural and Forest Meteorology, 149(6-7), pp.1095-1104. doi:10.1016/j.agrformet.2009.01.006
Semenov, M.A. and Stratonovitch, P., 2013. Designing high-yielding wheat ideotypes for a changing climate. Food and Energy Security, 2(3), pp.185-196. doi:10.1002/fes3.34
Sievänen, R., Godin, C., DeJong, T.M. and Nikinmaa, E., 2014. Functional-structural plant models: a growing paradigm for plant studies. Annals of botany, 114(4), pp.599-603. doi:10.1093/aob/mcu175
Sinnathamby, S., Douglas-Mankin, K.R. and Craige, C., 2017. Field-scale calibration of crop-yield parameters in the Soil and Water Assessment Tool (SWAT). Agricultural water management, 180, pp.61-69. doi:10.1016/j.agwat.2016.10.024
Small, H., 1973. Co-citation in the scientific literature: A new measure of the relationship between two documents. Journal of the American Society for information Science, 24(4), pp.265-269.
Smith, A., Snapp, S., Dimes, J., Gwenambira, C. and Chikowo, R., 2016. Doubled-up legume rotations improve soil fertility and maintain productivity under variable conditions in maize-based cropping systems in Malawi. Agricultural Systems, 145, pp.139-149. doi:10.1016/j.agsy.2016.03.008

Somasundaram, V., Mithra, K.S., 2008. Madhuram: A Simulation Model for Sweet Potato Growth. World Journal of Agricultural Sciences, 4(2), pp.241-254.

Srinivas, K., Sawargaonkar, G.L., Kesava Rao, A.V.R. and Wani, S.P., 2020. Improved Livelihoods Through Sustainable and Diversified Cropping Systems. In Community and Climate Resilience in the Semi-Arid Tropics (pp. 81-118). Springer, Cham. doi:10.1007/978-3-030-29918-7_6

Srivastava, A.K., Gaiser, T., Cornet, D. and Ewert, F., 2012. Estimation of effective fallow availability for the prediction of yam productivity at the regional scale using model-based multiple scenario analysis. Field Crops Research, 131, pp.32-39. https://doi.org/10.1016/j.fcr.2012.01.012

Srivastava, A.K. and Gaiser, T., 2010. Simulating biomass accumulation and yield of yam (Dioscorea alata) in the Upper Ouémé Basin (Benin Republic)-I. Compilation of physiological parameters and calibration at the field scale. Field crops research, 116(1-2), pp.23-29.

Srivastava, A.K., Gaiser, T. and Ewert, F., 2016. Climate change impact and potential adaptation strategies under alternate climate scenarios for yam production in the sub-humid savannah zone of West Africa. Mitigation and Adaptation Strategies for Global Change, 21(6), pp.955-968.

Steduto, P. and Albrizio, R., 2005. Resource use efficiency of field-grown sunflower, sorghum, wheat and chickpea: II. Water use efficiency and comparison with radiation use efficiency. Agricultural and Forest Meteorology, 130(3-4), pp.269-281. doi:10.1016/j.agrformet.2005.04.003

Steinbuch, L., Brus, D.J., Van Bussel, L.G. and Heuvelink, G.B., 2016. Geostatistical interpolation and aggregation of crop growth model outputs. European Journal of Agronomy, 77, pp.111-121. doi:10.1016/j.eja.2016.03.007

Sultan, B., Defrance, D. and Iizumi, T., 2019. Evidence of crop production losses in West Africa due to historical global warming in two crop models. Scientific reports, 9(1), pp.1-15. doi:10.1038/s41598-019-49167-0

Tingem, M. and Rivington, M., 2009. Adaptation for crop agriculture to climate change in Cameroon: turning on the heat. Mitigation and Adaptation Strategies for Global Change, 14(2), pp.153-168. doi:10.1007/s11027-008-9156-3

Tingem, M., Rivington, M., Bellocchi, G., Azam-Ali, S. and Colls, J., 2008. Effects of climate change on crop production in Cameroon. Climate Research, 36(1), pp.65-77. doi:10.3354/cr00733

Truong, S.K., McCormick, R.F. and Mullet, J.E., 2017. Bioenergy sorghum crop model predicts VPD-limited transpiration traits enhance biomass yield in water-limited environments. Frontiers in plant science, 8, p.335. doi:10.3389/fpls.2017.00335

Tsegay, A., Vanuytrecht, E., Abrha, B., Deckers, J., Gebrehiwot, K. and Raes, D., 2015. Sowing and irrigation strategies for improving rainfed tef (Eragrostis tef (Zucc.) Trotter) production in the water scarce Tigray region, Ethiopia. Agricultural Water Management, 150, pp.81-91. doi:10.1016/j.agwat.2014.11.014

Ullah, A., Ahmad, I., Ahmad, A., Khaliq, T., Saeed, U., Habib-ur-Rahman, M., Hussain, J., Ullah, S. and Hoogenboom, G., 2019. Assessing climate change impacts on pearl millet under arid and semi-arid environments using CSM-CERES-Millet model. Environmental Science and Pollution Research, 26(7), pp.6745-6757. doi:10.1007/s11356-018-3925-7

Upadhyaya, H.D., Reddy, K.N., Vetriventhan, M., Ahmed, M.I., Krishna, G.M., Reddy, M.T. and Singh, S.K., 2017. Sorghum germplasm from West and Central Africa maintained in the ICRISAT genebank: Status, gaps, and diversity. The Crop Journal, 5(6), pp.518-532.

Upadhyaya, H.D., Reddy, N.K., Murali, K.G., Ahmed, I.M., E, M., Reddy, T.M. and Singh, S.K., 2017. Geographical distribution, diversity and gap analysis of East African sorghum collection conserved at the ICRISAT genebank. Australian Journal of Crop Science, 11(4), pp.424-437.

Van Gaelen, H., Tsegay, A., Delbecque, N., Shrestha, N., Garcia, M., Fajardo, H., Miranda, R., Vanuytrecht, E., Abrha, B., Diels, J. and Raes, D., 2015. A semi-quantitative approach for modelling crop response to soil fertility: evaluation of the AquaCrop procedure. The Journal of Agricultural Science, 153(7), pp.1218-1233.

Van Gaelen, H., Tsegay, A., Delbecque, N., Shrestha, N., Garcia, M., Fajardo, H., Miranda, R., Vanuytrecht, E., Abrha, B., Diels, J. and Raes, D., 2015. A semi-quantitative approach for modelling crop response to soil fertility: evaluation of the AquaCrop procedure. The Journal of Agricultural Science, 153(7), pp.1218-1233. doi:10.1017/S0021859614000872

Van Ittersum, M.K., Van Bussel, L.G., Wolf, J., Grassini, P., Van Wart, J., Guilpart, N., Claessens, L., De Groot, H., Wiebe, K., Mason-D'Croz, D. and Yang, H., 2016. Can sub-Saharan Africa feed itself?. Proceedings of the National Academy of Sciences, 113(52), pp.14964-14969. doi:10.1073/pnas.1610359113

Van Loon, M.P., Deng, N., Grassini, P., Edreira, J.I.R., Wolde-Meskel, E., Baijukya, F., Marrou, H. and Van Ittersum, M.K., 2018. Prospect for increasing grain legume crop production in East Africa. European Journal of Agronomy, 101, pp.140-148. doi:10.1016/j.eja.2018.09.004

Visses, F.D.A., Sentelhas, P.C. and Pereira, A.B., 2018. Yield gap of cassava crop as a measure of food security-an example for the main Brazilian producing regions. Food Security, 10(5), pp.1191-1202. doi:10.1007/s12571-018-0831-2

Walker, S., Bello, Z.A., Mabhaudhi, T., Modi, A.T., Beletse, Y.G. and Zuma-Netshiukhwi, G., 2012, January. Calibration of AquaCrop model to predict water requirements of traditional African vegetables. In II All Africa Horticulture Congress 1007(pp. 943-949). doi:10.17660/ActaHortic.2013.1007.113

Wang, G., McGiffen Jr, M.E., Lindquist, J.L., Ehlers, J.D. and Sartorato, I., 2007. Simulation study of the competitive ability of erect, semi-erect and prostrate cowpea (Vigna unguiculata) genotypes. Weed research, 47(2), pp.129-139.

Washburn, J.D., Burch, M.B. and Franco, J.A.V., 2020. Predictive breeding for maize: Making use of molecular phenotypes, machine learning, and physiological crop models. Crop Science, 60(2), pp.622-638. doi:10.1002/csc2.20052

Wei, M., Geladi, P., Lestander, T.A., Xie, G. and Xiong, S., 2015. Multivariate modelling on biomass properties of cassava stems based on an experimental design. Analytical and bioanalytical chemistry, 407(18), pp.5443-5452.

White, J.W., 2009. Bringing genetics and genomics to crop simulations: Experiences with wheat, sorghum and common bean in solving the GEM-to-P problem. Crop Modeling and Decision Support, pp.44-53. doi:10.1007/978-3-642-01132-0_5

Williams, J.T., 2002. Global research on underutilized crops: An assessment of current activities and proposals for enhanced cooperation. Bioversity International.

Xie, Y., James, K. and Liu, B., 2003. Validation of the ALMANAC model with different spatial scale. Ying Yong Sheng tai xue bao= The Journal of Applied Ecology, 14(8), pp.1291-1295.

Xie, Y., Kiniry, J.R. and Williams, J.R., 2003. The ALMANAC model's sensitivity to input variables. Agricultural Systems, 78(1), pp.1-16. doi:10.1016/S0308-521X(03)00002-7

Xu, L., Shi, P.T., Ye, Z.H., Yan, S.M. and Yu, X.P., 2013. Rapid analysis of adulterations in Chinese lotus root powder (LRP) by near-infrared (NIR) spectroscopy coupled with chemometric class modeling techniques. Food chemistry, 141(3), pp.2434-2439.

3 THE APPLICATION OF A NON-PARAMETRIC MACHINE LEARNING ALGORITHM TO DELINEATE BIOCLIMATIC REGIONS WITH HIGH RAINFALL VARIABILITY FOR WATER-SCARCE ENVIRONMENTS

Mugiyo, H., Chimonyo, V. G. P., Masemola, C. R., Sibanda, M., Kunz, R.P., Nhamo, L., Modi, A. T., and Mabhaudhi, T.

Abstract

Mapping high-risk agricultural drought areas are critical for informing policy and decision-making to formulate drought adaptation strategies. This study used the Vegetation Drought Response Index (VegDRI), a hybrid drought index that integrates the Standardised Precipitation Index (SPI), Temperature Condition Index (TCI), and the Vegetation Condition Index (VCI) to delineate bioclimatic zones with both high rainfall variability and water scarcity for South Africa. Historical satellite climate data (1981-2019) was used with land use/cover maps to generate five scales ranging from very severe to no drought. A machine learning algorithm, the Classification and Regression Tree (CART) in R statistic and ArcGIS, was used for analysis and map graphics. Average sorghum yields obtained at the district level were used to validate results obtained from the mapping exercise. The VegDRI (74.1%), VCI (71.8%), TCI (66.2%), and SPI (59%) showed higher performance in explaining sorghum yield, respectively. Most of South Africa's arable land is prone to drought, with 16% experiencing very severe drought, 34% – severe drought, 38% – moderate drought, 11% slight drought, and 1% no drought conditions. The predictive accuracy of drought risk maps is computed from the cell-by-cell comparison. However, high Kappa values of VegDRI with VCI (0.80-0.98) and TCI (0.72-0.90) do not necessarily indicate an accurate mapping of drought risk maps. VegDRI is a useful index in designing climate-smart practices for improved food and nutrition security under increasing water scarcity.

Keywords: Adaptation; Climate variability; Food security; Underutilised crops; Water scarcity

3.1 Introduction

Drought is one of the most complex natural hazards, and it has a substantial impact on water, food, and nutrition security (Mishra and Singh, 2011). Severe dry episodes in sub-Saharan Africa (SSA) have often been linked with the effects of El Niño-Southern Oscillation (ENSO), which often leads to precipitation and temperature anomalies around the globe (Timmermann et al., 2018). Since 1900, 80% of the most severe droughts experienced in the region have been linked to mature El Niño events (Malherbe et al., 2016). The 2015/16 ENSO induced drought, one of the strongest events in recorded history, has had unforgettable effects on agriculture, water, food, and nutrition security across SSA (Heino et al., 2018; Nhamo et al., 2019b). Evidence suggests that climate change has increased the frequency and severity of droughts, regardless of the ENSO (AGRA, 2014; Miralles et al., 2014). It is, therefore, necessary to understand drought and, more importantly, assess where it is expected to be severe. Only then can appropriate risk control and mitigation measures can be taken (IPCC, 2015).

Drought can exist in different forms: meteorological, agricultural, hydrological, and socio-economic drought (Kogan and Sullivan, 1993; Mishra and Singh, 2010). There is no single technical definition of drought because of the substantial variability in water supply and demand worldwide (Mishra and Singh, 2010). Monitoring the hazard in terms of progression and possible impact is important across various industries, especially agriculture, central to livelihoods and human well-being (Zargar et al.,). At present, there are more than 150 drought indices (Zargar et al.,), and these reflect different types and conditions, including intensity and severity (Mishra and Singh, 2011). For example, the rainfall anomaly index (RAI) addresses drought that affects agriculture and water resources (Kosgei, 2009; Foufou et al., 2017), the Palmer Drought Severity Index (PDSI), which is based on water demand (evapotranspiration) and losses (runoff) (Ebrahimpour et al., 2015) and the commonly used Standardised Precipitation Index (SPI), which is a precipitation-based index (McKee, 1993). However, traditional indices methods primarily require multiple observations to determine weights to map drought risk zones. Several data mining methods can be used to overcome this limitation. However, common data mining methods also have limitations when handling large amounts of data. These problems may be solved using machine learning-related algorithms (Shen et al., 2019a).

Across the region, climate-based drought indices using point-based meteorological observations have been used to help quantify drought impacts on crop production (Botai et al., 2017; Adisa et al., 2019). Given the three physical forms of drought, there is no single unifying approach to quantify drought severity (Algorithm, 1999; Wang et al., 2016). Even within an individual category, the supremacy of a specific index is not immediately clear (Halwatura et al., 2017). However, for any selected drought index, Wang et al. (2016) indicated that the drought index should have certain qualities such as robustness, tractability, transparency, sophistication, extendibility, and dimensionality to improve drought classification bioclimatic zones under water stress. Bioclimatic zones are areas with similar climates, vegetation, and soils, where agricultural activities are closely related to the conditions of each zone (Rivas-Martínez et al., 2011). In the characterisation of bioclimatic zones, consideration should be given to the use of long term historical climatic data. Therefore, to capture the complexity of drought in a bioclimatic zone, a hybrid method that integrates historical climate data, satellite-based earth observations and biophysical information is required (Tadesse and Wilhite, 2011). In characterising bioclimatic zones, consideration should also be given to the use of long term historic near real-time climatic data from earth observed (EO) data (Brown et al., 2008). Remote sensing is essential for assessing climate change and the impact on agricultural production over time, which are necessary for developing context-based adaptation strategies. Remote sensing data offers a synoptic vision covering bioclimatic zones instantly and high repetitiveness adapted to drought monitoring over time (Park et al., 2016).

The purpose of combining different indices from three physical forms of drought is hypothesised to detect agricultural drought more accurately and to be more useful for informing drought management strategies (Mubiru et al., 2018). The Vegetation Drought Response Index (VegDRI) is a hybrid drought index that integrates traditional climate-based drought indicators and satellite-derived vegetation index metrics with other biophysical information (e.g. land use land cover (LULC) type, soils, elevation, and ecological setting). The resultant map produced has a resolution of 5 km showing historical water-stressed zones (Brown et al., 2014). The VegDRI was developed by the National Drought Mitigation Centre (NDMC) and the U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Centre as an operational tool to monitor drought-induced vegetation stress (Brown et al., 2008). It provides drought-specific information that addresses challenges faced by traditional climate and satellite-based indices (Quiring and Ganesh, 2010). However, it cannot be used as an indicator of hydrological drought or low flow conditions in streams or rivers (Nam et al., 2018). The VegDRI has been used to monitor vegetation drought stress in South Korea (Brown et al., 2008). The VegDRI portray vegetation conditions as plants respond to solar energy, soil moisture. The VegDRI has not be used under South African conditions, where drought is a major factor affecting agriculture. Therefore, it offers new insights into assessing the impacts of drought from local to regional scales (Otkin et al., 2016; Nam et al., 2018).

Agricultural drought involves complex processes such as soil water stress, vegetation growth status and meteorological precipitation loss (Dai, 2011, 2012). In the construction of comprehensive drought models, machine learning algorithms can extract more useful features from many drought factors beyond the reach of other traditional indices (Park et al., 2016; Shen et al., 2019a). The rise of machine learning has introduced non-linear empirical models such as classification and regression tree (CART) algorithm to analyse the non-linear relationship between predictor variables and the response variable (Nam et al., 2018). However, few studies on drought monitoring use machine learning algorithms in SSA (Tadesse et al., 2008; Rojas et al., 2011; Pulwarty and Sivakumar, 2014). Therefore, this study used machine learning methods to construct models by considering several various hazard factors and explored the use of multiple remote sensing data sources for regional, remote sensing comprehensive drought delineation.

Previous studies on bioclimatic zoning indicated no single index could describe all aspects of droughts (Unganai and Kogan, 1998; Climate and Dei, 2009; Botai et al., 2019). There is a need to explore meteorological and agricultural factors in tandem to capture the complexity of drought (Hao et al., 2017; Shen et al., 2019b). As such, a multi-index approach is needed for operational drought risk identification. Therefore, using a non-parametric machine learning-related algorithm can explore the relationships between meteorological and agricultural factors to delineate drought risk zones. In South Africa, there is no prior delineation of drought-based bioclimatic zones using machine-related learning algorithms. The methodological approach adopted is to propose an improvement of the VCI, TCI and SPI through the VegDRI to better detect the agricultural drought risk zones without knowledge of the causal mechanisms of these factors. This study provides a detailed, spatially explicit understanding of the drought risk zone using machine learning algorithms in South Africa, focusing on developing a customized version of the VegDRI, including VCI, TCI, and SPI. The approach provides a high spatial resolution for agricultural drought-prone areas and delineates bioclimatic zones with high rainfall variability and water scarcity. Secondary to this, a correlation test between the VegDRI and normalised crop yield data for sorghum was used to test and validate the applicability and usefulness of the VegDRI index.

3.2 Methodology

3.2.1 The Geography of South Africa

South Africa is located on the southernmost tip of Africa between 22°S and 35°S, covering a land area of 1 219 912 km^2. The country is characterised by a mild, temperate climate (Aliber and Cousins, 2013), where a small proportion of land (10.3%) is considered arable for agriculture. South Africa is a water-scarce country (Ziervogel et al., 2014), and about 61% of the country receives less than 500 mm of rainfall annually (**Figure 3.1**). The amount of rainfall received is considered the minimum for successful dryland farming (Smithers and Schulze, 2000). Where rainfall exceeds 500 mm, major crops including maize (Zea mays), soybean (Glycine max), tobacco (Nicotiana tabacum), sugar cane (Saccharum officinarum), and other high-value horticultural crops are produced. Drought is a significant threat to crop production, water resources and, more importantly, food and nutrition security in South Africa (Malherbe et al., 2016).

3.2.2 Vegetation drought response index model generation using a CART model

The development of the VegDRI model involved the assembling of a training database of the satellite and climate-based variables for a total of 38 years from 1981 to 2019.

The VegDRI models for each month (from 1981 to 2019) were generated using the CART algorithm, which Breiman, (2001) originally developed.

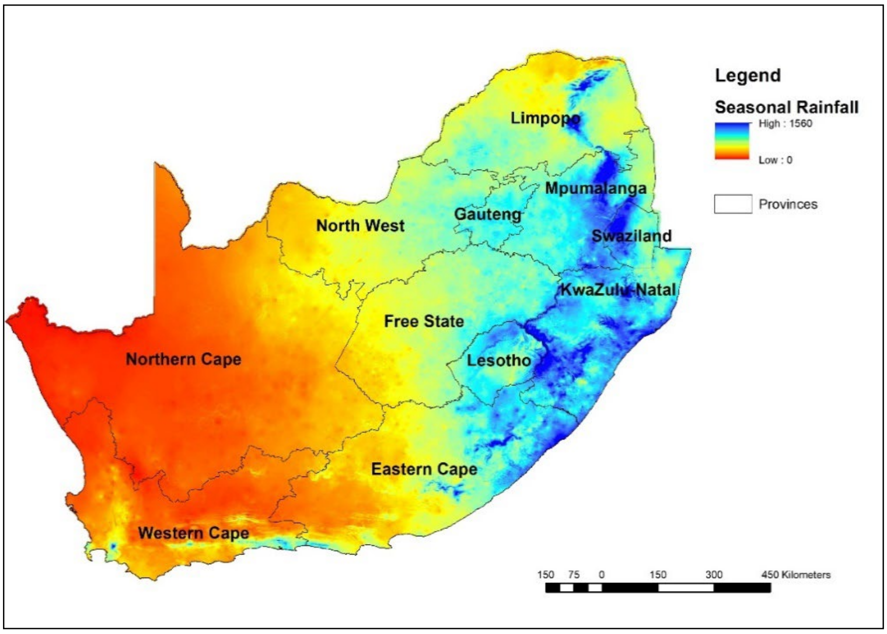


Figure 3.1: Seasonal average rainfall distribution from 1981-2019 rainfall data for South Africa (CHIRPS datasets)

The CART is a supervised learning algorithm that creates a training model to predict the class or value of the target variable using decision simple decision rules inferred from training data. During training, the CART algorithm performs repeated binary recursive partitioning that subdivides the training data until the partitioning process is terminated by user-defined criteria (Brown et al., 2013).

For the development of VegDRI, 80% of the dataset was used for training and 20% for validation of the training model. The dataset was randomly sampled and split into calibration and validation datasets. This procedure was implemented 100 times to evaluate the stability of model. The VegDRI map contains five categories of varying levels of drought-induced vegetation stress, based on the PDSI drought classification scheme (Palmer, 1965). The methodology utilised in the present study is illustrated in **Figure 3.2**. The details of some of the processing and analysis methods are given in the subsequent sub-sections.

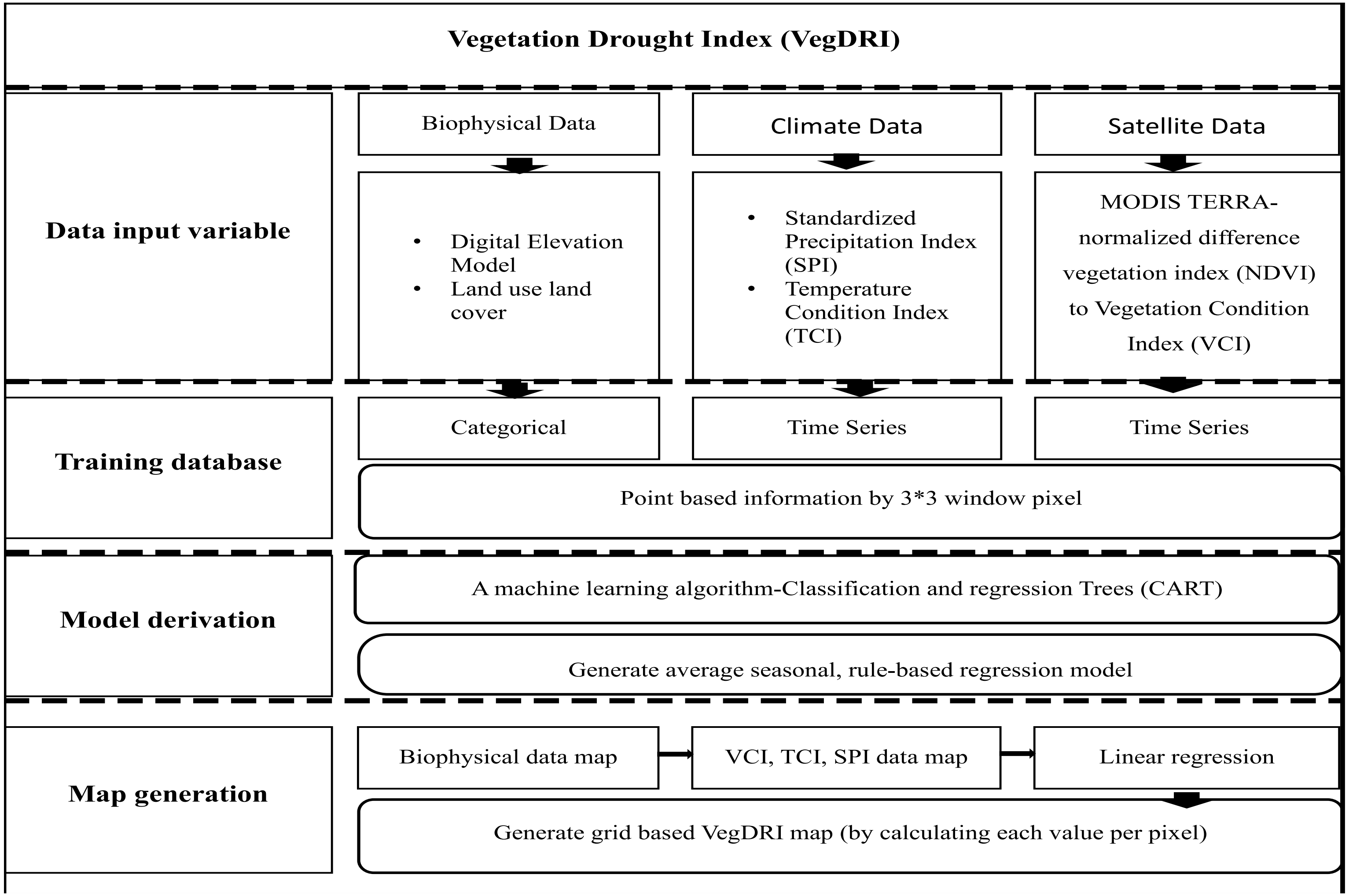


Figure 3.2: Flow chart of generating vegetation drought index (Nam et al., 2018).

3.2.2.1 VegDRI model implementation

The input data used in VegDRI consists of three major variable categories: satellite, climate, and biophysical data (**Table 3.1**; Brown et al., 2014). A 38-year historical record (1981-2019) of climate-based drought indices and satellite-derived vegetation condition index (VCI) observations were included in the input database. The vegetation indices such as the Normalised Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI) were mined from a big data software called Application for Extracting and Exploring Analysis Ready Samples (AρρEEARS) (AppEEARS Team, 2019). AρρEEARS enables users to subset geospatial datasets using spatial, temporal, and band/layer parameters. The NDVI and VCI are readily available, and pre-processing stages such as geometric correction, radiometric correction, and image enhancement have already been undertaken (Crespi and De Vendictis, 2009; Richter and Schläpfer, 2011). Amongst the biophysical variables, elevation was unchanged in the VegDRI trend analysis, and land use /land cover for 2016 was used to mask agricultural land. A long-term seasonal average of satellite and climate indices defined bioclimatic zones (**Table 3.2**). The datasets were resampled to 5 km resolutions by the bilinear interpolation method (Du et al., 2013). The analysis was done in R package 3.5.1 (R Core Team, 2014) and map presentation in ArcGIS 4.6 environment.

The VegDRI model uses the classification and regression tree (CART) algorithm to generate bioclimatic zones from satellite, climate, and biophysical datasets (Nam et al., 2018). The CART algorithm analyses the non-linear relationship between predictor variables and the response variable (Nam et al., 2018). Rule-based linear regression models were applied to the geospatial data to produce a 5 km resolution grid-based VegDRI map by calculating the VegDRI values for each pixel. According to Lemma (1996), the probability of drought occurrence in a given area can be classified into high, moderate, and low drought probability zones when drought occurs in >50%, 30-50%, and < 30% of the years, respectively. Based on this criterion, the frequency maps of each drought class were reclassified into five categories based on the frequency of drought occurrence in study periods: 2> classified as no drought;

-0.99-1 classified as slight drought; -2.99-(-1) classified as moderate drought; -3 classified as severe drought; 4< classified as very severe drought (**Table 3.2**).

Table 3.1: Data input variables for the VegDRI model

Data type	Data set name	Format	Resolution	Source
Satellite data	Standardised seasonal greenness using MODIS Terra/Vegetation condition index	Raster	5 km	https://lpdaacsvc.cr.usgs.gov
	Temperature Condition Index (TCI)	Raster	5 km	https://lpdaacsvc.cr.usgs.gov
Climate data	Precipitation Gridded precipitation	Point Raster	 5 km	https://sasri.sasa.org.za/pls/sasri https://climateserv.servirglobal.net
	Standardised precipitation index	Raster	5 km	https://climateserv.servirglobal.net
Biophysical data	Digital elevation model	Raster	0.25 Km	http://www.cgiar-csi.org
	Land use land cover of 2018	Raster	0.016 Km	https://egis.environment.gov.za/gis_data_downloads

Table 3.2: The Vegetation drought index classification (Brown et al., 2014)

Value range	Bioclimatic class	Reclassification*
Greater than 4.00	Extremely wet	No Drought
3.00-3.99	Severely wet	
2.00-2.99	Moderately wet	
1.00-1.99	Slightly wet	Slight Drought
0.99 to (-0.99)	Near normal	
-1.99 to (-1.00)	Mild dry	Moderate Drought
-2.99 to (-2.00)	Moderately dry	
-3 to (-3.00)	Severely dry	Severe Drought
Less than (-4.00)	Extremely dry	Very Severe Drought

* *Indicate that the colour corresponds with the drought classification on the map*

3.2.3 Climate and Satellite data inputs for VegDRI

3.2.3.1 Climate data

Long-term rainfall data is essential in climate analyses and applications. Rainfall data from station observations are sometimes patchy and unavailable in many parts of the world due to sparse or lack of weather station networks and limited reporting of gauge observations (Malherbe et al., 2016). To address this limitation, rainfall estimates from satellites have been used as an alternative or a supplement to station observations (Funk et al., 2015). Gridded climate data (rainfall, air temperature, and ET) was obtained from https://climateserv.servirglobal.net over 38 years from 1981 to 2019. A detailed description of the Climate Hazards Group Infrared Precipitation (CHIRPS) products have been provided in Funk et al. (2015). The purpose of the CHIRPS dataset was to provide high-resolution data for areas where climate data is not readily available. The CHIRPS data were compared with recorded data across SA from four automatic weather stations (AWS), namely Wartburg-Byruns Hill, Ulakazi, KwaDukuza, and Tugela Mouth, which were selected based on data available from the South African Sugarcane Research Institute (SASRI) (https://sasri.sasa.org.za/pls/sasri). The coefficient of determination (R^2), bias, and efficiency was applied to evaluate any difference between seasonal climatic data from the automatic weather station and CHIRPS precipitation (**Table 3.3**). The comparison process performed in R-Instat software assumed that both AWS data and CHIRPS datasets have similar distributions (Willmott, 1981; Eum et al., 2012) (**Table 3.3**).

Table 3.3: Descriptions of validation statistics used in the article

Statistics	Formula		Range	Best value
Bias	$Bias = \frac{\Sigma S}{\Sigma G}$	Equation 3.1	0 to ∞	1
Efficiency	$Eff = \frac{1\, \Sigma(S - G)^2}{\Sigma(S - \bar{G})^2}$	Equation 3.2	∞ to1	1
Correlation coefficient	CC=$\frac{(G1-\bar{G})(S1-\bar{S})}{\sqrt{\overline{(G1-\overline{G})^2}\,\overline{(S1-\overline{S})^2}}}$	Equation 3.3	−1 to 1	-1 or 1

Note. G=gauge rainfall measurements; $\bar{G}$=average of the gauge measurements; *S* =satellite rainfall estimate; *N* =number of data pairs

3.2.4 Standardised Precipitation Index (SPI)

The Standardised Precipitation Index (SPI) is designed to quantify the precipitation anomaly for a specified time for a location based on the long-term precipitation record over that specific time interval (McKee, 2012). The SPI quantifies the degree of wetness/dryness by comparing accumulated rainfall over different periods with the historical rainfall period (McKee, 1993). SPI is highly related to drought conditions because it reflects energy and water exchanges among vegetation, soil, and atmosphere and considers soil moisture characteristics (Mishra and Singh, 2010). The positive and negative SPI values represent more and less precipitation than the historical mean rainfall (McKee, 1993). The SPI is useful for distinguishing dry from wet years or deficit from surplus years. The SPI uses a probability distribution function, such as gamma, to transform precipitation data into a normal distribution (McKee et al., 1993). It can be calculated for any period of interest, and different timescales are appropriate for monitoring various types of drought (Adisa et al., 2019; Botai et al., 2019). The magnitude of drought classified as very severe dry (<-2), severe dry (-1.5 to -1.99), moderate dry (-1.0 to -1.49), light drought (-0.99 to 0.99), and no drought (>1+) (McKee, 2012). The index was recommended as a standard worldwide meteorological drought index by the World Meteorological Organization (WMO, 2012). However, it is point-based and limited in covering vast areas to show the spatial distribution of drought (McKee, 2012). It requires spatial interpolation, which often produces high uncertainty in interpolated regions (Peters et al., 2002).

3.2.5 Vegetation Condition Index (VCI)

Vegetation Condition Index (VCI) from MOD13Q1 is calculated from remote sensing data obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS) optical satellite imagery (Solano et al., 2010). The index is used to assess drought severity in areas where episodes are localised and ill-defined (Quiring and Ganesh, 2010). This is achieved by comparing the current state of the vegetation as measured by NDVI to the range of values observed over the same period in previous years in the R environment (UNOOSA, 2019). The VCI is calculated as:

$$VCI_{ijk} = \frac{\mathrm{VI}_{ijk} - VI_{i,min}}{VI_{i,max} - VI_{i,min}} * 100 \qquad \text{Equation 3.4}$$

where VCI_{ijk} is the VCI value for the pixel *i* during week/month/DOY*j* for year *k*, VI_{ijk} is the weekly/monthly/DOYs VI value for pixel *i* in week/month/DOY *j* for year *k* whereby both the NDVI or EVI can be used as VI, $VI_{i,\ min}$ and $VI_{i,max}$ is the multi-year minimum and maximum VI, respectively, for pixel *i*. The state of drought presented as a percentage, Lower and higher values indicate bad and good vegetation state conditions, respectively (**Table 3.4**).

3.2.6 Temperature Condition Index (TCI)

The Temperature Condition Index determines stress on vegetation caused by temperature and excessive wetness (Villamarín et al., 2013). The degree of hotness or coldness of an environment determines the suitability of crop species (García-León et al., 2019). Temperature affects biochemical reactions such as photosynthesis, respiration, and ultimately the entire crop production (Lobell, 2007).

Table 3.4: Vegetation drought severity index

Value (%)	Category	Reclassification*
90-100	No Drought	No Drought (80-100%)
80-90	No drought	
70-80	No drought	Slight Drought (70-80%)
50-60	No drought	Moderate Drought (40-50%)
40-50	No drought	
30-40	Light drought	Very Severe Drought (20-40%)
20-30	Moderate drought	
0-10	Extreme drought	Very Severe Drought (0-10%)

* *Indicate that the colour corresponds with the drought classification on the map*

Conditions are estimated relative to the maximum and minimum temperatures and modified to reflect different vegetation responses to temperature at a specified time and location (Kogan, 1995). The TCI is a practical approach for monitoring drought occurrence after the crops turn green; as a result, the index can be used to indicate zones under water stress and high rainfall variability (Villamarín et al., 2013). Temperature Condition Index values vary from zero, for extremely unfavourable conditions, to 100, for optimal conditions. The temperature condition index is given by Equation 3.5.

$$TCI\ 100 * \frac{BT_{max} - BT}{BT_{max} - BT_{min}} \qquad \text{Equation 3.5}$$

While Bio-temperature (BT), BT_{max}, and BT_{min} are the smoothed ten-day radiant temperature, it is multi-year maximum; it is multi-year minimum respectively, for each pixel, in a given area.

3.2.7 Drought indices evaluation

This study evaluates the performance of drought indices based on correlations between drought indices and historical sorghum yield in South Africa. Historical sorghum yields were sourced from the Department of Agriculture, Forestry, and Fisheries (DAFF). This approach makes assumptions about the nature of the relationship between agricultural drought and average Nkangala district sorghum yields from Mpumalanga province in South Africa. The study assumed that water requirements, the depth of water needed to meet the water consumed through evapotranspiration (ETo) by a disease-free sorghum crop, growing in large fields under non-restricting soil conditions including soil water and fertility, and achieving full production potential under the given growing environment (Assefa et al., 2014). The average district indices (pixel) were masked only from crop production land use (https://egis.environment.gov.za/gis_data_downloads). The correlations test between the VegDRI, VCI, TCI, and SPI against drought-tolerant crop yield data were to test and validate the possible use of the VegDRI index.

To assess the relative importance of each drought index, we performed pixel-to-pixel comparisons between VegDRI with VCI, TCI, and SPI and calculated the mean difference in pixel scores. The mean differences were calculated for the period between 2000-2019. In addition, a two-sample Student's t-test was used to examine whether the mean difference in corresponding pixel scores from VegDRI map to either VCI, TCI or SPI was greater than would be expected by chance alone. The comparison assumed a null hypothesis that both maps were identical to each other regardless of which input parameters were used (Van Vliet et al., 2011). The coefficient of determination (R^2) was used to evaluate model performance by comparing it with sorghum yield. Then we utilized weighted kappa statistics to compare the relative difference of each map. Kappa statistics were to evaluate inter-rater reliability when judging a common stimulus. The 'raters' were the drought indices being compared. At the same time, the stimulus was the data provided by the variables (each map being compared), and the agreement objective was the pixel score generated by each drought index. A kappa value of 1 indicates perfect agreement between raters, and 0 indicates no more agreement than that expected by chance (Hernandez, 2012; Merow et al., 2013; Pecchi et al., 2019).

3.3 Results

3.3.1 Precipitation evaluation

The performance of CHIRPS and in-situ or observed precipitation products were assessed based on the empirical distribution function (ECDF) of daily scale precipitation at two thresholds (2.5 and 4.95 mm/day) at four weather stations (**Table 3.5**). CHIRPS precipitation data was highly correlated with observed weather data across all weather stations used in South Africa. Based on the results, CHIRPS datasets are safe to use in agricultural drought analysis.

Table 3.5: Validation statistics for seasonal daily rainfall products over KwaZulu-Natal using point-to-pixel comparisons

Location	Coordinates	CHIRPS (mm)*	Correlation coefficient	Efficiency	Bias
Wartburg	29^0 55 0" S,	2.5	0.68	0.66	0.78
Bruyns Hill	31 46 0 E	4.95	0.78	0.70	0.88
Umlakazi	28 55 0 S	2.5	0.62	0.64	0.72
	31 46 0 E	4.95	0.76	0.69	0.85
KwaDukuza	29 29 0 S	2.5	0.60	0.63	0.70
	31 12 0 E	4.95	0.78	0.70	0.88
Tugela Mouth	29 14 0 S	2.5	0.68	0.66	0.78
	31 8 45 E	4.95	0.79	0.73	0.89

*****_2.5 mm represent meteorological rainfall per day, 4.95 mm represent rainfall which influences crop production per day_

3.3.2 Temperature condition index map

Figure 3.3 presents the TCI for South Africa based on the long-term averages (1981-2019) data. The spatial degree of hotness varied across the country, and this translates to different drought severity. The results indicated that about 10% of the arable land is classified as very severe drought, 44% severe drought, 22% moderate drought, 22% slight drought, and 2% no drought for South Africa. Very high to severe drought conditions were indicated in the Northern Cape and Eastern Cape provinces (**Figure 3.3**). There is a spatial variation of moderate to slight drought in central provinces, northeast, and south-eastern provinces of South Africa (**Figure 3.3**).

3.3.3 Vegetation condition index

The level of drought severity based on the VCI ranged from very severe drought 26%, severe drought 31%, moderate drought 14%, slight drought 23%, and no drought 6% of arable land for South Africa. The distribution of VCI was consistent with TCI. The extent of very severe to severe drought covered the northwest to south-west provinces of South Africa. The central to eastern provinces were characterised by moderate and no drought conditions (**Figure 3.4**).

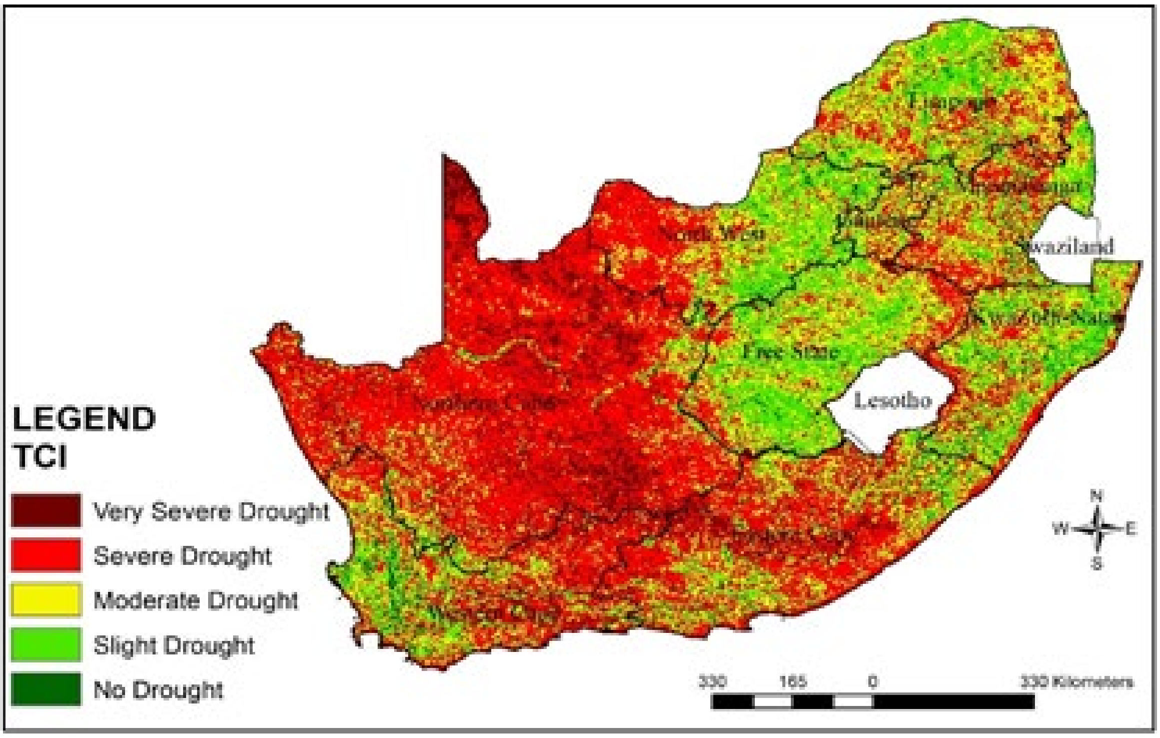


Figure 3.3: Average temperature condition index (TCI) based on temperature data from 1981-2019 for South Africa

3.3.4 Standard precipitation index in South Africa

The intensity of precipitation anomaly varies across South Africa, with 25% very severe dry zones, 29% severe drought, 18% moderate drought, 21% slight drought, and 7% experiencing no drought zones (**Figure *3.5***). The spatial aridity was high in south-eastern and central provinces of the country. The precipitation anomaly was classified as very severe to severe is high in western provinces and part of eastern Limpopo province.

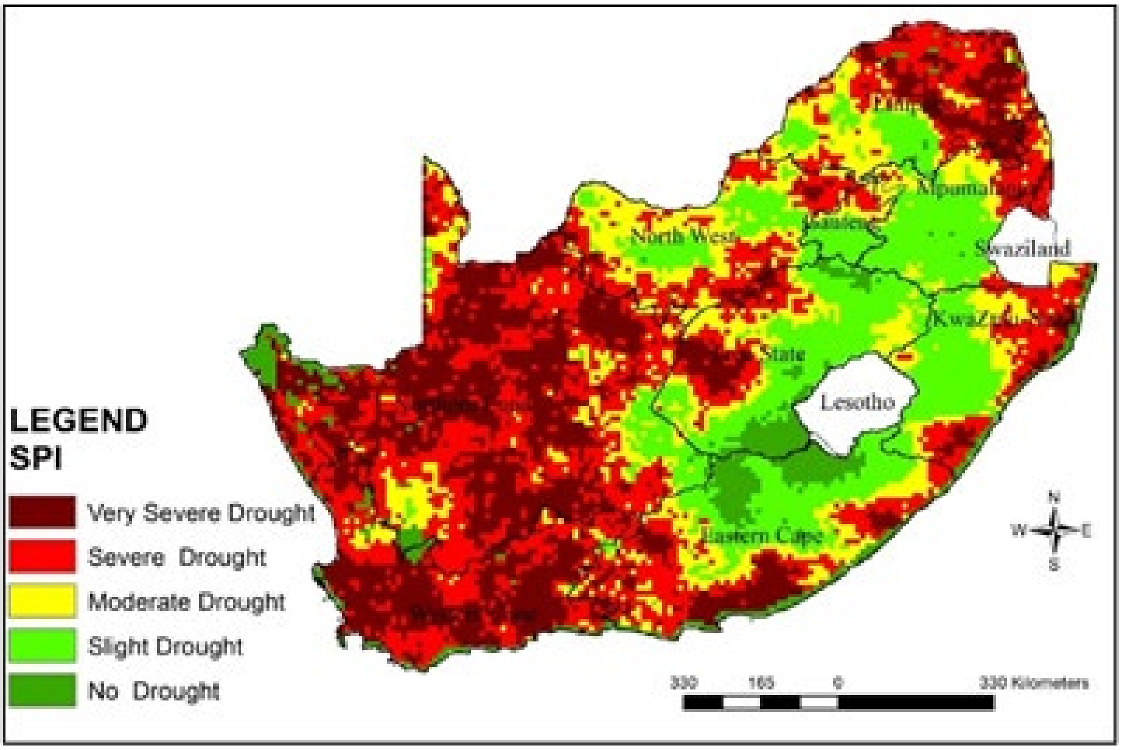


Figure 3.4: Long term average standard precipitation index (SPI) for 6 months from 1981-2019 from CHIRPS

3.3.5 Vegetation Drought Response Index (VegDRI)

Figure 3.6 shows the long-term seasonal time series of the VegDRI for South Africa. The VegDRI-South Africa map shows a variation of very severe drought 16%, severe drought 34%, moderate drought 38%, slight drought 11%, and no drought conditions 1% detected over South Africa. Over the Northern Cape and Eastern Cape provinces, drought was very severe to severe, indicating acute water scarcity. Moderate to no drought conditions are reported from the central province to the eastern provinces of South Africa.

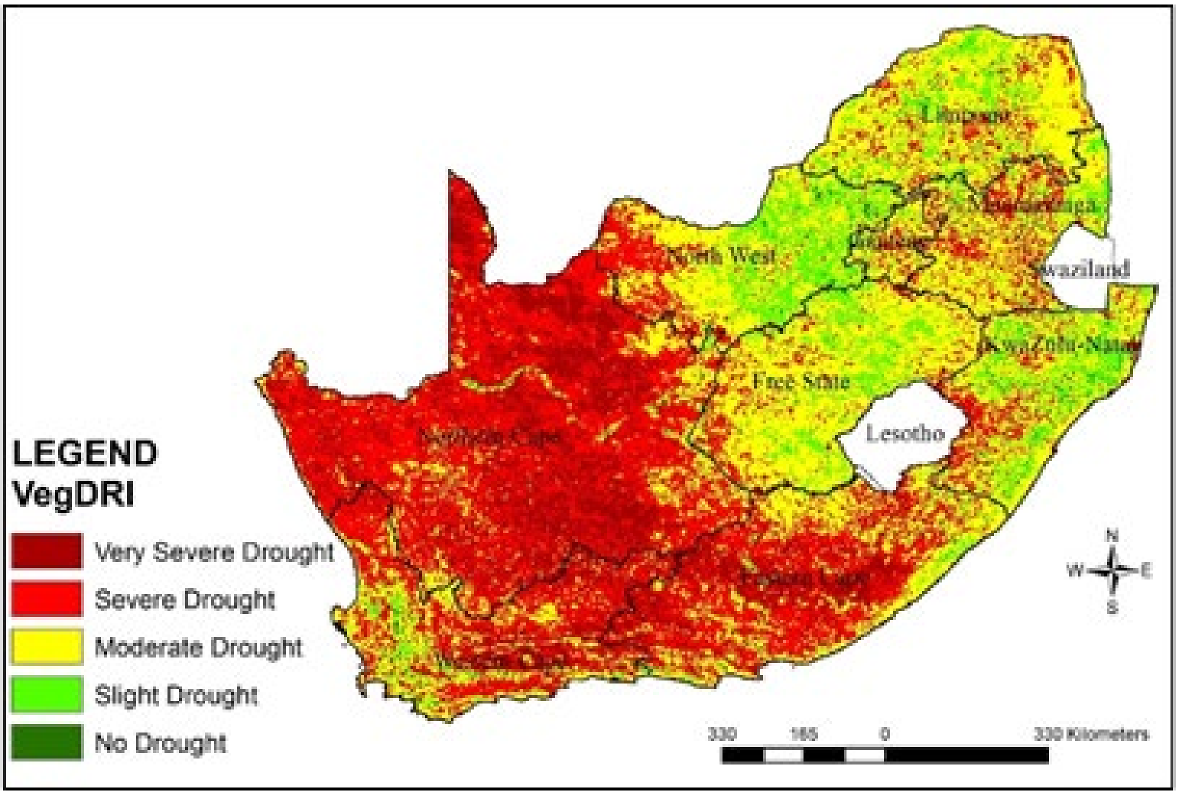


Figure 3.5. Average seasonal Vegetation Drought Response Index

3.3.6 Drought indices evaluation

The performance of each drought index was evaluated using the coefficient of determination (r^2), measuring the fitness between actual sorghum yield and predicted values (drought indices). Amongst the four indices, VegDRI (74.1%) performed the best in predicting sorghum average yields for the period 2010 to 2019, followed by VCI (71.8%), TCI (66.2%), and SPI (59%) (**Figure 3.7**). All indices responded to low rainfall in the 2015/16 agricultural season and recorded the lowest sorghum yield (**Figure 3.7**). The three indices (VegDRI, VCI, and TCI) performed systematically better than the precipitation-based SPI in explaining sorghum yield.

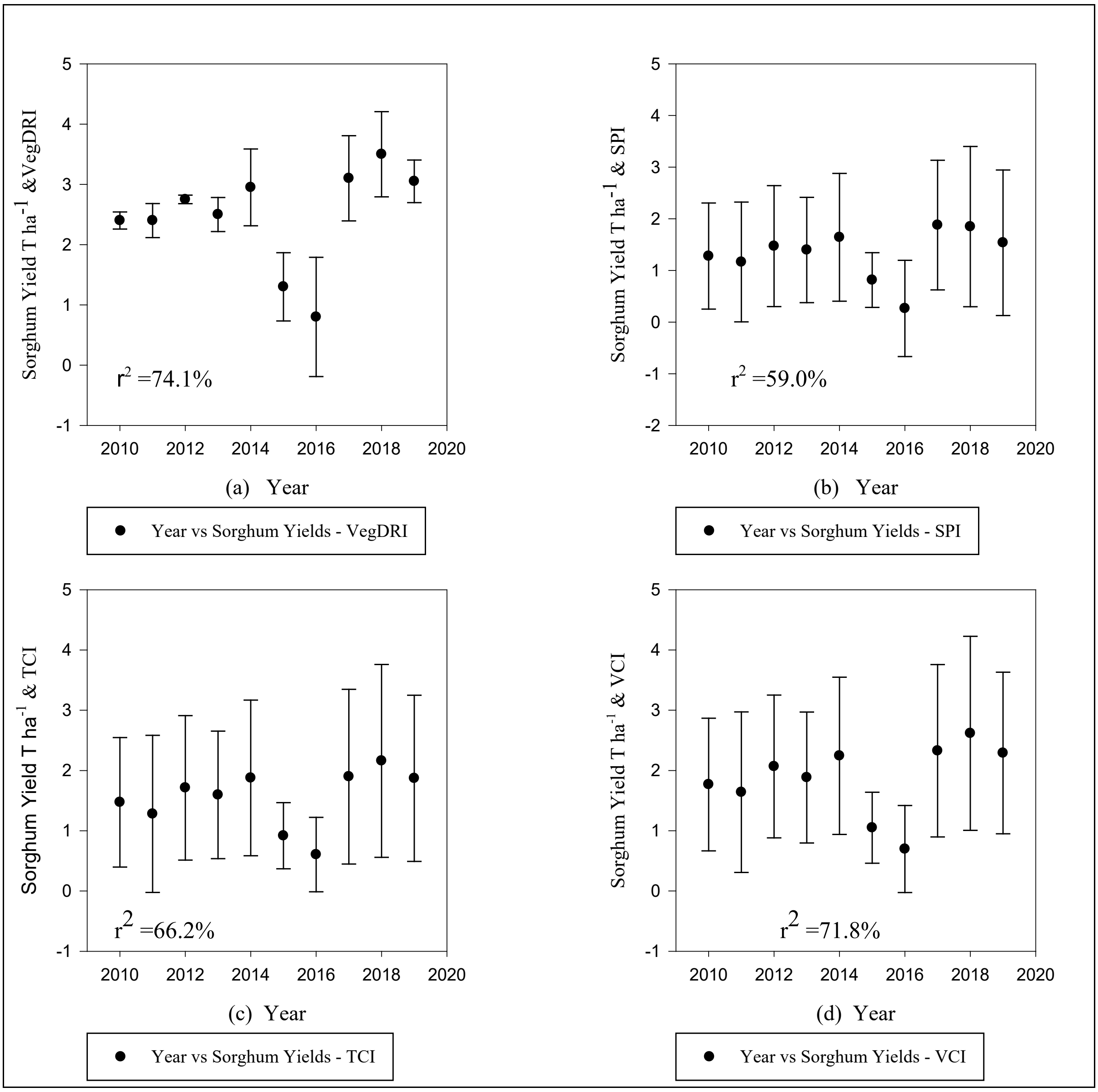


Figure 3.6: Correlation between district sorghum yields and drought indices (a) VegDRI vs Sorghum yields, (b) standard precipitation index vs sorghum yields, (c) Temperature condition index (TCI) vs sorghum yields, (d) Vegetation condition index (VCI) vs sorghum yields respectively for the period between 2010 to 2019.

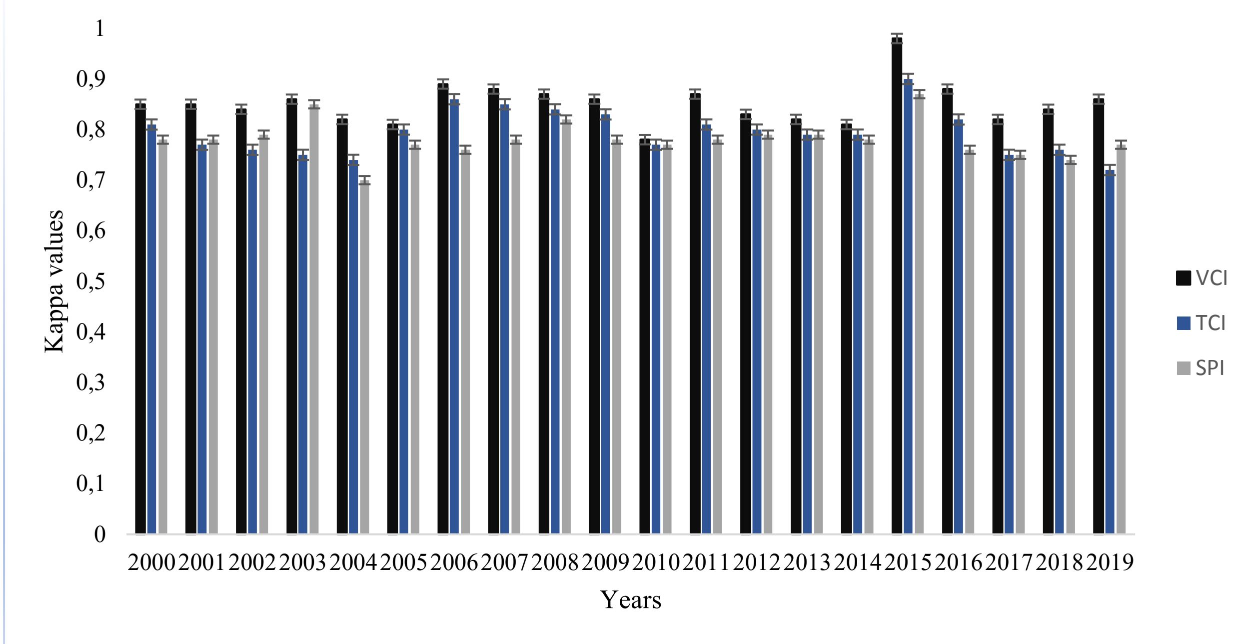


Figure 3.7: Kappa statistic, comparison of VegDRI vs (VCI, TCI and SPI) from 2000-2019. Error bars indicate 95% confidence intervals.

The highest Kappa coefficients were observed between VegDRI vs VCI, followed by TCI, and the lowest inter-rater reliability or agreement was on SPI with a value of 0.70. The highest Kappa coefficients were observed in agricultural season 2015, VCI (0.98), TCI (0.90) and SPI (0.87).

3.4 Discussion

The identification of bioclimatic zones characterised as water-stressed and with high rainfall variability is a pre-requisite to spatial and temporal variation analysis that can inform crop management strategies to improve food security in marginal lands of South Africa (Masih et al., 2014; Shiferaw et al., 2014; Baudoin et al., 2017). The identified water-stressed bioclimatic zones or agricultural risk zones produced by integrating VCI, TCI, and SPI drought indices indicate that South Africa can be classified into slight, moderate, and severe agricultural drought risk zones, respectively (Brown et al., 2013; Nam et al., 2018). The indices evaluated in this study provide options for identifying the severity and location but do not show the duration, onset, and cessation of drought conditions. The combination of VCI, TCI, and SPI allow us to detect drought in the agricultural areas of South Africa, and VegDRI was found to be more effective compared to other indices (Brown et al., 2014). Based on the results from the hybrid index, VegDRI can be used for various applications such as agricultural drought detection, drought duration, crop yields, and crop production during the growing season (Brown et al., 2013; Nam et al., 2018)

The relationships between SPI, TCI, VCI, and VegDRI against sorghum yield data were used to evaluate bioclimatic zones under water stress and high rainfall variability. Under rainfed conditions, crop production is a function of rainfall; crop failure is most often associated with water deficit or agricultural drought (Consoli and Vanella, 2014). Thus, regression analysis between VegDRI and average sorghum grain yield anomaly is indispensable for validation (Singh Choudhary et al., 2012; Jiao et al., 2019b; Möllmann et al., 2019). The overall fit of VegDRI (74.1%), VCI (71.8%), and TCI (66.2%) were slightly better than those obtained from SPI (59%) (Figure 7). The results were consistent with Estes et al. (2013), where maize yield was predicted using MODIS TCI and NDVI in South Africa. The results were also consistent with Johnson (2014), where maize and soybean yields were predicted using MODIS TCI and NDVI. The area that experiences no drought is very limited in South Africa’s agro-ecosystems (Strydom et al., 2020).

Precipitation and water-related indices are closely related to meteorological drought, while vegetation-related indices, TCI, and SPI are more related to agricultural drought (Tadesse et al., 2017). The cultivated sorghum in South Africa is grown in the northern provinces' drier areas, which concur with mapped zones, especially in moderate to slight drought classes of generated indices (Van der Merwe et al., 2016; Malobane et al., 2018). The Free State produces about 50% of South Africa’s sorghum with an average production yield of 2 tonnes ha$^{-1.}$ Sorghum is produced on a wide range of soils in different farming systems and under fluctuating rainfall conditions of approximately 400 mm in the drier western parts of the country to about 800 mm in the wetter eastern parts of South Africa (Chimonyo et al., 2016). Therefore, VegDRI based agricultural drought assessment can better capture agricultural drought conditions or areas under water stress. There was a relationship between sorghum yields and TCI, and this implies that the index determines the stress on vegetation caused by temperatures and excessive wetness. The conditions from TCI are estimated relative to the maximum and minimum temperatures and modified to reflect different vegetation responses to heat. The correlation between TCI and sorghum district yields is lower than VegDRI and VCI because TCI has the potential for cloud contamination, especially in mid-January to April, which might reduce the surrogate of the index and sorghum (Suryabhagavan, 2017). Based on the results, the operational drought index for forecasting crop yields should be based on drought indicators at a higher frequency and less contamination by clouds (Park et al., 2016). The TCI and VCI indices have a high correlation compared to SPI because VCI is provided at a maximum of 8-day frequency, whereas accumulated SPI is only available monthly, making it less surrogate to sorghum yields (Kogan, 1995; Tsiros et al., 2004). The VCI and TCI related to vegetation health give a better picture of characterising bioclimatic zone under water scarcity and rainfall variability than drought index that only rely on rainfall SPI, mainly because vegetation related indices inherently use the water balance to measure crop performance (Jiao et al., 2019a).

The SPI scored the least correlation with sorghum yield because SPI is normalised. Therefore, drier and wetter climates can be represented in the same way; thus, wet periods can also be monitored using the SPI (Adisa et al., 2019). SPI is a measure of water supply only and a widely used index to characterise meteorological drought on a range of timescales. Still, it does not account for evapotranspiration and crop water requirement (Mishra and Singh, 2011). This limits its ability to capture the effect of increased temperatures associated with climate change on water demand and availability on crops. Alternative indices that deal with evapotranspiration, such as the Standardised Precipitation-Evapotranspiration Index (SPEI), can be used to delineate the bioclimatic zones under water stress (Mishra and Singh, 2011). It must be stressed that the SPI is not suitable for climate change analysis because the temperature is not an input parameter (UNOOSA, 2019). Kappa values presented in figure 8 for VegDRI and VCI are very close to 1 compared to TCI and SPI. This indicates a very high agreement between the VegDRI and VCI. Weighted kappa values between 0.8 and 1 are generally accepted as having an excellent agreement between the raters; values falling below 0.8 may be considered less statistically significant (Van Vliet et al., 2011; Pecchi et al., 2019). However, this high agreement between VegDRI vs VCI and VegDRI vs TCI does not necessarily indicate an accurate delineation of drought in South Africa (Moeletsi et al., 2013; Botai et al., 2019). The Kappa coefficient of agreement is a statistic for discrete multivariate analysis (Van Vliet et al., 2011). It expresses the agreement between two categorical datasets corrected for the agreement as expected by chance, depending on the distribution of class sizes in both datasets only. Therefore, the drought indices produced, especially the VegDRI, need to be ground-truthed.

The mapped bioclimatic zones with moderate to severe drought are the most water-stressed zones in South Africa (Aliber and Cousins, 2013). In these zones, compounding factors such as poverty and inappropriate land use increase vulnerability to drought. Also, smallholder farmers located in these bioclimatic zones lack irrigation facilities to mitigate water stress effects (Cai et al., 2017). Each drought event's spatial and temporal variability makes it difficult to prepare and respond effectively. In South Africa, agriculture is the most vulnerable and sensitive sector to climate variability and change, which mostly manifests through rainfall variability and recurrent droughts (Nhamo et al., 2019a). Using satellite data as an input parameter for drought indices, spatial-temporal variation of seasonal agricultural drought patterns and severity can be detected and mapped with the help of remote sensing and GIS (Park et al., 2016).

The study used a machine-learning algorithm to analyse and mine higher spatial resolution climatic datasets to fill the gaps where climatic data was unavailable. Comparisons of CHIRPS data with available climatic records were used as a benchmark to determine the strengths and limitations of remotely sensed products. A non-parametric Kolmogorov-Smirnov (K-S) significance test with a 95% confidence level was applied to precipitation between in-situ/observed data, assuming both in-situ and CHIRPS data have similar distributions (Funk et al., 2015; Dinku et al., 2018). The in-situ data recorded through traditional rain gauges represent point-scale observations, which are not truly representative of the area-averaged precipitation (Table 5). Precipitation from infrared and microwave-based algorithms also have limitations due to terrain and wet and dry regional climates (Dinku et al., 2018). The analysis of climatic data depends on its distribution pattern, especially in marginal areas. Schwarz et al. (2020) higher spatial resolution datasets must be considered to generate drought-related risks maps in agriculture in agriculture. The choice of a rainfall product can significantly influence the performance of such applications(Le Coz and Van de Giesen, 2020). However, the study used CHIRPS datasets to evaluate or compare rainfall products over different parts of South Africa. In SA, rainfall products from the gauge-only, satellite-based, and radar are recommended. In addition, the use of global rainfall products such as the African Rainfall Climatology version 2 (ARC2), the Rainfall Estimate version 2 (RFE2), and the Tropical Applications of Meteorology Using Satellite Data and Ground-Based Observations (TAMSAT) African Rainfall Climatology and Time Series (TARCAT) need to be compared with CHIRPS datasets (Le Coz and Van de Giesen, 2020).

The results show that VegDRI can delineate bioclimatic zones classified as under stress and high rainfall variability (Brown et al., 2014). The South Africa VegDRI map can be used with traditional drought indicators (VCI, TCI, and SPI) to inform various management decisions, such as crop selection within bioclimatic zones, justifying disaster management actions, identifying potential zones for livestock production, and assessing fire risk zones. However, the interpretation of our results relative to climate change is limited because we used a historical data set (1981-2019). As such, future studies should focus on using data from global circulation models (GCMs) to inform climate change scenarios more specifically. However, the current maps remain useful for informing the areas currently classified as water-stressed and with high rainfall variability for sustainable intensification management strategies. To validate and operationalise the results, it is essential to ground-truth the mapped bioclimatic zones. It is important to note that the impacts of drought can be as varied as its causes. Results from this study highlight the potential for the use of a hybrid index, the VegDRI, in agricultural decision support systems such as drought risk maps for agricultural drought early warning systems, crop yield forecasting models, and water resource management tools

3.5 Limitations

Our methodology focused on assessing bioclimatic zones under water stress and with high rainfall variability using mainly biophysical factors. Such impacts depend on the socio-economic context in which drought occurs, in terms of who or what is exposed to the drought and the specific vulnerabilities of the detected entities. Therefore, there is a need to identify innovative ways to derive maximum value from the possible integration of GIS with block-chain and the Internet of Things (IoT) technologies to integrate socio-economic factors. Using machine learning and deep learning algorithms can predict and forecast complex local drought conditions. Features of both nonlinearity and unstableness usually characterize drought time series; there is a need to evaluate different deep learning algorithms in mapping drought risk zones in the SSA region. In addition, the drought indices were evaluated only against the district sorghum average yields instead of other drought tolerance crops. Input data for calculating the VegDRI and statistics from the sorghum crop are independent and from different sources. However, that did not prevent us from obtaining strong correlations between VegDRI. This makes it possible to say that the VegDRI a good indicator of agricultural drought and can, therefore, be used to detect drought-prone zones in South Africa.

3.6 Implications of the drought risk maps for crop production

The agricultural drought risk maps generated are useful to guide decision-making on drought mitigation and adaptation using the integrated climate risk management approach (risk reduction); insurance (risk transfer); livelihoods diversification and microcredit (prudent risk-taking); and savings (risk reserves) (Andersson-Sköld et al., 2015; Gopichandran et al., 2016). Through its innovative nature, R4 enables vulnerable farmers to adapt to climate risks by adopting appropriate sustainable intensification and climate-smart strategies. The generated maps are useful to farmers, agronomists in extension, researchers, non-governmental organisations (NGOs), the private sector such as insurance companies and banks to develop drought resilience strategies (Table 3.6). Additionally, the generated maps can help to increase the value and relevance of information available to decision-makers, thereby enhancing and supporting drought response and mitigation activities. The information generated from drought indices in the form of accessible formats such as maps generated and trend analysis increases the value and relevancy of drought to support drought response and mitigation activities in marginal areas (Park et al., 2016). Drought risk mapping is a key element of drought management. It helps identify the areas that are most prone to droughts, allowing policy-makers and agriculturists to plan and give guided recommendations to improve agriculture production in a sustainable manner (Shiferaw et al., 2014).

Table 3.6: Resilience strategies and usefulness of maps generated in crop production

Strategy	Key findings	Specific use	Proposed adaptation and mitigation strategies	Recommendations
1. Risk reduction	Identified drought-prone areas and areas with low risk	• To indicate where drought-tolerant crops such as NUS can be promoted as alternative crop choices • To understand the regions within South Africa which are at greater risk of drought hazard	• To inform site-specific crop diversification recommendations as a sustainable intensification strategy • Investing in climate risk assets such as the construction of dams and irrigation facilities • Mainstreaming weather information into agricultural extension support using bulletins to guide preparedness efforts • Crop diversification at a spatial and temporal scale • Ex- and in-situ rainwater	• A higher spatial resolution VegDRI would be more applicable for local-scale monitoring and decision • Climate scenarios should be included to allow for more proactive agricultural planning • Researchers need to consider the inclusion of socio-economic parameters in delineating drought risk zones

			harvesting and conservation techniques	
		• Early warning action	• Maps can be used as a base for monitoring, assessing, forecasting likelihoods of drought and wet spells in high-risk areas	• Gridded climatic need to be validated with locally generated datasets (South Africa Weather Service)
		Promoting green zones for climate action in agriculture	• Promote tolerance crops such as NUS in dry regions to gain agro-ecosystem services and improve food security in marginal lands	
2. Risk Transfer	Refined maps of where the risk of drought is low or high	• Weather index insurance • Area yield index insurance	• Insuring smallholder farmers from drought	• Maps work as a base map for drought monitoring and initiate weather index claims for insurance companies like Africa Risk Capacity (ARC),
3. Risk		• Sustainable	• Livelihood diversification	• Diversification of crop-

Prudence and Reserves		transformation of existing farming systems	such as livestock production • Access to microcredit to promote alternative productions that are less vulnerable • Saving and lending groups to caution hazards and puerile	livestock systems to spread the risk (intercropping, rearing small livestock, market gardening, and promotion of NUS to complement major crops to improve food and nutrition in marginal lands
4. Policy and funding context	The arable land of SA constitutes 16% of extreme/very severe, 34%-severe, 38%-moderate, 11%-slight, and 1%-no drought conditions	• Evidence-based policy formulation	• To generate policies that support good agricultural practices	• Harmonisation of existing policies and institutes that speak to land, environment, agriculture, and health

3.7 Conclusions

This study used CART, a machine learning algorithm. We established drought indices, SPI, TCI, and VCI, to generate a hybrid drought index – VegDRI to characterise bioclimatic zones with high rainfall variability and water scarcity for South Africa. VegDRI was able to characterise water-stressed bioclimatic zones with high rainfall variability better than the established drought indices. The VegDRI approach can be adapted for other regions in sub-Saharan Africa using available climate, satellite, and biophysical data. It can be applied to any vegetated area where remote sensing data are accessible even with limited in situ data availability. Future research can incorporate hydrology, soil water, evapotranspiration, and socio-economic factors to delineate bioclimatic zones with high rainfall variability and water scarcity to improve drought management. The predictive accuracy of drought risk maps is computed from the cell-by-cell comparison. However, the absolute value of the Kappa coefficient depends on input data used to delineate drought indices. However, the high agreement of VegDRI with VCI and TCI does not necessarily indicate an accurate mapping of drought risk maps. Ground truthing is recommended to validate the new VegDRI map in South Africa. The adjusted maps can show homogenous areas with similar water requirements for crop production in marginal areas of South Africa. The results from this study highlight the potential for the use of a hybrid index, the VegDRI, in agricultural decision support systems such as drought risk maps for agricultural drought early warning systems, crop yield forecasting models, or water resource management tools.

3.8 References

Adisa, O.M., Botai, J.O., Adeola, A.M., Botai, C.M., Hassen, A., Darkey, D., Tesfamariam, E., Adisa, A.T. and Adisa, A.F., 2019. Analysis of drought conditions over major maize producing provinces of South Africa. *Journal of Agricultural Meteorology*, *75*(4), pp.173-182. doi: 10.2480/agrmet.D-18-00049.

AGRA. 2014. Africa agriculture status report 2018. *Hydrogeology Journal.* doi: 10.1007/s10040-019-01977-2.

Ashok, K.M. and Vijay, P.S., 2011. Drought modeling: A review. *Journal of Hydrology*, *403*, pp.157-175. doi: 10.1016/j.jhydrol.2011.03.049.

Algorithm, A.C., 1999. Accepting the standardized precipitation index : cultural interests while very long term durations time use ; the Palmer Hydrologic Drought Index , Since many users may not have either the back – For a given time scale , SPI values are positive consideration. 35(2).

Aliber, M. and Cousins, B., 2013. Livelihoods after Land Reform in South Africa. *Journal of Agrarian Change*, *13*(1), pp.140-165. doi: 10.1111/joac.12012.

Andersson-Sköld, Y., Thorsson, S., Rayner, D., Lindberg, F., Janhäll, S., Jonsson, A., Moback, U., Bergman, R. and Granberg, M., 2015. An integrated method for assessing climate-related risks and adaptation alternatives in urban areas. *Climate Risk Management*, *7*, pp.31-50. doi: 10.1016/j.crm.2015.01.003.

Team, A., 2019. Application for extracting and exploring analysis ready samples (AppEEARS). *USGS/Earth Resources Observation and Science (EROS)* Center, Sioux Falls, South Dakota, USA.

Assefa, Y., Roozeboom, K., Thompson, C., Schlegel, A., Stone, L. and Lingenfelser, J.E., 2014. Corn and grain sorghum morphology, physiology and phenology. *Corn and Grain Sorghum Comparison*, pp.3-14.

Baudoin, M.A., Vogel, C., Nortje, K. and Naik, M., 2017. Living with drought in South Africa: lessons learnt from the recent El Niño drought period. *International journal of disaster risk reduction*, *23*, pp.128-137. . doi: 10.1016/j.ijdrr.2017.05.005.

Botai, J.O., Botai, C.M., De Wit, J.P., Muthoni, M. and Adeola, A.M., 2019. Analysis of drought progression physiognomies in South Africa. *Water*, *11*(2), p.299. doi: 10.3390/w11020299.

Botai, C.M., Botai, J.O., De Wit, J.P., Ncongwane, K.P. and Adeola, A.M., 2017. Drought characteristics over the western cape province, South Africa. *Water*, *9*(11), p.876. doi: 10.3390/w9110876.

Breiman, L., 2001. Random Forest, vol. 45. *Mach Learn*, *1*

Brown, J.F., Wardlow, B.D., Tadesse, T., Hayes, M.J. and Reed, B.C., 2008. The Vegetation Drought Response Index (VegDRI): A new integrated approach for monitoring drought stress in vegetation. *GIScience & Remote Sensing*, *45*(1), pp.16-46. doi: 10.2747/1548-1603.45.1.16.

Cai, X., Magidi, J., Nhamo, L. and Van Koppen, B., 2017. *Mapping irrigated areas in the Limpopo Province, South Africa*(Vol. 172). International Water Management Institute (IWMI).

Chimonyo, V.G.P., Modi, A.T. and Mabhaudhi, T., 2016. Simulating yield and water use of a sorghum-cowpea intercrop using APSIM. *Agricultural Water Management*, *177*, pp.317-328. doi: 10.1016/j.agwat.2016.08.021.

Consoli, S. and Vanella, D., 2014. Mapping crop evapotranspiration by integrating vegetation indices into a soil water balance model. *Agricultural Water Management*, *143*, pp.71-81. doi: 10.1016/j.agwat.2014.06.012.

Crespi, M. and De Vendictis, L., 2009. A procedure for high resolution satellite imagery quality assessment. *Sensors*, *9*(5), pp.3289-3313. doi: 10.3390/s90503289.

Dai, A., 2011. Characteristics and trends in various forms of the Palmer Drought Severity Index during 1900-2008. *Journal of Geophysical Research: Atmospheres*, *116*(D12). doi: 10.1002/wcc.81.

Dai, A., 2012. Increasing drought under global warming in observations and models. *Nature Climate Change.* 3(1): 52-58. doi: 10.1038/nclimate1633.

Didan, K., Munoz, A.B., Solano, R. and Huete, A., 2015. MODIS vegetation index user's guide (MOD13 series). *University of Arizona: Vegetation Index and Phenology Lab*.

Dinku, T., Funk, C., Peterson, P., Maidment, R., Tadesse, T., Gadain, H. and Ceccato, P., 2018. Validation of the CHIRPS satellite rainfall estimates over eastern Africa. *Quarterly Journal of the Royal Meteorological Society*, *144*, pp.292-312. . doi: 10.1002/qj.3244.

Du, L., Tian, Q., Yu, T., Meng, Q., Jancso, T., Udvardy, P. and Huang, Y., 2013. A comprehensive drought monitoring method integrating MODIS and TRMM data. *International Journal of Applied Earth Observation and Geoinformation*, *23*, pp.245-253. doi: 10.1016/j.jag.2012.09.010.

Ebrahimpour, M., Rahimi, J., Nikkhah, A. and Bazrafshan, J., 2015. Monitoring agricultural drought using the standardized effective precipitation index. *Journal of Irrigation and Drainage Engineering*, *141*(1), p.04014044. doi: 10.1061/(ASCE)IR.1943-4774.0000771.

Estes, L.D., Bradley, B.A., Beukes, H., Hole, D.G., Lau, M., Oppenheimer, M.G., Schulze, R., Tadross, M.A. and Turner, W.R., 2013. Comparing mechanistic and empirical model projections of crop suitability and productivity: implications for ecological forecasting. *Global Ecology and Biogeography*, *22*(8), pp.1007-1018. doi: 10.1111/geb.12034.

Eum, H.I., Gachon, P., Laprise, R. and Ouarda, T., 2012. Evaluation of regional climate model simulations versus gridded observed and regional reanalysis products using a combined weighting scheme. *Climate Dynamics*, *38*(7), pp.1433-1457. doi: 10.1007/s00382-011-1149-3.

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A. and Michaelsen, J., 2015. The climate hazards infrared precipitation with stations – a new environmental record for monitoring extremes. *Scientific data*, *2*(1), pp.1-21. doi: 10.1038/sdata.2015.66.

García-León, D., Contreras, S. and Hunink, J., 2019. Comparison of meteorological and satellite-based drought indices as yield predictors of Spanish cereals. *Agricultural Water Management*, *213*, pp.388-396. doi: 10.1016/j.agwat.2018.10.030.

Gopichandran, R., Asolekar, S.R., Jani, O., Kumar, D. and Hiremath, A.M., 2015. Green energy and climate change. *An Integrated Approach to Environmental Management*, p.127.

Haied, N., Foufou, A., Chaab, S., Azlaoui, M., Khadri, S., Benzahia, K. and Benzahia, I., 2017. Drought assessment and monitoring using meteorological indices in a semi-arid region. *Energy Procedia*, *119*, pp.518-529. . doi: 10.1016/j.egypro.2017.07.064.

Halwatura, D., McIntyre, N., Lechner, A.M. and Arnold, S., 2017. Capability of meteorological drought indices for detecting soil moisture droughts. *Journal of Hydrology: Regional Studies*, *12*, pp.396-412. . doi: 10.1016/j.ejrh.2017.06.001.

Hao, Z., Hao, F., Singh, V.P., Ouyang, W. and Cheng, H., 2017. An integrated package for drought monitoring, prediction and analysis to aid drought modeling and assessment. *Environmental modelling & software*, *91*, pp.199-209. doi: 10.1016/j.envsoft.2017.02.008.

Heino, M., Puma, M.J., Ward, P.J., Gerten, D., Heck, V., Siebert, S. and Kummu, M., 2018. Two-thirds of global cropland area impacted by climate oscillations. *Nature communications*, *9*(1), pp.1-10. doi: 10.1038/s41467-017-02071-5.

Hernandez, D.A.C., Delfin, H. and MelÃ, V., 2012. Predictive models review of species in biological control. *Tropical and Subtropical Agroecosystems*, *15*(2).

Jarraud, M., 2012. WMO statement on the status of the global climate in 2012. *World meteorological organization, Geneva*, *2*, pp.55-67.

Jiao, W., Tian, C., Chang, Q., Novick, K.A. and Wang, L., 2019. A new multi-sensor integrated index for drought monitoring. *Agricultural and forest meteorology*, *268*, pp.74-85. doi: 10.1016/j.agrformet.2019.01.008.

Jiao, W., Wang, L., Novick, K.A. and Chang, Q., 2019. A new station-enabled multi-sensor integrated index for drought monitoring. *Journal of hydrology*, *574*, pp.169-180. doi: 10.1016/j.jhydrol.2019.04.037.

Kogan, F.N., 1995. Application of vegetation index and brightness temperature for drought detection. *Advances in space research*, *15*(11), pp.91-100. doi: 10.1016/0273-1177(95)00079-T.

Kogan, F., Sullivan, 1993. Development of global drought watch system using NOAA/AVHRR data. *Advances in space Research*, *13*, pp.219-222. doi: 10.1016/0273-1177(93)90548-P.

Kosgei, J.R., 2009. *Rainwater harvesting systems and their influences on field scale soil hydraulic properties, water fluxes and crop production* (Doctoral dissertation).

Le Coz, C. and Van de Giesen, N., 2020. Comparison of rainfall products over sub-Saharan Africa. *Journal of Hydrometeorology*, *21*(4), pp.553-596. doi: 10.1175/JHM-D-18-0256.1.

Lobell, D.B., 2007. Changes in diurnal temperature range and national cereal yields. *Agricultural and forest meteorology*, *145*(3-4), pp.229-238. doi: 10.1016/j.agrformet.2007.05.002.

Malherbe, J., Dieppois, B., Maluleke, P., Van Staden, M. and Pillay, D.L., 2016. South African droughts and decadal variability. *Natural Hazards*, *80*(1), pp.657-681. . doi: 10.1007/s11069-015-1989-y.

Malobane, M.E., Nciizah, A.D., Wakindiki, I.I. and Mudau, F.N., 2018. Sustainable production of sweet sorghum for biofuel production through conservation agriculture in South Africa. *Food and Energy Security*, *7*(3), p.e00129. doi: 10.1002/fes3.129.

Masih, I., Maskey, S., Mussá, F.E.F. and Trambauer, P., 2014. A review of droughts on the African continent: a geospatial and long-term perspective. *Hydrology and Earth System Sciences*, *18*(9), pp.3635-3649.

McKee, T.B., Doesken, J.J. and Kleist, J., 1993. Analysis of Standardized Precipitation Index (SPI) data for drought assessment. *Water*, *26*, pp.1-72. doi: 10.1088/1755-1315/5.

Merow, C., Smith, M.J. and Silander Jr, J.A., 2013. A practical guide to MaxEnt for modeling species' distributions: what it does, and why inputs and settings matter. *Ecography*, *36*(10), pp.1058-1069. doi: 10.1111/j.1600-0587.2013.07872.x.

Miralles, D.G., Van Den Berg, M.J., Gash, J.H., Parinussa, R.M., De Jeu, R.A., Beck, H.E., Holmes, T.R., Jiménez, C., Verhoest, N.E., Dorigo, W.A. and Teuling, A.J., 2014. El Niño-La Niña cycle and recent trends in continental evaporation. *Nature Climate Change*, *4*(2), pp.122-126. . doi: 10.1016/j.jhydrol.2010.07.012.

Moeletsi, M.E., Moopisa, S.G., Walker, S. and Tsubo, M., 2013. Development of an agroclimatological risk tool for dryland maize production in the Free State Province of South Africa. *Computers and electronics in agriculture*, *95*, pp.108-121. . doi: 10.1016/j.compag.2013.04.006.

Möllmann, J., Buchholz, M. and Musshoff, O., 2019. Comparing the hedging effectiveness of weather derivatives based on remotely sensed vegetation health indices and meteorological indices. *Weather, Climate, and Society*, *11*(1), pp.33-48. doi: 10.1175/WCAS-D-17-0127.1.

Mubiru, D.N., Radeny, M., Kyazze, F.B., Zziwa, A., Kinyangi, J. and Mungai, C., 2018. Soils, Environment and Agro-meteorology Unit, National agricultural research laboratories CGIAR research program on climate change, Agriculture and Food Security Program, Department of Extension and Innovation Studies, College of Agricultural and Envir. Clim. Risk Manag. *Climate Risk Management*. doi: 10.1016/j.crm.2018.08.004.

Nam, W.H., Tadesse, T., Wardlow, B.D., Hayes, M.J., Svoboda, M.D., Hong, E.M., Pachepsky, Y.A. and Jang, M.W., 2018. Developing the vegetation drought response index for South Korea (VegDRI-SKorea) to assess the vegetation condition during drought events. *International journal of remote sensing*, *39*(5), pp.1548-1574. doi: 10.1080/01431161.2017.1407047.

Nhamo, L., Mabhaudhi, T. and Modi, A.T., 2019. Preparedness or repeated short-term relief aid? Building drought resilience through early warning in southern Africa. *Water Sa*, *45*(1), pp.75-85. doi: 10.4314/wsa.v45i1.09.

Nhamo, L., Matchaya, G., Mabhaudhi, T., Nhlengethwa, S., Nhemachena, C. and Mpandeli, S., 2019. Cereal production trends under climate change: Impacts and adaptation strategies in southern Africa. *Agriculture*, *9*(2), p.30. doi: 10.3390/agriculture9020030.

Otkin, J.A., Anderson, M.C., Hain, C., Svoboda, M., Johnson, D., Mueller, R., Tadesse, T., Wardlow, B. and Brown, J., 2016. Assessing the evolution of soil moisture and vegetation conditions during the 2012 United States flash drought. *Agricultural and forest meteorology*, *218*, pp.230-242. doi: 10.1016/j.agrformet.2015.12.065.

Palmer, W.C., 1965. *Meteorological drought* (Vol. 30). US Department of Commerce, Weather Bureau.

Park, S., Im, J., Jang, E. and Rhee, J., 2016. Drought assessment and monitoring through blending of multi-sensor indices using machine learning approaches for different climate regions. *Agricultural and forest meteorology*, *216*, pp.157-169. doi: 10.1016/j.agrformet.2015.10.011.

Pecchi, M., Marchi, M., Burton, V., Giannetti, F., Moriondo, M., Bernetti, I., Bindi, M. and Chirici, G., 2019. Species distribution modelling to support forest management. A literature review. *Ecological Modelling*, *411*, p.108817. doi: 10.1016/j.ecolmodel.2019.108817.

Peters, A.J., Walter-Shea, E.A., Ji, L., Vina, A., Hayes, M. and Svoboda, M.D., 2002. Drought monitoring with NDVI-based standardized vegetation index. *Photogrammetric engineering and remote sensing*, *68*(1), pp.71-75.

Pulwarty, R.S. and Sivakumar, M.V., 2014. Information systems in a changing climate: Early warnings and drought risk management. *Weather and Climate Extremes*, *3*, pp.14-21. doi: 10.1016/j.wace.2014.03.005.

Quiring, S.M. and Ganesh, S., 2010. Evaluating the utility of the Vegetation Condition Index (VCI) for monitoring meteorological drought in Texas. *Agricultural and Forest Meteorology*, *150*(3), pp.330-339. doi: 10.1016/j.agrformet.2009.11.015.

Richter, R. and Schläpfer, D., 2011. Atmospheric/topographic correction for airborne imagery. *ATCOR-4 user guide*, pp.565-02.

Rivas-Martínez, S., Rivas-Saenz, S. and Penas, A., 2002. *Worldwide bioclimatic classification system*. Kerkwerve, The Netherlands: Backhuys Pub..

Rojas, O., Vrieling, A. and Rembold, F., 2011. Assessing drought probability for agricultural areas in Africa with coarse resolution remote sensing imagery. *Remote sensing of Environment*, *115*(2), pp.343-352. doi: 10.1016/j.rse.2010.09.006.

Schwarz, M., Landmann, T., Cornish, N., Wetzel, K.F., Siebert, S. and Franke, J., 2020. A spatially transferable drought hazard and drought risk modeling approach based on remote sensing data. *Remote Sensing*, *12*(2), p.237. doi: 10.3390/rs12020237.

Shen, R., Huang, A., Li, B. and Guo, J., 2019. Construction of a drought monitoring model using deep learning based on multi-source remote sensing data. *International Journal of Applied Earth Observation and Geoinformation*, *79*, pp.48-57. doi: 10.1016/j.jag.2019.03.006.

Shen, Z., Zhang, Q., Singh, V.P., Sun, P., Song, C. and Yu, H., 2019. Agricultural drought monitoring across Inner Mongolia, China: Model development, spatiotemporal patterns and impacts. *Journal of Hydrology*, *571*, pp.793-804. doi: 10.1016/j.jhydrol.2019.02.028.

Shiferaw, B., Tesfaye, K., Kassie, M., Abate, T., Prasanna, B.M. and Menkir, A., 2014. Managing vulnerability to drought and enhancing livelihood resilience in sub-Saharan Africa: Technological, institutional and policy options. *Weather and climate extremes*, *3*, pp.67-79. doi: 10.1016/j.wace.2014.04.004.

Singh Choudhary, S.S., Garg, P.K. and Ghosh, S.K., 2012. Mapping of agriculture drought using remote sensing and GIS. *International Journal of Scientific Engineering and Technology*, *1*(4), pp.149-157.

Smithers, J.C. and Schulze, R.E., 2000. *Long duration design rainfall estimates for South Africa*. Pretoria: Water Research Commission.

Strydom, S., Jewitt, G.P.W., Savage, M.J. and Clulow, A.D., 2020. Long-term trends and variability in the microclimates of the uMngeni Catchment, KwaZulu-Natal, South Africa and potential impacts on water resources. *Theoretical and Applied Climatology*, *140*(3), pp.1171-1184. doi: 10.1007/s00704-020-03127-1.

Suryabhagavan, K.V., 2017. GIS-based climate variability and drought characterization in Ethiopia over three decades. Weather Clim Extremes 15: 11-23. doi: 10.1016/j.wace.2016.11.005.

Tadesse, T., Haile, M., Senay, G., Wardlow, B.D. and Knutson, C.L., 2008, November. The need for integration of drought monitoring tools for proactive food security management in sub-Saharan Africa. In *Natural resources forum* (Vol. 32, No. 4, pp. 265-279). Oxford, UK: Blackwell Publishing Ltd. doi: 10.1111/j.1477-8947.2008.00211.x.

Tadesse, T. and Wilhite, D.A., 2007. Modern drought monitoring tool for decision support system. In *Encyclopedia of Digital Government* (pp. 1212-1218). IGI Global.

Team, R.C., 2014. R: A Language and Environment for Statistical Computing http://www. *R-project. org*.

Timmermann, A., An, S.I., Kug, J.S., Jin, F.F., Cai, W., Capotondi, A., Cobb, K.M., Lengaigne, M., McPhaden, M.J., Stuecker, M.F. and Stein, K., 2018. El Niño-southern oscillation complexity. *Nature*, *559*(7715), pp.535-545. doi: 10.1038/s41586-018-0252-6.

Tsiros, E., Domenikiotis, C., Spiliotopoulos, M. and Dalezios, N.R., 2004, September. Use of NOAA/AVHRR-based vegetation condition index (VCI) and temperature condition index (TCI) for drought monitoring in Thessaly, Greece. In *EWRA Symposium on water resources management: risks and challenges for the 21st century, Izmir, Turkey* (pp. 2-4).

Unganai, L.S. and Kogan, F.N., 1998. Drought monitoring and corn yield estimation in Southern Africa from AVHRR data. *Remote sensing of environment*, *63*(3), pp.219-232. doi: 10.1016/S0034-4257(97)00132-6.

UNOOSA., 2019. In Detail: Recommended Practice drought monitoring using the Vegetation Condition Index (VCI) | UN-SPIDER Knowledge Portal. UN-SPIDER.

Van der Merwe, J.D., Cloete, P.C. and Van der Hoeven, M., 2016. Promoting food security through indigenous and traditional food crops. *Agroecology and Sustainable Food Systems*, *40*(8), pp.830-847.

Vicente-Serrano, S.M., Beguería, S. and López-Moreno, J.I., 2010. A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. *Journal of climate*, *23*(7), pp.1696-1718.

Villamarín, C., Rieradevall, M., Paul, M.J., Barbour, M.T. and Prat, N., 2013. A tool to assess the ecological condition of tropical high Andean streams in Ecuador and Peru: The IMEERA index. *Ecological indicators*, *29*, pp.79-92. doi: 10.1016/j.ecolind.2012.12.006.

Van Vliet, J., Bregt, A.K. and Hagen-Zanker, A., 2011. Revisiting Kappa to account for change in the accuracy assessment of land-use change models. *Ecological modelling*, *222*(8), pp.1367-1375.

Wang, W., Ertsen, M.W., Svoboda, M.D. and Hafeez, M., 2016. Propagation of drought: from meteorological drought to agricultural and hydrological drought. *Advances in Meteorology*, *2016*.

Willmott, C.J., 1981. On the validation of models. *Physical geography*, *2*(2), pp.184-194. doi: 10.1080/02723646.1981.10642213

Zargar, A., Sadiq, R., Naser, B. and Khan, F.I., 2011. A review of drought indices. *Environmental Reviews*, *19*(NA), pp.333-349.

Ziervogel, G., New, M., Archer van Garderen, E., Midgley, G., Taylor, A., Hamann, R., Stuart-Hill, S., Myers, J. and Warburton, M., 2014. Climate change impacts and adaptation in South Africa. *Wiley Interdisciplinary Reviews: Climate Change*, *5*(5), pp.605-620. doi: 10.1002/wcc.295.

4 MULTI-CRITERIA SUITABILITY ANALYSIS FOR NEGLECTED AND UNDERUTILISED CROP SPECIES IN SOUTH AFRICA

Mugiyo, H., Chimonyo, V.G.P., Sibanda, M., Kunz, R.P., Nhamo, L., Masemola, C.R., Dalin, C., Modi, A.T. and Mabhaudhi, T.[1]

Abstract

Several neglected and underutilised species (NUS) provide solutions to climate change and creating a Zero Hunger world, the Sustainable Development Goal 2. Several NUS are drought and heat stress-tolerant, making them ideal for improving marginalised cropping systems in drought-prone areas. However, owing to their status as NUS, current crop suitability maps do not include them as part of the crop choices. This study aimed to develop land suitability maps for selected NUS [sorghum, (*Sorghum bicolor*), cowpea (*Vigna unguiculata*), amaranth and taro (*Colocasia esculenta*)] using Analytic Hierarchy Process (AHP) in ArcGIS. Multidisciplinary factors from climatic, soil and landscape, socio-economic and technical indicators overlaid using Weighted Overlay Analysis. Validation was done through field visits, and area under the curve (AUC) was used to measure AHP model performance. The results indicated that sorghum was highly suitable (S1) = 2%, moderately suitable (S2) = 61%, marginally suitable (S3) = 33%, and unsuitable (N1) = 4%, cowpea S1= 3%, S2 = 56%, S3 = 39%, N1 = 2%, amaranth S1 = 8%, S2 = 81%, S3 = 11%, and taro S1 = 0.4%, S2 = 28%, S3 = 64%, N1 = 7%, of calculated arable land of SA (12 655 859 ha). Overall, the validation showed that the mapping exercises exhibited a high degree of accuracies (i.e. sorghum AUC = 0.87, cowpea AUC = 0.88, amaranth AUC = 0.95 and taro AUC = 0.82). Rainfall was the most critical variable and criteria with the highest impact on land suitability of the NUS. Results of this study suggest that South Africa has a huge potential for NUS production. The maps developed can contribute to evidence-based and site-specific recommendations for NUS and their mainstreaming. Also, the maps can be used to design appropriate production guidelines and to support existing policy frameworks which advocate for sustainable intensification of marginalised cropping systems through increased crop diversity and the use of stress-tolerant food crops.

Keywords: AHP, Food and nutrition security GIS; Land suitability analysis; Marginal areas

[1] Published in PLOS ONE, https://doi.org/10.1371/journal.pone.0244734

4.1 Introduction

The world is challenged by the need to feed a growing population with healthy food while minimising the negative impacts on the environment and adapting to changing climate (De la Hey and Beinart, 2017). Despite the importance of smallholder agriculture to global food production and poverty reduction (Garrity et al., 2010), there has been a decline in the level of agricultural production in the Sub Saharan Africa (SSA) region (Hardy et al., 2011). More so in South Africa (SA), the contribution of agriculture to household food consumption among smallholder farmers continues to fall (De la Hey and Beinart, 2017). It is understood that inherent water scarcity, exacerbated by climate variability and changes in land use, has contributed to reduced land available for agricultural expansion for the production of major crops especially in resource-poor farming systems (The World Bank and Statistics SA, 2018). Considering these challenges, agriculture requires innovative approaches that seek to address, not only issues of food and nutrition security but also environmental degradation, adapt to climate variability and land use planning. Sustainable intensification of smallholder food production systems is considered essential to meeting the United Nations Sustainable Development Goal 1 (poverty eradication) and 2 (zero hunger) (Shumsky et al., 2014). There is a need to introduce and promote practices that fit "into" or "with" current smallholder production systems while complementing existing efforts to improve resilience to climate variability and change as well as intensifying productivity for sustainable food and nutrition security (Mabhaudhi et al., 2019b).

Neglected and underutilised crop species are an option for redressing food and nutrition challenges faced in marginalised communities (Baldermann et al., 2016). These crops are native to specific areas in geological time (Raihana et al., 2015) and are known to be suitable in marginal areas characterised by severe dry spells and flash floods (Massawe et al., 2016). Across the world, several research initiatives examined the mechanisms that allow for stress adaptation within a range of NUS (10, 11, and 12). For instance, in SA Chibarabada et al (Chibarabada et al., 2020) modelled productivity of ground nuts under water deficit conditions, in Malaysia Peter et al. (Gregory et al., 2019) examined the adoption of underutilised crops, while Ebert

(Ebert, 2014) from Taiwan, assessed the potential of underutilized traditional vegetables and legume crops in contributing to food and nutritional security. These studies illustrate that, while NUS may be well adapted to multiple stress conditions, they are grown in geographical pockets that are often far from where they could provide the most positive contribution to food and nutrition security (Massawe et al., 2016). The lack of scientific evidence has resulted in the slow promotion of NUS into existing food systems, be it formal or informal (Mabhaudhi et al., 2019a). As such, policy frameworks on agriculture, health and environment continue to remain silent on the potential use of NUS in contributing towards increasing adaptation of marginalised agricultural systems to climate risks. In addition, little mentioned about their contribution towards good health as well as nutrition and rehabilitation of degraded agricultural lands. As such, information detailing the suitability of NUS is essential if they are to be recognised as a sustainable and plausible option for contributing towards the sustainable development and improved resilience of marginalised farming communities (Boatemaa et al., 2019).

Land suitability analysis assesses the appropriateness of crops to a specific practice or land use (Ziadat, 2007). Specifically, land suitability evaluates land capability as well as other factors such as land quality, land ownership, customers demand, economic values and proximity to different accesses (Malczewski, 2006). Multi-criteria decision making (MCDM), also referred to as, Multi-criteria decision analysis (MCDA) can be used to define land potential to solve complex problems of land-use and land-use changes (Nguyen et al., 2015; Rabia et al., 2013; Zabel et al., 2014). Multi-criteria decision-analysis methodologies can overcome problems related to vagueness in definition and other uncertainties, especially in the context of NUS suitability analysis (Ranjitkar et al., 2016). Land suitability analysis can be done by using geographic information system based MCDM to identify suitable areas for cultivating NUS. To improve the interpretations of MCDA, Saaty (1980) introduced the Analytic Hierarchy Process (AHP) as a method to capture aspects of a decision in both a subjective and objective manner to reduce confounding (Romano et al., 2015; Singha and Swain, 2016). The AHP methodology provides scope for combining expert opinions with numerical predictions from biophysical models to provide an integrated approach to resource management (Chen and Paydar, 2012; Saaty, 2016). Similar techniques have been used in agriculture to identify land suitable for: agricultural land reform (Musakwa, 2018); rain fed wheat (Kazemi and Akinci, 2018); citrus (Zabihi et al., 2015); rice in Kenya (Kihoro et al., 2013); wheat and rye-grass production (Benke and Pelizaro, 2010).

Currently, the delineation of South Africa's rainfed agricultural land use is for few major cash crops such as maize, sugar cane, and soybean. The few crops reflect the current lack of agro-biodiversity, which culminates in increased sensitivity of agriculture to climate risks (Kepe and Tessaro, 2014). An example is the 2015/16 ENSO drought that caused South Africa to import more than 30% of its annual cereal grain requirements due to poor harvests. In general, NUS are hypothesised to be suitable for marginal agro-ecologies (Mabhaudhi et al., 2019b) and can help increase the resilience of rainfed cropping systems in the wake of climate variability and change. In this regard, NUS can offer ecologically viable options for increasing agriculture productivity, especially in marginal areas, as they are locally adapted and would not strain the environment further (Chivenge et al., 2015). Therefore, the promotion of indigenous crops such as sorghum-Sorghum bicolor, cowpea-Vigna unguiculata and taro-Colocasia esculenta is integral to ensuring that households consume more diverse diets (Thow et al., 2018). Mapping NUS production potential zones in SA, will help inform decision on where NUS can be promoted as part of the crop choice, assist decision-makers in formulating policies with a sustainable intensification concept and then the creation of markets for NUS, which will enhance food and nutrition security. Therefore, the main objective of the research is to identify potential areas suitable for sorghum-, cowpea, taro, and amaranth – using a GIS-based MCDA-AHP.

4.2 Methodology

4.2.1 Multi-criteria decision analysis (MCDA) approach

Crop suitability is a function of crop requirements and land characteristics, therefore matching the land characteristics with the crop requirements gives the suitability (Han and Chen, 2018). Suitability analysis has to be carried out in such a way that farming systems and local needs are reflected well in the final decisions (Reshmidevi et al., 2009). The MCDA combines qualitative and quantitative criteria while specifying the degree and nature of the relationships between those criteria to support spatial decision-making (Malczewski, 2004).

The process of evaluating the suitability of land for a specific purpose requires a comprehensive analysis of natural factors and the socio-economic factors which influence the land (Mendoza and Martins, 2006; Raza et al., 2018). The elements used can be divided into high and lower factors based on experts' opinion weights (Zabihi et al., 2015). High-level factors in crop suitability analysis are natural or biophysical factors that directly affect the growth of crops, for example, rainfall, and temperature and soil fertility. The lower level factors are social and economic factors which indirectly affect crop growth, but influence land use degree of appropriateness to a purpose (Yi and Wang, 2013). The interactions, dependencies and feedback between higher and lower-level elements form a multi-criteria land evaluation approach for a sustainable NUS production. **Figure 4.1** presents a conceptual framework for developing NUS Cropland suitability maps using GIS.

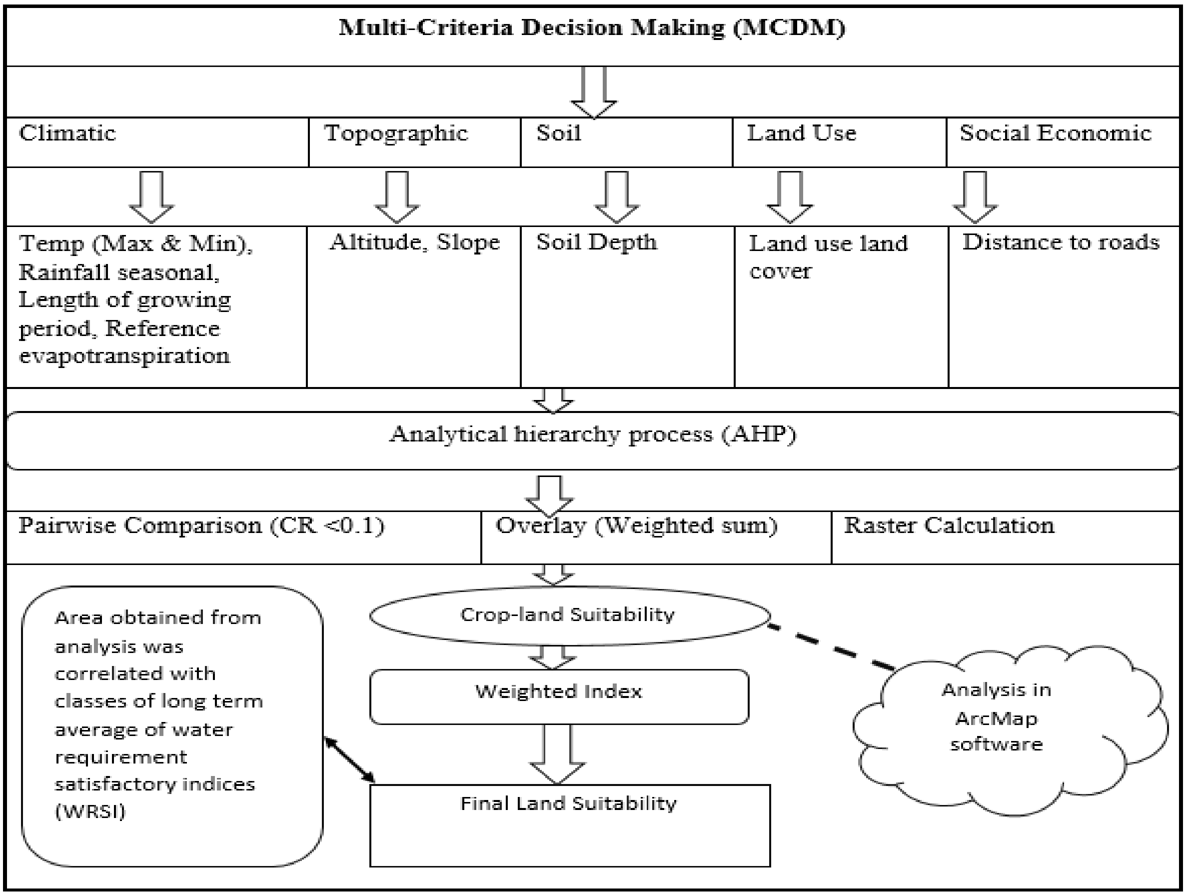


Figure 4.1: Framework used in computing suitability indices for neglected and underutilised crop species in South Africa (Developed by the authors).

The general land use suitability model is:

$$S\ (a1\ldots,an) = \sum_{j=1}^{n} wjbj \qquad \text{Equation 4.1}$$

where S ($a_{1\ldots,}a_n$) is suitability measure, and b_j is the j^{th} largest of the a_1 factors affecting the suitability of the sites (Jeong et al., 2014; Romano et al., 2015). A weighted average is an average where each observation in the data set is multiplied by a predetermined weight before calculation equation 4.1 (Nzeyimana et al., 2014). The ordered weighted averaging (OWA) operator is a non-linear operator as a result of the process of determining the bj, and this was achieved by choosing different weights to implement different aggregation operators' equation 4.1.

4.2.1.1 Data sources

For this study, data were obtained from the South African Quaternary Catchments database (**Table 4.1**). The multidisciplinary data was grouped into climatic, soil and landscape attributes, social-economic and technical indicators. Nine parameters were used, and these included five climatic, three soil, and one social parameter (**Table 4.1**). High-resolution climatic parameters were derived from 1950 to 2000, a 50-year time series of continuous daily data from selected 1 946 stations Quaternary Catchments covering South Africa (Schulze, 2002). The datasets were developed by the Water Research Commission funded in a project titled “Mapping the Mean Annual Precipitation and Other Rainfall Statistics” (Smithers and Schulze, 2000). The spatial resolution of climatic data was one arc minute; this implies that one grid is represented as 1.7 x 1.7 km. Lynch (2004) calculated monthly precipitation by using a geographically weighted regression method, and monthly means of daily average temperatures were derived from (Lynch, 2004). Abrams (2018) indicated that over 70% of South African food production is rainfed. In South Africa only 1,5% of the land is under irrigation, producing approximately 30% of the country’s crops. Therefore, all climatic parameters were calculated using seasonal and not annual data. Wet periods can be calculated from daily precipitation events like the start of the season, dry spells, end of the season. In SA, precipitation is undoubtedly the dominating factor determining crop production, especially in marginal areas where irrigation facilities are limited for smallholder farmers (Tibesigwa et al., 2017).

All thematic variables used in this study were converted to raster layers. Before the analysis, all thematic layers were resampled into the World Geodetic System 1984 (WGS84) geo-referencing system (Macomber, 1984). The resolution of finer grid layers was resampled to 1.7 km resolution of climatic factors. All the transformations of the GIS layers were done in ArcGIS.

4.2.2 Analytic Hierarchy Process (AHP)

The analytic hierarchy process (AHP) is the most widely accepted method and is considered by many as the most robust of MCDA (Kaim et al., 2018). The AHP helps to capture both subjective and objective aspects of a decision by reducing complex decisions to a series of pairwise comparisons and then synthesising the results (Nguyen et al., 2015). Since AHP considers a set of evaluation criteria and a set of alternative options among which the best decision is to be made, a 9-point scale measurement was used in this study (**Table 4.2**). In this study, the AHP calculator was used to calculate weights (Nasrollahi et al., 2017). The assignments of weights were based on information from literature, as well as the team's local knowledge and expert consultation (soil scientist, GIS and remote sensing specialists from the University of KwaZulu-Natal) (**Table 4.3**).

Table 4.1: Factors used to delineate land suitability maps for neglected and underutilised crop species

Factors	Source
Climate-related factors	
Precipitation (mm) 1.7 km resolution	South African Quaternary Catchments database – Water Research Commission
Temperature 1.7 km resolution	South African Quaternary Catchments database – Water Research Commission
Reference crop evapotranspiration (ETo) millimetres (mm) or (lm^{-2}) 1.7 km resolution	South African Quaternary Catchments database – Water Research Commission
Length of growing period (LGP) 1.7 km resolution	South African Quaternary Catchments database – Water Research Commission
Water Requirement Satisfaction Index (WRSI)-at 10 km resolution	Fewsnet https://earlywarning.usgs.gov/fews
Soil and landscape attributes used to delineate land suitability maps for neglected and underutilised crop species	
Soil depth at 250 m resolution	South African Quaternary Catchments database – Water Research Commission
Elevation (mm) 30 m resolution	http://earthexplorer.usgs.gov
Slope	South African Quaternary Catchments database – Water Research Commission
Social and economic factors used to delineate land suitability maps for NUS.	
Distance from road/accessibility	South African Quaternary Catchments database – Water Research Commission

Table 4.2: The fundamentals for pairwise comparison (Saaty, 1990)

Intensity of importance	Definition	Explanation
1	equal importance	Two activities contribute equally to the objective
3	moderate importance of one over another	Experience and judgment slightly favour one activity over another
5	the strong or essential importance	Experience and judgment strongly favour one activity over another
7	very strong or demonstrated importance	Activity is strongly favoured, and its dominance showed in practice
9	extreme importance	The evidence favouring one activity over another is of the highest possible order of affirmation
2,4,6 and 8	Even numbers represent intermediate values between the two adjacent judgements	When compromise is needed

Factor weights were calculated by comparing two factors together at a time. The AHP weights were calculated using Microsoft Excel. Table 3 shows a pairwise comparison matrix for the research

The pairwise comparisons in the AHP were determined according to the scale introduced by Saaty (Saaty, 1980), with values from 9 to 1/9. A rating of 9 indicates that concerning the column factor, the row factor is more important. On the other hand, a rating of 1/9 indicates that relative to the column factor, the row factor is less important. In cases where the column and row factors are equally important, they have a rating value of 1. Through the pairwise comparison matrix, the AHP calculates the weighting for each criterion by taking the Eigenvector corresponding to the largest Eigenvalue of the matrix and then normalising the sum of the components to unity (Chandio et al., 2013).

Table 4.3: Pairwise comparison matrix

Factors	Rainfall	Temp	ET_o	LGP	Elevation	Slope	LULC	Soil Depth	Distance to Road	Weight
Rainfall	1	2	2	2	5	5	3	2	9	0.24
Temp	1/2	1	2	3	3	3	3	2	8	0.18
ET_o	1/2	1/2	1	1/3	5	3	3	2	5	0.13
LGP	1/2	1/3	3	1	5	3	3	3	5	0.17
Elevation	1/5	1/3	1/5	1/5	1	2	1/2	1/2	2	0.04
Slope	1/5	1/3	1/3	1/3	2	1	2	2	5	0.08
LULC	1/3	1/3	1/3	1/3	2	1/2	1	1/2	3	0.06
Soil Depth	1/2	1/2	1/2	1/3	2	1/2	2	1	5	0.08
Distance from road	1/9	1/8	1/5	1/5	1/2	1/5	1/3	1/5	1	0.02

Maximum eigenvalue (λmax) = 9.6082, n=9, Consistency index $(\mathrm{CI}) = (\lambda\mathrm{max} - \mathrm{n})/(\mathrm{n} - 1)$=0.07602, Random index (RI) = 1.45, Consistency Ratio $(\mathrm{CR}) = \mathrm{CI}/\mathrm{RI}$=0.052428

The ratio scales were derived from the principal Eigenvectors, and the consistency index was derived from the principal Eigenvalue. An eigenvalue is a number, which explains how much variance is spread out (Ceballos-Silva and López-Blanco, 2003). According to Brandt et al. (Brandt et al., 2017) and Feng et al. (Feng et al., 2017), the AHP has a limitation of coming up with weights; it is subjective. The inconsistency can be improved by:

- Deriving pairwise matrix based on a scientific objective in non-scare data situation (Alexander and Benjamin, 2012) (**Table 4.3**),
- Estimating the relative importance of factors individually and based more on scientists' opinion through informal interviews with key informants like a ministry of Agriculture (Akinci et al., 2013) and
- Giving attention to an upper limit, the upper limit is a consistency ratio (CR) that must be less than 0.1 for a pairwise matrix judgment to be accepted (Milad Aburas et al., 2015).

To minimise the interrelationship among various factors included in the AHP approach, data reduction method such as Ordered Weighted Averaging (OWA) was used (Jelokhani-Niaraki and Malczewski, 2015). The weighted linear combination allows the variability of continuous and discrete factors to be retained and standardised to a standard numeric range (Romano et al., 2015).

4.2.3 Fitting neglected and underutilised crop species in ecophysiology based on drought-tolerance characteristics

Agro-climatic indices were calculated to estimate phenological phases of crops to fit NUS in an environment (**Table 4.4**). The dynamic consideration of crop phenology allows assessing effects of agro-climate-factors to phenological development of NUS. The overall suitability was estimated based on Liebig's law of the minimum (Mesgaran et al., 2017). The Liebig's law of the minimum to provide a flexible framework to assess climate suitability of crops in a situation where the crop suitability is subjected to imprecision and vagueness, or the pairwise comparisons are subjective especially when fuzzy AHP was used to classify NUS (Kazemi and Akinci, 2018; Ugbaje et al., 2019). It is based on three types of mathematical functions; the equations transform each variable to a suitability value varying from 1 (unsuitable) to 1 (optimum or highly suitable). Liebig's law of the minimum is the outcome of AHP using the minimum t-norm between variables (Kim et al., 2018). The mathematical expression for this type of relationship was formulated as follows.

$$S(V) = \begin{matrix} 0 \\ \frac{\{V - Vmin\}}{\{Vol - Vmin\}} \\ 1 \end{matrix} if\ V \leq Vmin;\ if\ Vmin < V < Vol;\ if\ V \geq Vol \qquad \text{Equation 4.2}$$

where S (V) is the suitability index as a function of the individual variable; V is the parameter; V_{min} indicates the minimum value of V required for crop growth; Vol is the lowest optimum value of V at or beyond which the highest suitability can be obtainedIn general, an increase in precipitation increases the suitability of crop in semi-arid regions. Based on the water use of a crop, the lower limit of precipitation was used to delineate area suitable for a crop, for example, 111 mm per year was used for amaranth (**Table 4.4**). According to FAO, a minimum of 500 mm rainfall per year is required to achieve reasonable economic yields, therefore, we used 500 mm as the upper threshold in our stepwise function (Steduto et al., 2012). Some variable like the terrain is inversely correlated with growth suitability (**Table 4.4**); following criterion was used to mark the suitability of NUS.

$$S(V) = \begin{matrix} 1 \\ \frac{\{Vmax - V\}}{\{Vmax - Vou\}} \\ 0 \end{matrix} if\ V \leq Vou;\ if\ Vou < V < Vmax;\ if\ V \geq Vmax \qquad \text{Equation 4.3}$$

where V_{max} is the maximum value of variable V beyond which no cropping is possible; Vou is the uppermost optimum value of V for cropping. In all areas with 0 to 5% slope has no limitation about the steepness and above 5% optimal upper bound (Vou) field tends to have challenges in using have machines.

Table 4.4: Characteristics of sorghum (Chimonyo et al., 2016), cowpea (Chimonyo et al., 2016), taro (Mabhaudhi et al., 2014a) and amaranth (Nyathi et al., 2018)

	Sorghum (*Sorghum bicolor*)	Cowpea (*Vigna unguiculata*)	Taro (*Colocasia esculenta*)	Amaranth- (*Amaranthus*)
Water use (mm)	261-415	133-265	800^{-1} 288	111-448
Precipitation per season (mm)	450-800	400-700	800-2000	400-650
Time to maturity (Days)	100-120	90-150	240-300	20-45
Temperature range (˚C)	26-30	25-30	25-32	18-30
Yield (kg ha^{-1})	2802-4304	776-1120	3830-17 330	3400-5200

4.2.4 Qualitative land suitability classification

In this study, five different classes from FAO land suitability framework were used to quantify the magnitude of suitability for NUS within South Africa (**Table 4.5**). It classified the land into four suitability classes: land suitability orders, land suitability classes, land suitability sub-classes and land suitability units (Cools et al., 2003). In FAO, orders indicate lands suitable for crops (S) or not suitable for crops (N) while classes show the degree of land suitability, such as (S1) highly suitable, (S2) moderately suitable, (S3) marginally not suitable, (N1) currently not suitable and (N2) permanently not suitable, and then subclass explains limitations. The classification designates a single index of use as best on each land unit (Fontes et al., 2009).

Table 4.5: Suitability indices for the different suitability classes (FAO, 2007)**.**

Suitability Class	Suitability index (SI)	Description Class
S1	Highly suitable (>80)	Land having no limitations for a given use, or constraints that do not reduce the productivity and benefits appreciably, with no need for a high level of input
S2	Moderately suitable (60-80)	Land having minor limitations that could reduce productivity or benefits, additive inputs are required to reach the same yield as that of class S1
S3	Marginally suitable (45-59)	Land having moderate limitations for a particular use, in which the amount of surplus input is only marginally justified
N1	Currently unsuitable (30-44)	Land with severe limitations for land use under consideration. Every sustainable use is precluded, and the costs for correction are unacceptable with the existing condition. Only new technologies could improve land productivity
N2	Permanently unsuitable (<30)	Land-use type under analysis is not acceptable at all for the land.

4.2.5 Validation of cropland suitability

The validation data was gathered through field surveys in one KwaZulu-Natal location conducted between 1st of October to 21st of November 2019. A total of 60 GPS locations of taro, amaranth, sorghum and cowpea were randomly collected during the survey. The GPS locations were measured at the centre of an identified field. The GPS locations were captured in excel and GPS locations were converted to a point map in a GIS. The crop presence was captured as one of the attribute tables. A total of 600 points were randomly generated in a GIS across South Africa. These points were used to represent the absence (value 0) of the crops. We used a ratio of 1:10 between known present points to pseudo-absence; hence, 600 pseudo absence points were generated (Tshabalala et al., 2019). These two-point maps were merged into one layer, which was then overlaid with the MCDM/AHP derived suitability maps. A new table containing the presence and absence as well as the crop suitability information was produced and exported as an excel spreadsheet. This data was then used to measure the magnitude of agreement between the generated NUS suitability maps, and the field measured locations of crops using the receiver operating characteristic (ROC), and the area under the curve (AUC) derived based on the logistic regression. Each crops accuracy assessment using the logistic regression analysis was carried out in the statistical package R version 3.6.1 (R Core Team 2019, 2019) using the 'RATTLE' library (Williams, 2011). The ROC plot has an x-axis indicating the false-positive error rate, which signifies a wrong prediction by the model. The y-axis shows the positive rate, indicating a correct prediction by the model (Williams, 2011). An AUC value that is less than or equal to 0.5 indicates a random prediction, while AUC values higher than 0.5 and closer to 1 indicates a better prediction by the model (Jiménez-Valverde, 2012; Senay and Worner, 2019). The composite operator helps illustrate how well two layers or maps agree in terms of how the categories are clustered spatially.

We further checked the magnitude of dryness of classes of a correlation analysis between the general NUS land suitability index and the mean average of Water Requirement Satisfaction Index (WRSI) from 1981 to 2017 from Famine Early Warning Systems Network (FEWSNET) was used to compare the results. Water Requirement Satisfaction Index was developed by the FAO and mostly used by FEWSNET to monitor and investigate crop production in agricultural drought-prone parts of the world. The WRSI is an indicator of crop performance based on the availability of water to the crop during a growing season (Singh Rawat et al., 2019). The classes of WRSI are crop failure – less 49%, Poor – 50-79%, average – 80-94, and good – 95-100%.

4.3 Results

4.3.1 Sorghum land suitability map

Figure 4.2 presents the results of the analysis of the suitability of sorghum-based on MCDA-AHP and OWA operators. These results show the existing distribution of the land suitability classes, excluding areas where present land use is nature conservation, plantation, urban and water. Results indicated that there is about 2% of land that is highly suitable (S1) for the production of sorghum. Moderately suitable (S2) land constitutes the most substantial proportion (61%) of the calculated arable land of South Africa (12 655 859 ha) while marginally suitable (S3) and unsuitable (N1) constitutes 33% and 4%, respectively of calculated arable land (**Figure 4.2**). Large areas suitable (S1 and S2) land was concentrated in eastern provinces and suitability intensity decrease towards western provinces (**Figure 4.2**). A total of 60 GPS location was used to confirm the presence of sorghum within selected locations in KwaZulu-Natal province.

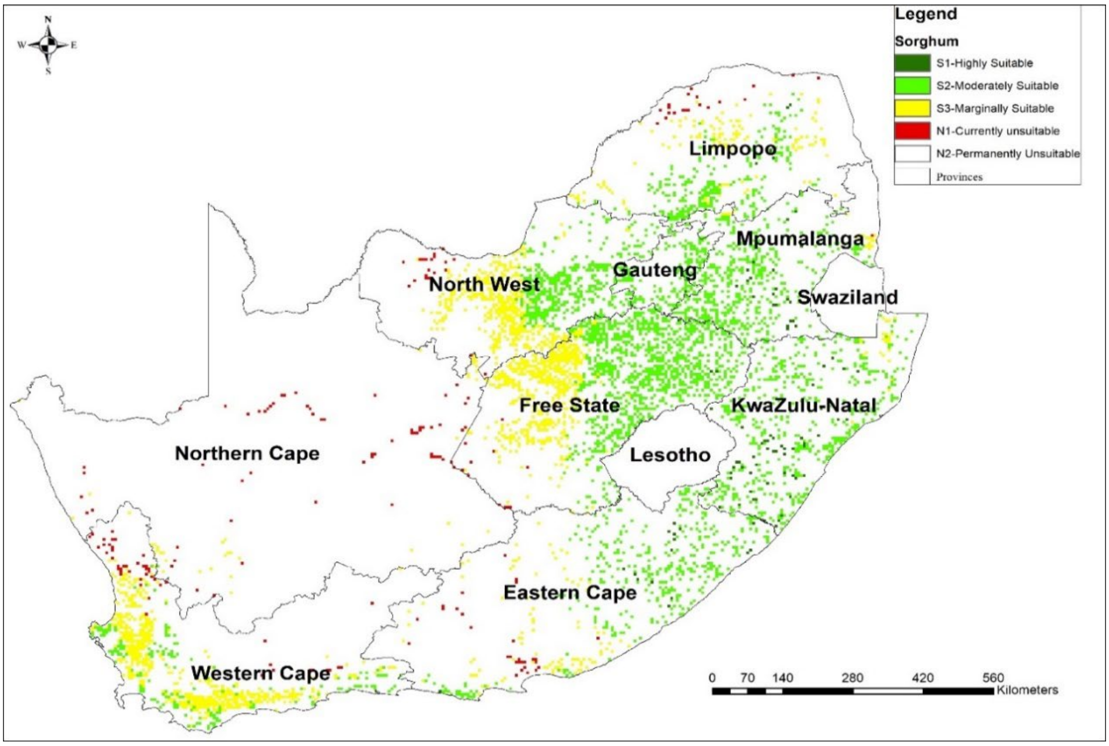


Figure 4.2: Suitability map for sorghum production in South Africa computed using MCDA-AHP and OWA operators [Source, *South African Quaternary Catchments database, (https://doi.org/10.6084/m9.figshare.13179881), in ArcGIS 10.5]*

4.3.2 Cowpea land suitability map

Cowpea suitability varies across the country. The results indicated that there is about 3% of the land is highly suitable (S1) for the production of cowpea. Moderately suitable (S2) land constitutes the most substantial proportion with 56% of the calculated arable land of South Africa (12 655 859 ha) while marginally suitable (S3) and unsuitable (N1) constitutes 39% and 2%, respectively of calculated arable land (**Figure 4.3**). The spatial suitability is high in south-eastern provinces and central provinces of South Africa. The intensity of suitability decreases from the central part of the country to the western regions of the country (**Figure 4.3**). Similar to sorghum, the distribution of suitability was consistent, but not in the order with rainfall, slope, soil depth and ETO distribution.

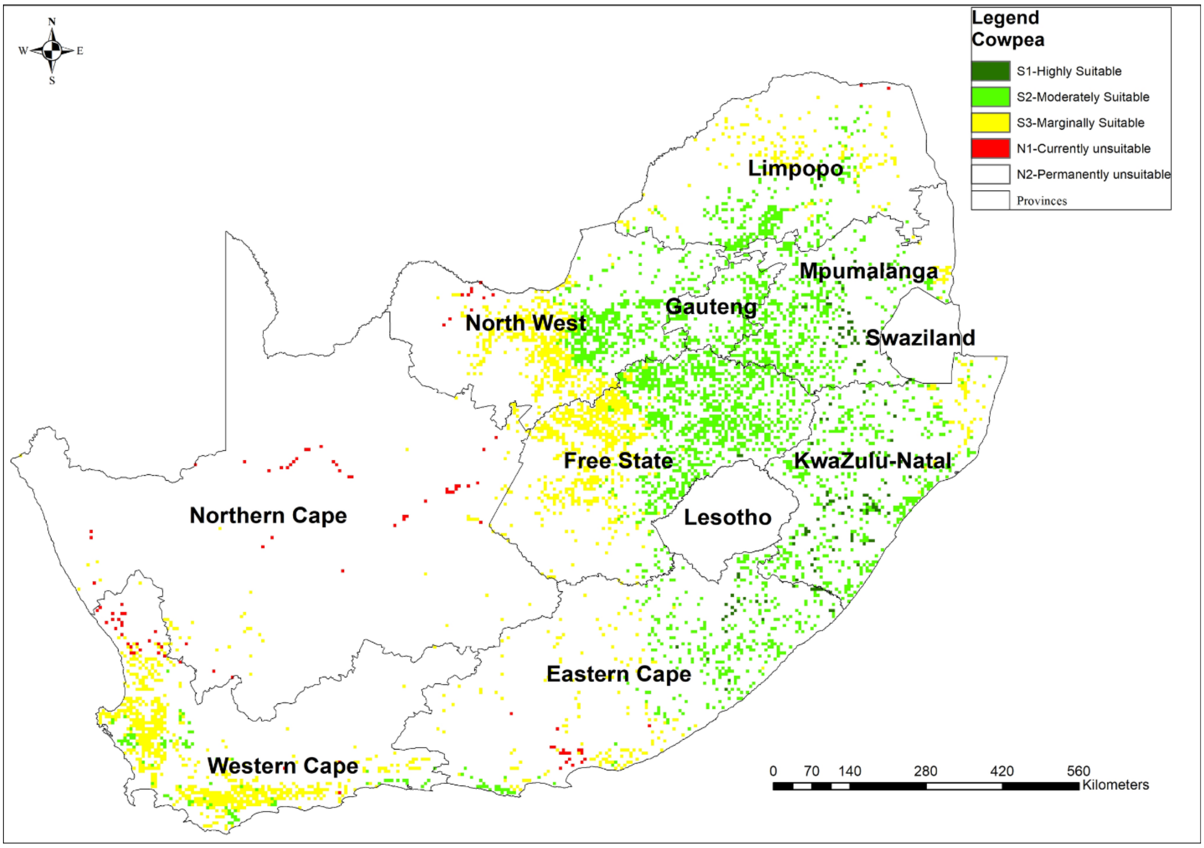


Figure 4.3: Suitability map for cowpea production in South Africa computed using MCDA-AHP and OWA operators [Source, South African Quaternary Catchments database, (https://doi.org/10.6084/m9.figshare.13179881), in ArcGIS 10.5]

4.3.3 Taro land suitability map

Figure 4.4 presents the spatial distribution of the suitability scores for taro-based on MCDA-AHP method. The results indicated that there is about 0.4% of the land that is highly suitable (S1) for the production of taro. Moderately suitable (S2) land constitutes 28% of the calculated arable land of South Africa (12 655 859 ha) while marginally suitable (S3) constitutes the most substantial proportion 64% and (N1) 7% of calculated arable land. Taro suitability is high in KwaZulu-Natal and Mpumalanga provinces. Limpopo, North West, Northern Cape and Western Cape are marginally suitable for taro (**Figure 4.4**). The distribution of taro suitability was consistent maximum temperature and length of the growing season and rainfall distribution.

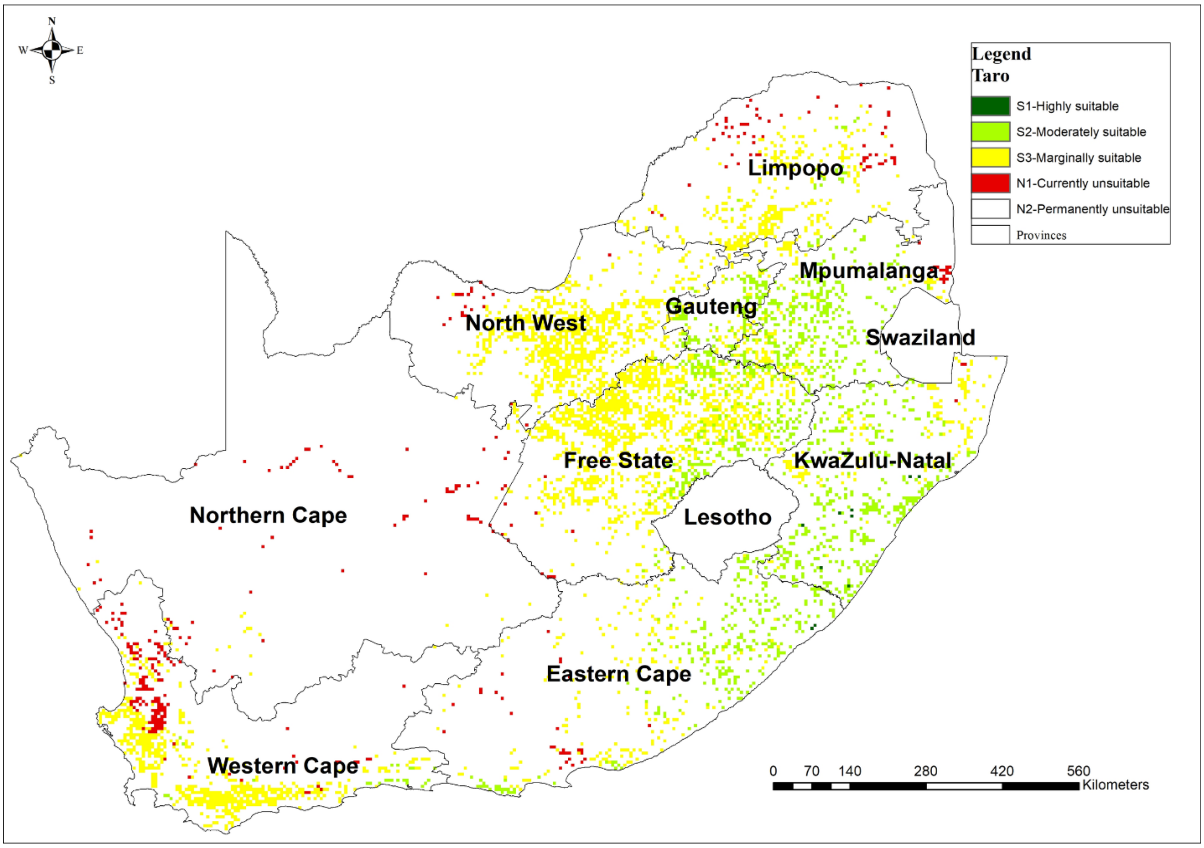


Figure 4.4: Suitability map for taro production in South Africa computed using MCDA-AHP and OWA operators. [Source, *South African Quaternary Catchments database, (* https://doi.org/10.6084/m9.figshare.13179881*), in ArcGIS 10.5]*

4.3.4 Amaranth Suitability

The land suitability analyses indicated that amaranth is highly suitable across South Africa (**Figure 4.5**) The results indicated that there is about 8% of the land that is highly suitable (S1) for the production of amaranth. Moderately suitable (S2) land constitutes the most substantial proportion with 81% of the calculated arable land of South Africa (12 655 859 ha) while marginally suitable (S3) constitutes 11% of calculated arable land (**Figure 4.5**). Amaranth is high suitable across South Africa in most cropping areas, even in the Western Cape, where the investigated crops had low suitability (**Figure 4.5**). The observed suitability could be associated with the growth requirements of the crops that allow for its production even under marginal conditions. From field visits, farmers confirmed that amaranth is suitable and grow naturally in KwaZulu-Natal environments.

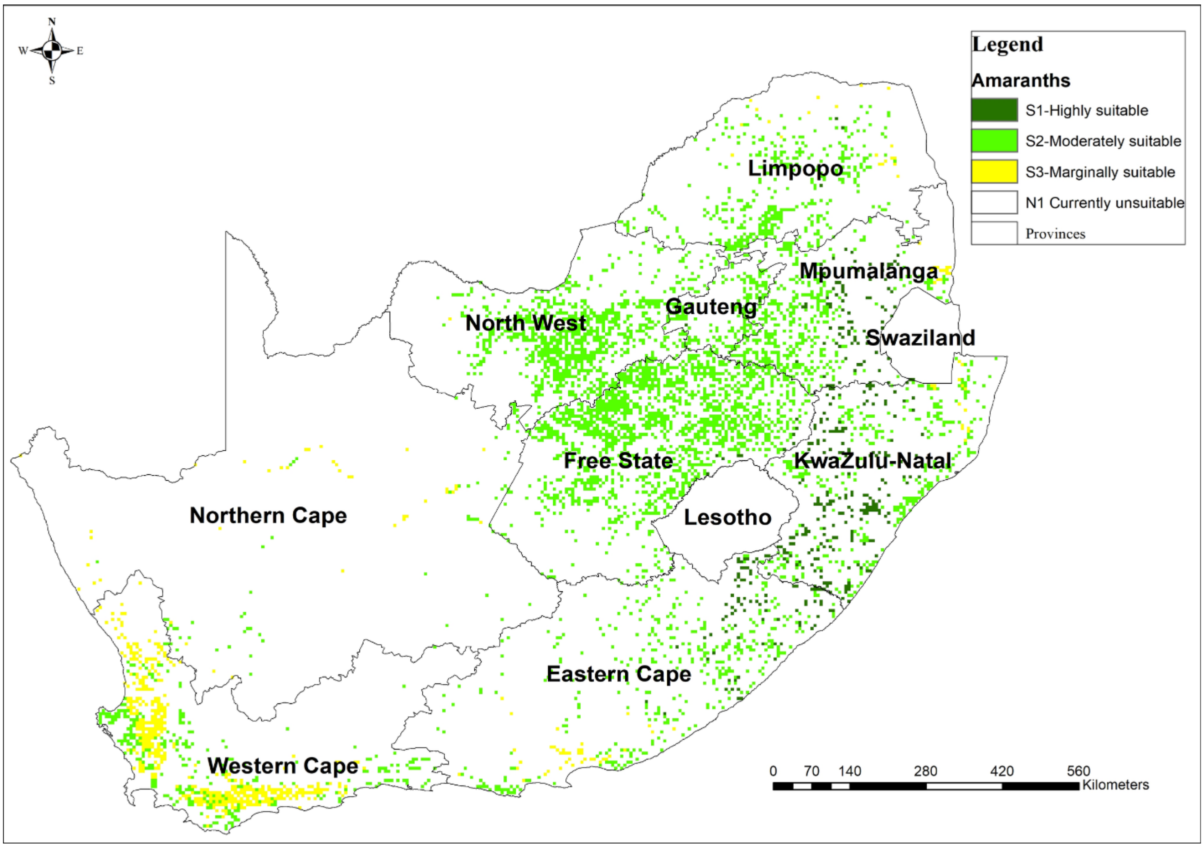


Figure 4.5: Suitability map for amaranth production in South Africa computed using MCDA-AHP and OWA operators. [Source, South African Quaternary Catchments database, (https://doi.org/10.6084/m9.figshare.13179881), in ArcGIS 10.5]

4.3.5 Water requirement satisfactory indices for a period of 1981 to 2017

The Water Requirement Satisfaction Index classification in driest areas of the country, which a mainly the Northern provinces were not applicable. In the Western Cape Province, there was no start of the season, and this is consistent with the low rainfall received and high ET_0 characteristic of this region **Figure 4.6**.

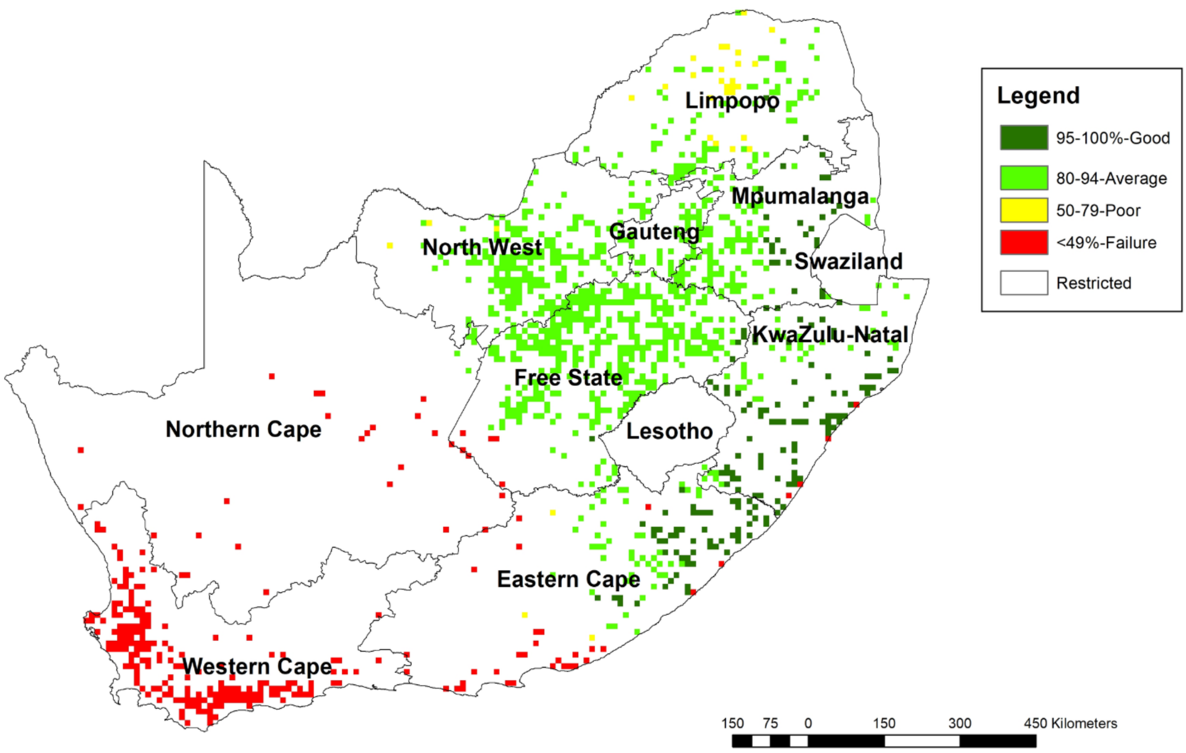


Figure 4.6: Average water requirement satisfactory indices for a period of 1981 to 2017 in cropping lands in South Africa. [Source, Famine Early Warning Systems Network,(https://earlywarning.usgs.gov/fews, and from USGS Earth Explorer (http://earthexplorer.usgs.gov). and from USGS Earth Explorer (http://earthexplorer.usgs.gov).), in ArcGIS 10.5]

4.3.6 Multi-criteria model accuracy validation

The area under curve (AUC) of sorghum (0.87) cowpea (0.88), amaranth (0.95) and taro (0.82) values were greater than 0.5 **Figure 4.7**. Considering that the AUCs of all the crops were above 0.8, this indicates that all the models were in this study were accurate in estimating the NUS suitability.

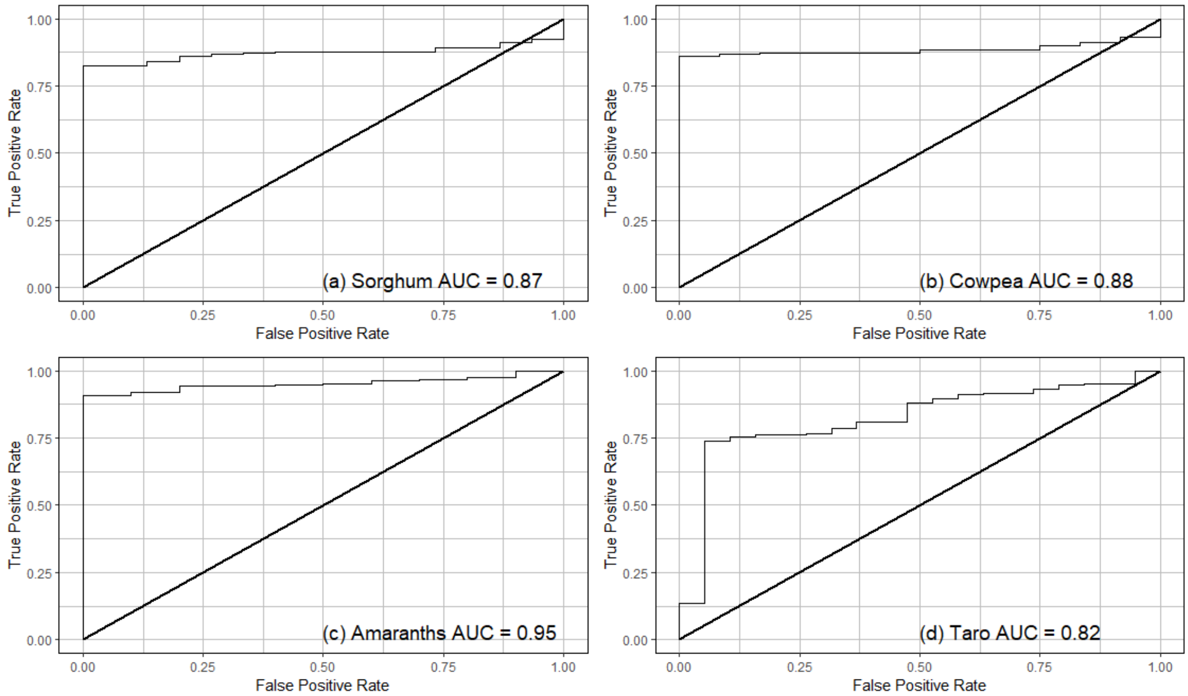


Figure 4.7: The Receiver Operating Characteristic (ROC), used to generate the Area Under the curve (AUC) which is used for model validation of the logistic regression model for spatial prediction of (a) sorghum, (b) cowpea, (c) amaranth and (d) taro.

4.4 Discussion

In this study, we assessed the land suitability of NUS using climatic, soil-landscape, as well as socio-economic factors. Use of AHP provides scope for combining expert opinion with measurements in making pairwise comparisons between criteria at each level of the hierarchy to come up with relative weights. According to the local experts' judgment, rainfall was the most critical variable, followed by temperature, while soil depth and distance from the road were least important. The ranking of the variables is somewhat consistent with what was reported as important crop limiting factors for South Africa (75). Malczewski (36) noted that the relationship between the objectives and attributes has a hierarchical structure. The consistency ratio was calculated as 0.05 and is considered as acceptable (24,76).

To reduce the risk associated with over-fitting or noise modelling, nine thematic input layers were used by employing matrix pairwise comparison. The matrix pairwise comparison was obtained from different expects, and factor weights were calculated using a pairwise comparison matrix. The accuracy of weights used is subjective as it depends on expert opinion; however, the results of the relative weights were used in land suitability evaluation because the Consistency Ratios were within the established acceptable limits (0.1) (Saaty and Saaty, 1980). The challenge of a deterministic MCDA-AHP method is that assigning weights may be subjective, and the setting of weights represent imprecise point estimates, and the process does not indicate error or confidence (Benke and Pelizaro, 2010). However, the use of AHP methodology provides scope for combining expert opinion with measurements (Bagherzadeh and Gholizadeh, 2016; Mendoza and Martins, 2006; Mustafa et al., 2011). Expert opinion weighted distance from the road with the lowest weight, because the social-economic factor does not affect crop growth directly, but it influences the adoption of NUCS by farmers. Accessibility to markets is highly influenced by road network because it affects markets. There are other socio-economic factors (availability of extension services, access to markets and credit, etc.), which can be included in MCDA to develop cropland suitability mapping (Akpoti et al., 2019).

Based on the analyses, there are potential environmental benefits to growing NUS in SA. The introduction of NUS into regions classified as moderately suitable (S3) to highly suitable (S1) could increase the crop choices available, and also contribute to biodiversity (SDG 15). The low environmental impacts and increased biodiversity brought about by the introduction of NUS can be viewed as a climate change adaptation strategy (SDG 13) for increasing farmer resilience (Drimie and Pereira, 2016). More so, for marginalised farming communities that have limited access to improved technologies such as hybrid seed and fertilisers (Modi, 2003). In this regard, the introduction of NUS into existing cropping systems can be viewed as a sustainable intensification approach (Harvey, 2010). Also, promoting NUS in marginal lands can contribute to food and nutrition security (SDG 2), poverty alleviation (SDG 1) through creating new value chains and human health and wellbeing (SDG 3).

The area under the curve (AUC) of sorghum, cowpea, amaranth and taro was above 0.8 indicating that the land classification based on the logistic regression were highly accurate. These high accuracies could be explained by the robustness, holistic nature and optimal performance of the GIS based MCDA and AHP modelling which was able to characterise land that is optimal for the NUS production in this study. Sun et al., (Sun et al., 2017) provide an essential guarantee of the AHP model as a decision-support tool for improving the efficiency of water use. Amongst the four crops, taro had the lowest AUC because the crop generally has a high water requirement compared to the other crops (Mabhaudhi et al., 2014a, 2014b).

The results of total area suitable for the production of sorghum, taro, and cowpea were consistent with what has been reported to be available arable land (approximately 10.3%) in South Africa (Shackleton et al., 2014). About 70% of South Africa's land is categorised as unsuitable for rainfed crop production due to a combination of poor rainfall distribution and soils with low fertility, yet NUS are naturally suitable in marginal areas. However, there were variations in the magnitude of suitability for each of the NUS crops investigated. The results indicated that sorghum and cowpea were suited for drought and heat stress-prone areas such as KwaZulu-Natal, Eastern Cape and Limpopo provinces where the majority of agricultural households reside (Chivenge et al., 2015). Based on AHP analysis, these crop species are, therefore, well adapted to high climate risk and can be produced under water-limited and extremely hot (33-38oC) conditions. Amaranth was highly suitable across most cropping lands in South Africa, and this is because the crop has a short growing period and low water requirement (Nyathi et al., 2018).

The suitability of taro in KwaZulu-Natal, Mpumalanga and Gauteng provinces is consistent with the observed length of the growing period, Specifically, taro takes up to 300 days to mature and it has high water use rate (651-1701 mm) (Mabhaudhi et al., 2013). In this regard, the areas suitable for taro production in South Africa were low and mostly confined to areas receiving high rainfall. The high water requirements would suggest that the crop may be more suited for areas prone to flash flooding as it is also tolerant to aeration stress (Mabhaudhi et al., 2013). Therefore, our results can be used to indicate areas where the investigated crops can be introduced as part of sustainable intensification approaches for climate change adaption (Schiefer et al., 2016). The results are vital in increasing the options for crop choice for marginalised farmers throughout South Africa. However, the information on suitability needs to be complemented with information on "better bet" agronomic management to realise the full potential of the crops in question (Massawe et al., 2016). Cowpea, sorghum, and amaranths are highly suitable in areas which receive more than 500 mm per season and most of these areas are highly urbanised (i.e. Gauteng province). Therefore, the opportunity cost of promoting NUS near urban areas might be affected by the land value near urban areas, then high valued horticultural crops and dairy production with higher market demands are more preferred by peri-urban farmers (Massawe et al., 2016).

Our methodology focused on assessing crop suitability using mainly physical factors and a single socio-economic factor. Neglected and underutilised crop species are important within smallholder farming systems and address several socio-economic indicators such as widening food value chains, increase food and nutrition security and reducing gender inequality (Akinola et al., 2020). Promoting or introducing NUS in mapped zones can be an essential part of the solution towards addressing food insecurity, specifically malnutrition, reducing vulnerability to climate variability and change, environmental degradation, and gender inequality. It is argued that holistic land suitability maps, which take into consideration several socio-economic indices, could be more useful to policy-makers and enhancing the participation of marginalised farmers in the food system (Mabhaudhi et al., 2019b). The exclusion of key socio-economic indicators in developing suitability maps might affect uptake and adoption of these crop species in areas where they are found to be biophysically suitable. Therefore, to generate information of socio-economic indicators, there is need for future studies to identify innovative ways to derive maximum value from the possible integration of GIS with block-chain, big data, and Internet of Things (IoT) technologies to mine updated data, especially on climatic data and social-economic factors (Sharma et al., 2018; Wolfert et al., 2017). To achieve this, farmers, private sector and the government will need to support further research on NUS value chains.

The results show that NUS are suitable in a wide range of agro-ecological zones, especially in areas observed to have high ecological risks. Therefore, mainstreaming them into existing systems as alternative crop species to commercially important crops might be a sound adaptation strategy to climate variability and change. However, the interpretation of our results relative to climate change is limited by the fact that we used a historical data set (1950-2000). While this spans across half a decade, most of the extreme climate hazards have been observed in the last 30 years (1990-present) (IPCC, 2018). As such, future studies should focus on using data from global circulation models (GCMs) to inform climate change scenarios more specifically. However, the current maps remain useful in identifying areas that are currently suitable for NUS production for the first time in South Africa.

High coefficient of determination between MCDA-AHP and WRSI indicated that the climatic parameters used were sufficient to delineate marginal areas within South Africa. Water Requirement Satisfaction Index was developed by the FAO and mostly used by FEWSNET to monitor and investigate crop production in agricultural drought-prone parts of the world (Consoli and Vanella, 2014). It is used to monitor crop performance during the growing season and based upon how much water is available for the crop by calculating a ratio of actual to potential evapotranspiration (Consoli and Vanella, 2014). These ratios are crop-specific and are based upon crop development and known relationships between yields and drought stress (Consoli and Vanella, 2014). Short duration crops such as amaranth and crops that have a low water requirement fit well in all environments of South Africa. While the WRSI uses climate-related stress factors other than soil available water, the relationship between two independent classifications showed that this study's NUS land suitability was satisfactory. The negative coefficient of determination (R=-0.15) observed for taro suitability, and WRSI might be due to crop water requirements and length of the growth period, which overlaps into the dry season.

Taro is predominantly a wetland crop; however, upland varieties exist and these have been shown to have lower levels of water use and also to possess drought tolerance through avoidance and escape mechanisms (Mabhaudhi et al., 2013). However, escape mechanisms (i.e. phenological plasticity) make taro suitability to be negatively correlated with WRSI. One of the significant limitations of WRSI index is that it uses satellite-based rainfall estimates which are influenced by cold-cloud-duration (CCD) especially in February to March because of overcasting clouds in subtropics. Therefore, there is a degree of error that could influence WRSI classification, especially on the balance of evapotranspiration in a lean season in South Africa (Duchemin et al., 2006; Liu et al., 2010). To overcome these challenges, future studies could employ unarmed aerial vehicles derived data with very-high-spatial resolution images and LiDAR (Light Detection and Ranging) technology, which can provide 3D models of farmland (Gago et al., 2015). LiDAR technology could provide accurate maps of natural resources and farmlands for sustainable production of NUS in South Africa (Lin, 2015; Rosell and Sanz, 2012).

Sorghum, cowpea and amaranth have characteristics that allow them to grow under water-stressed environments compared to major crops which is in agreement with WRSI classification (Consoli and Vanella, 2014). This means selected NUS could make use of land that is unsuitable for growing cash crops, offering a complement crop production scenario rather than a substitution production scenario (Mabhaudhi et al., 2019). This study is a first step towards the reclassification of land in South Africa in acknowledgement of NUS in national cropping systems.

4.5 Recommendations

The land suitability maps generated in this study can be used to indicate where NUS can be promoted as alternative crop choices or to complement the current range of crops grown within marginalised cropping systems. As such, the maps can be used to inform site-specific crop diversification recommendations as a sustainable intensification strategy (Schiefer et al., 2016). To mainstream NUS into cropping systems found in the delineated regions of suitability maps developed in this study, a transdisciplinary approach is required. Moreover, there is a need to create a conducive environment for all participating stakeholders. This can be achieved if there is a harmonisation of existing policies that speak to land, environment, agriculture and health, and new policies on land use are co-designed based on evidence. Policies such as the National Environmental Management: Biodiversity Act of 2004, National Food and Nutrition Security Policy (Department of Agriculture, 2013) and Draft Policy on Preservation and development of Agricultural Land Bill 2015 could foster co-development of NUS technologies and aid in addressing challenges in the land, environment, agriculture and health domains.

We identified several challenges in defining the suitability of NUS. Key among these included urbanisations and increase in food and nutrition insecurity, bush encroachment, as well as the competition between agriculture and protected natural habitats. In this regard, agronomists, climatologists, ecologists and economists need to collaborate in co-designing the suitability indices to inform policy and practice. Such collaborations will ensure that suitability maps for NUS are holistic and relevant in addressing crosscutting challenges. To make current land suitability maps more relevant to addressing global grand challenges, researchers need to consider the inclusion of socio-economic parameters. The AHP is one of the most relied on methods in MCDM; however, the consistency is difficult to achieve where there are more than nine criteria/indicators under consideration (Saaty, 2016). Nevertheless, its ability to measure consistency is one of the factors that gives this method an edge over others. Therefore, parameters considered in MCDA should be context-specific and informed by an outcomes-based approach.

While our results remain applicable for use, future research should consider using data with a finer resolution to improve the accuracy of mapping. This will aid in improving delineation of land suitability in marginalised agricultural communities that are known to be highly heterogeneous. The application of unarmed aerial vehicles could be used to validate satellite-derived data and to capture high-resolution images. One such sensor is LiDAR (Light Detection and Ranging) technology, which can provide 3D models of farmland (Gago et al., 2015). LiDAR technology can provide accurate maps of natural resources and farmlands for sustainable production of NUS in South Africa (Lin, 2015; Rosell and Sanz, 2012). The use of high-resolution images in developing land suitability of NUS is of utmost importance in solving land use challenges. However, the process is often difficult, labour intensive and costly. The return on investment (ROI) of LiDAR in delineating areas suitable for NUS may be low as NUS still lacks developed markets and value chains (Escolà et al., 2017). Overall, the cost benefit of using LiDAR for smallholder farmer settings needs to be evaluated to determine the feasibility of such investments (Escolà et al., 2017).

Climate change is projected to shift current agro-ecological zones and land-use patterns (Mabhaudhi et al., 2013). We recommend that land suitability analysis should include climate scenarios in their simulation. The inclusion of climate scenarios in land suitability analysis will allow for more proactive agricultural planning by informing policies such as the National Climate Change and Health Adaptation Plan on the projected suitability of agricultural land to produce diverse crops in the short-, medium- and long term.

Future studies should focus on using new predictive tools in forecasting. It is observed that the majority of the studies in resource allocation utilised primitive GIS techniques. Future studies should focus on combining the Environmental Policy Integrated Climate (EPIC) models with other methods for assessing the spatial distribution and stimulating the production of crops. The EPIC model is used for predicting crop production levels incorporating the near-real-time changes in crop environment can be integrated with other techniques for improved decision making.

4.6 Conclusion

We investigated the potential spatial suitability distribution for sorghum, cowpea, amaranth and taro in South Africa. This study used the AHP model in GIS to integrate nine multidisciplinary thematic factors from climatic indicators from 1950 to 2000 (seasonal rainfall, seasonal maximum and minimum temperature), soil and landscape attributes (soil depth, slope, elevation), social-economic (road) and technical indicators (LULC). Rainfall was the most critical variable and criteria with the highest impact on land suitability of the NUS in this study. Neglected and underutilised crop species can be grown on marginal land. They can complement major crops and create greater diversity in cropping systems for building resilient cropping systems. The analysis indicated that sorghum, cowpea, and amaranth can be grown in marginal areas in S3 zones where land has moderate limitations for agricultural use. The suitability for sorghum, cowpea, and amaranth concurred with the water requirement satisfactory index (WRSI). Matching crop requirements with available resources through land suitability analysis is essential to sustainable agriculture.

Mapping NUS production potential zones in SA is key to promoting NUS production by providing evidence to assist decision- and policy-makers on crop choice. Specifically, the results help inform the Climate Smart Agriculture Strategy, National Policy on Comprehensive Producer Development Support and Indigenous Food Crops Strategy currently under development in South Africa. The suitability maps are also helpful in informing decisions on climate change adaptation (climate-smart agriculture) and sustainable agriculture practices, as well as informing decisions on the creation of markets for NUS.

The findings are useful in informing land-use classification, especially in marginal environments. The method used can be adopted to other SSA countries and other regions that share a similar context with regards to promoting cultivation of NUS. Promoting NUS within marginal production areas has the potential to create new and sustainable economic pathways and improve availability and access to nutrient-dense foods. The importance of smallholder farmers to sustainable food systems, and their participation in local food systems, must be emphasised. Finally, policies such as the National Food and Nutrition Security Policy and National Developmental Plan of South Africa (National Planning Commission, 2012) need to give a clear road map for NUS production, especially by explicitly mentioning NUS and targeting them for production on marginal lands that are currently not suitable commercial crops production as a strategy to improve food and nutrition security within these areas.

4.7 References

Aburas, M.M., Abullah, S.H., Ramli, M.F. and Ash'aari, Z.H., 2015. A review of land suitability analysis for urban growth by using the GIS-based analytic hierarchy process. Asian Journal of Applied Sciences, 3(6).

Akıncı, H., Özalp, A.Y. and Turgut, B., 2013. Agricultural land use suitability analysis using GIS and AHP technique. Computers and electronics in agriculture, 97, pp.71-82. https://doi.org/10.1016/j.compag.2013.07.006

Akinola, R., Pereira, L.M., Mabhaudhi, T., De Bruin, F.M. and Rusch, L., 2020. A review of indigenous food crops in Africa and the implications for more sustainable and healthy food systems. Sustainability, 12(8), p.3493. https://doi.org/10.3390/su12083493

Akpoti, K., Kabo-bah, A.T. and Zwart, S.J., 2019. Agricultural land suitability analysis: State-of-the-art and outlooks for integration of climate change analysis. Agricultural systems, 173, pp.172-208. https://doi.org/10.1016/j.agsy.2019.02.013

Alexander, K.W., Benjamin, M. and Grephas, O.P., 2012. Urban landuse suitability assessment using geoinformation techniques for Kisumu municipality in Kenya. International Journal of Research and Reviews in Applied Sciences, 13.

Bagherzadeh, A. and Gholizadeh, A., 2016. Modeling land suitability evaluation for wheat production by parametric and TOPSIS approaches using GIS, northeast of Iran. Modeling Earth Systems and Environment, 2(3), pp.1-11. https://doi.org/10.1007/s40808-016-0177-8

Baldermann, S., Blagojević, L., Frede, K., Klopsch, R., Neugart, S., Neumann, A., Ngwene, B., Norkeweit, J., Schröter, D., Schröter, A. and Schweigert, F.J., 2016. Are neglected plants the food for the future?. Critical Reviews in Plant Sciences, 35(2), pp.106-119. https://doi.org/10.1080/07352689.2016.1201399

Benke, K.K. and Pelizaro, C., 2010. A spatial-statistical approach to the visualisation of uncertainty in land suitability analysis. Journal of Spatial Science, 55(2), pp.257-272. https://doi.org/10.1080/14498596.2010.521975

Boatemaa, S., Barney, M., Drimie, S., Harper, J., Korsten, L. and Pereira, L., 2019. Awakening from the listeriosis crisis: Food safety challenges, practices and governance in the food retail sector in South Africa. Food Control, 104, pp.333-342. https://doi.org/10.1016/j.foodcont.2019.05.009

Brandt, P., Kvakić, M., Butterbach-Bahl, K. and Rufino, M.C., 2017. How to target climate-smart agriculture? Concept and application of the consensus-driven decision support framework “targetCSA”. Agricultural Systems, 151, pp.234-245. https://doi.org/10.1016/j.agsy.2015.12.011

Carr, M.K.V., 2013. Crop Yield Response to Water. FAO Irrigation and Drainage Paper 66. By P. Steduto, TC Hsiao, E. Fereres and D. Raes. Rome, Italy: Food and Agriculture Organization of the United Nations (2012), pp. 500, US $100.00. ISBN 978-92-5-107274-5. The whole report can be downloaded from: http://www. fao. org/docrep/016/i2800e/i2800e00. htm. Experimental Agriculture, 49(2), pp.311-311

Ceballos, S.A., J López B (2003) Evaluating biophysical variables to identify suitable areas for oat in Central Mexico: A multi-criteria and GIS approach. Agriculture, Ecosystems & Environment, 95, pp.371-377. https://doi.org/10.1016/S0167-8809(02)00180-9

Chandio, I.A., Matori, A.N.B., WanYusof, K.B., Talpur, M.A.H., Balogun, A.L. and Lawal, D.U., 2013. GIS-based analytic hierarchy process as a multicriteria decision analysis instrument: a review. Arabian Journal of Geosciences, 6(8), pp.3059-3066. https://doi.org/10.1007/s12517-012-0568-8

Chen, Y. and Paydar, Z., 2012. Evaluation of potential irrigation expansion using a spatial fuzzy multi-criteria decision framework. Environmental Modelling & Software, 38, pp.147-157. https://doi.org/10.1016/j.envsoft.2012.05.010

Chibarabada, T.P., Modi, A.T. and Mabhaudhi, T., 2020. Calibration and evaluation of aquacrop for groundnut (Arachis hypogaea) under water deficit conditions. Agricultural and Forest Meteorology, 281, p.107850. https://doi.org/10.1016/j.agrformet.2019.107850

Chimonyo, V.G.P., Modi, A.T. and Mabhaudhi, T., 2016. Simulating yield and water use of a sorghum-cowpea intercrop using APSIM. Agricultural Water Management, 177, pp.317-328. https://doi.org/10.1016/j.agwat.2016.08.021

Chivenge, P., Mabhaudhi, T., Modi, A.T. and Mafongoya, P., 2015. The potential role of neglected and underutilised crop species as future crops under water scarce conditions in Sub-Saharan Africa. International journal of environmental research and public health, 12(6), pp.5685-5711. https://doi.org/10.3390/ijerph120605685

Consoli, S. and Vanella, D., 2014. Mapping crop evapotranspiration by integrating vegetation indices into a soil water balance model. Agricultural Water Management, 143, pp.71-81. https://doi.org/10.1016/j.agwat.2014.06.012

Cools, N., De Pauw, E. and Deckers, J., 2003. Towards an integration of conventional land evaluation methods and farmers' soil suitability assessment: a case study in northwestern Syria. Agriculture, ecosystems & environment, 95(1), pp.327-342. https://doi.org/10.1016/S0167-8809(02)00045-2

de la Hey, M. and Beinart, W., 2017. Why have South African smallholders largely abandoned arable production in fields? A case study. Journal of Southern African Studies, 43(4), pp.753-770. https://doi.org/10.1080/03057070.2016.1265336

Department of Agriculture, F. and fisheries, 2013. National Policy on Food and Nutrition Policy.

Drimie, S. and Pereira, L., 2016. Advances in food security and sustainability in South Africa. In Advances in food security and sustainability (Vol. 1, pp. 1-31). Elsevier. https://doi.org/10.1016/bs.af2s.2016.09.002

Duchemin, B., Hadria, R., Erraki, S., Boulet, G., Maisongrande, P., Chehbouni, A., Escadafal, R., Ezzahar, J., Hoedjes, J.C.B., Kharrou, M.H. and Khabba, S., 2006. Monitoring wheat phenology and irrigation in Central Morocco: On the use of relationships between evapotranspiration, crops coefficients, leaf area index and remotely-sensed vegetation indices. Agricultural Water Management, 79(1), pp.1-27. https://doi.org/10.1016/j.agwat.2005.02.013

Ebert, A.W., 2014. Potential of underutilized traditional vegetables and legume crops to contribute to food and nutritional security, income and more sustainable production systems. Sustainability, 6(1), pp.319-335. https://doi.org/10.3390/su6010319

Feng, Q., Chaubey, I., Engel, B., Cibin, R., Sudheer, K.P. and Volenec, J., 2017. Marginal land suitability for switchgrass, Miscanthus and hybrid poplar in the Upper Mississippi River Basin (UMRB). Environmental modelling & software, 93, pp.356-365. https://doi.org/10.1016/j.envsoft.2017.03.027

Fontes, M.P., Fontes, R.M. and Carneiro, P.A., 2009. Land suitability, water balance and agricultural technology as a Geographic-Technological Index to support regional planning and economic studies. Land use policy, 26(3), pp.589-598. https://doi.org/10.1016/j.landusepol.2008.08.010

Gago, J., Douthe, C., Coopman, R.E., Gallego, P.P., Ribas-Carbo, M., Flexas, J., Escalona, J. and Medrano, H., 2015. UAVs challenge to assess water stress for sustainable agriculture. Agricultural water management, 153, pp.9-19. https://doi.org/10.1016/j.agwat.2015.01.020

Garrity, D.P., Akinnifesi, F.K., Ajayi, O.C., Weldesemayat, S.G., Mowo, J.G., Kalinganire, A., Larwanou, M. and Bayala, J., 2010. Evergreen Agriculture: a robust approach to sustainable food security in Africa. Food security, 2(3), pp.197-214. https://doi.org/10.1007/s12571-010-0070-7

Gregory, P.J., Mayes, S., Hui, C.H., Jahanshiri, E., Julkifle, A., Kuppusamy, G., Kuan, H.W., Lin, T.X., Massawe, F., Suhairi, T.A.S.T.M. and Azam-Ali, S.N., 2019. Crops For the Future (CFF): an overview of research efforts in the adoption of underutilised species. Planta, 250(3), pp.979-988. https://doi.org/10.1007/s00425-019-03179-2

Han, M. and Chen, G., 2018. Global arable land transfers embodied in Mainland China's foreign trade. Land use policy, 70, pp.521-534. https://doi.org/10.1016/j.landusepol.2017.07.022

Hardy, M., Dziba, L., Kilian, W. and Tolmay, J., 2011. Rainfed farming systems in South Africa. In Rainfed farming systems(pp. 395-432). Springer, Dordrecht. https://doi.org/10.1007/978-1-4020-9132-2

Harvey, M. and Pilgrim, S., 2011. The new competition for land: Food, energy, and climate change. Food policy, 36, pp.S40-S51.

Jelokhani-Niaraki, M. and Malczewski, J., 2015. Decision complexity and consensus in Web-based spatial decision making: A case study of site selection problem using GIS and multicriteria analysis. Cities, 45, pp.60-70. https://doi.org/10.1016/j.cities.2015.03.007

Jeong, J.S., García-Moruno, L., Hernández-Blanco, J. and Jaraíz-Cabanillas, F.J., 2014. An operational method to supporting siting decisions for sustainable rural second home planning in ecotourism sites. Land use policy, 41, pp.550-560. https://doi.org/10.1016/j.landusepol.2014.04.012

Jiménez-Valverde, A., 2012. Insights into the area under the receiver operating characteristic curve (AUC) as a discrimination measure in species distribution modelling. Global Ecology and Biogeography, 21(4), pp.498-507. https://doi.org/10.1111/j.1466-8238.2011.00683.x

Kaim, A., Cord, A.F. and Volk, M., 2018. A review of multi-criteria optimization techniques for agricultural land use allocation. Environmental Modelling & Software, 105, pp.79-93. https://doi.org/10.1016/j.envsoft.2018.03.031

Kazemi, H. and Akinci, H., 2018. A land use suitability model for rainfed farming by Multi-criteria Decision-making Analysis (MCDA) and Geographic Information System (GIS). Ecological engineering, 116, pp.1-6. https://doi.org/10.1016/j.ecoleng.2018.02.021

Kepe, T. and Tessaro, D., 2014. Trading-off: Rural food security and land rights in South Africa. Land use policy, 36, pp.267-274. https://doi.org/10.1016/j.landusepol.2013.08.013

Kihoro, J., Bosco, N.J. and Murage, H., 2013. Suitability analysis for rice growing sites using a multicriteria evaluation and GIS approach in great Mwea region, Kenya. SpringerPlus, 2(1), pp.1-9. https://doi.org/10.1186/2193-1801-2-26

Kim, H., Hyun, S.W., Hoogenboom, G., Porter, C.H. and Kim, K.S., 2018. Fuzzy union to assess climate suitability of annual ryegrass (Lolium multiflorum), Alfalfa (Medicago sativa) and Sorghum (Sorghum bicolor). Scientific reports, 8(1), pp.1-15. https://doi.org/10.1038/s41598-018-28291-3

Lin, Y., 2015. LiDAR: An important tool for next-generation phenotyping technology of high potential for plant phenomics?. Computers and electronics in Agriculture, 119, pp.61-73. https://doi.org/10.1016/j.compag.2015.10.011

Liu, J., Pattey, E., Miller, J.R., McNairn, H., Smith, A. and Hu, B., 2010. Estimating crop stresses, aboveground dry biomass and yield of corn using multi-temporal optical data combined with a radiation use efficiency model. Remote Sensing of Environment, 114(6), pp.1167-1177. https://doi.org/10.1016/j.rse.2010.01.004

Lynch, R.E.S., 2004. Mean Annual Precipitation. Dictionary Geotechnical Engineering. https://doi.org/10.1007/978-3-642-41714-6_130928

Mabhaudhi, T., Chibarabada, T.P., Chimonyo, V.G.P., Murugani, V.G., Pereira, L.M., Sobratee, N., Govender, L., Slotow, R. and Modi, A.T., 2018. Mainstreaming underutilized indigenous and traditional crops into food systems: A South African perspective. Sustainability, 11(1), p.172. . https://doi.org/10.3390/su11010172

Mabhaudhi, T., Chimonyo, V.G.P., Hlahla, S., Massawe, F., Mayes, S., Nhamo, L. and Modi, A.T., 2019. Prospects of orphan crops in climate change. Planta, 250(3), pp.695-708. https://doi.org/10.1007/s00425-019-03129-y

Mabhaudhi, T., Modi, A.T. and Beletse, Y.G., 2014. Parameterisation and evaluation of the FAO-AquaCrop model for a South African taro (Colocasia esculenta L. Schott) landrace. Agricultural and Forest Meteorology, 192, pp.132-139. https://doi.org/10.1016/j.agrformet.2014.03.013

Mabhaudhi, T., Modi, A.T. and Beletse, Y.G., 2014. Parameterization and testing of AquaCrop for a South African bambara groundnut landrace. Agronomy journal, 106(1), pp.243-251. https://doi.org/10.2134/agronj2013.0355

Mabhaudhi, T., Modi, A.T. and Beletse, Y.G., 2013. Response of taro (Colocasia esculenta L. Schott) landraces to varying water regimes under a rainshelter. Agricultural water management, 121, pp.102-112. https://doi.org/10.1016/j.agwat.2013.01.009

Macomber, M.M., 1984. World geodetic system 1984. Defense Mapping Agency Washington DC.

Malczewski, J., 2006. GIS-based multicriteria decision analysis: a survey of the literature. International journal of geographical information science, 20(7), pp.703-726. https://doi.org/10.1080/13658810600661508

Malczewski, J., 2004. GIS-based land-use suitability analysis: a critical overview. Progress in planning, 62(1), pp.3-65. https://doi.org/10.1016/j.progress.2003.09.002

Martínez-Casasnovas, J.A., Rufat, J., Arnó, J., Arbonés, A., Sebé, F., Pascual, M., Gregorio, E. and Rosell-Polo, J.R., 2017. Mobile terrestrial laser scanner applications in precision fruticulture/horticulture and tools to extract information from canopy point clouds. Precision Agriculture, 18(1), pp.111-132.

Massawe, F., Mayes, S. and Cheng, A., 2016. Crop diversity: an unexploited treasure trove for food security. Trends in plant science, 21(5), pp.365-368. https://doi.org/10.1016/j.tplants.2016.02.00

Mendoza, G.A. and Martins, H., 2006. Multi-criteria decision analysis in natural resource management: A critical review of methods and new modelling paradigms. Forest ecology and management, 230(1-3), pp.1-22. https://doi.org/10.1016/j.foreco.2006.03.02

Mesgaran, M.B., Madani, K., Hashemi, H. and Azadi, P., 2017. Iran's land suitability for agriculture. Scientific reports, 7(1), pp.1-12. https://doi.org/10.1038/s41598-017-08066-y

Modi, A.T., 2003. What do subsistence farmers know about indigenous crops and organic farming? Preliminary experience in KwaZulu-Natal. Development Southern Africa, 20(5), pp.675-684. https://doi.org/10.1080/0376835032000149306

Musakwa, W., 2018. Identifying land suitable for agricultural land reform using GIS-MCDA in South Africa. Environment, Development and Sustainability, 20(5), pp.2281-2299. https://doi.org/10.1007/s10668-017-9989-6

Mustafa, A.A., Singh, M., Sahoo, R.N., Ahmed, N., Khanna, M., Sarangi, A. and Mishra, A.K., 2011. Land suitability analysis for different crops: a multi criteria decision making approach using remote sensing and GIS. Researcher, 3(12), pp.61-84.

Nasrollahi, N., Kazemi, H. and Kamkar, B., 2017. Feasibility of ley-farming system performance in a semi-arid region using spatial analysis. Ecological Indicators, 72, pp.239-248. https://doi.org/10.1016/j.ecolind.2016.08.026

National Planning Commission, 2012. An integrated and inclusive rural economy. https://doi.org/ISBN: 978-0-621-41180-5

Nguyen, T.T., Verdoodt, A., Van Y, T., Delbecque, N., Tran, T.C. and Van Ranst, E., 2015. Design of a GIS and multi-criteria based land evaluation procedure for sustainable land-use planning at the regional level. Agriculture, Ecosystems & Environment, 200, pp.1-11. https://doi.org/10.1016/j.agee.2014.10.015

Nyathi, M.K., Van Halsema, G.E., Annandale, J.G. and Struik, P.C., 2018. Calibration and validation of the AquaCrop model for repeatedly harvested leafy vegetables grown under different irrigation regimes. Agricultural water management, 208, pp.107-119. https://doi.org/10.1016/j.agwat.2018.06.012

Nzeyimana, I., Hartemink, A.E. and Geissen, V., 2014. GIS-based multi-criteria analysis for Arabica coffee expansion in Rwanda. PloS one, 9(10), p.e107449. https://doi.org/10.1371/journal.pone.0107449

Rabia, A.H., Figueredo, H., Huong, T.L., Lopez, B.A.A., Solomon, H.W. and Alessandro, V., 2013. Land suitability analysis for policy making assistance: a GIS based land suitability comparison between surface and drip irrigation systems. International Journal of Environmental Science and Development, 4(1), p.1. https://doi.org/10.7763/IJESD.2013.V4.292

Raihana, A.N., Marikkar, J.M.N., Amin, I. and Shuhaimi, M., 2015. A review on food values of selected tropical fruits' seeds. International Journal of Food Properties, 18(11), pp.2380-2392. https://doi.org/10.1080/10942912.2014.980946

Ranjitkar, S., Sujakhu, N.M., Merz, J., Kindt, R., Xu, J., Matin, M.A., Ali, M. and Zomer, R.J., 2016. Suitability analysis and projected climate change impact on banana and coffee production zones in Nepal. PloS one, 11(9), p.e0163916. https://doi.org/10.1371/journal.pone.0163916

Raza, S.M.H., Mahmood, S.A., Khan, A.A. and Liesenberg, V., 2018. Delineation of potential sites for rice cultivation through multi-criteria evaluation (MCE) using remote sensing and GIS. International Journal of Plant Production, 12(1), pp.1-11. https://doi.org/10.1007/s42106-017-0001-z

Reshmidevi, T.V., Eldho, T.I. and Jana, R., 2009. A GIS-integrated fuzzy rule-based inference system for land suitability evaluation in agricultural watersheds. Agricultural systems, 101(1-2), pp.101-109. https://doi.org/10.1016/j.agsy.2009.04.001

Romano, G., Dal Sasso, P., Liuzzi, G.T. and Gentile, F., 2015. Multi-criteria decision analysis for land suitability mapping in a rural area of Southern Italy. Land use policy, 48, pp.131-143. https://doi.org/10.1016/j.landusepol.2015.05.013

Rosell, J.R. and Sanz, R., 2012. A review of methods and applications of the geometric characterization of tree crops in agricultural activities. Computers and electronics in agriculture, 81, pp.124-141. https://doi.org/10.1016/j.compag.2011.09.007

Rossiter, D.G., 2009. Land evaluation: towards a revised framework; Land and Water Discussion Paper 6, FAO. FAO, Rome (2007), 107 pp., ISSN: 1729-0554; Only available in PDF format as www. fao. org/nr/lman/docs/lman_070601_en. pdf; free.

Saaty, R.W., 2002. Decision making in complex environments: the analytic network process (ANP) for dependence and feedback; A Manual for the ANP Software Super Decisions. Pittsburgh, Creat Decis Foundation, PA, 15213, p.4922.

Saaty, R.W., 1980. The Analytic Hierarchy Process., Decision Analysis.

Satty, T.L., 1990. How to make a decision: The Analytical Hierarchy Process. European Journal of Operational Research. https://doi.org/10.1016/0377-2217(90)90057-I

Saaty, T.L., Saaty, R.W., 1980. The Analytic Hierarchy Process. Education 1-11. https://doi.org/10.3414/ME10-01-0028

Schiefer, J., Lair, G.J. and Blum, W.E., 2016. Potential and limits of land and soil for sustainable intensification of European agriculture. Agriculture, Ecosystems & Environment, 230, pp.283-293. https://doi.org/10.1016/j.agee.2016.06.021

Schulze, R.E., 2002. South African atlas of climatology and Weather.

Senay, S.D. and Worner, S.P., 2019. Multi-scenario species distribution modeling. Insects, 10(3), p.65. https://doi.org/10.3390/insects10030065

Shackleton, C.M., Hebinck, P., Kaoma, H., Chishaleshale, M., Chinyimba, A., Shackleton, S.E., Gambiza, J. and Gumbo, D., 2014. Low-cost housing developments in South Africa miss the opportunities for household level urban greening. Land use policy, 36, pp.500-509. https://doi.org/10.1016/j.landusepol.2013.10.002

Sharma, R., Kamble, S.S. and Gunasekaran, A., 2018. Big GIS analytics framework for agriculture supply chains: A literature review identifying the current trends and future perspectives. Computers and Electronics in Agriculture, 155, pp.103-120. https://doi.org/10.1016/j.compag.2018.10.001

Shumsky, S., Hickey, G.M., Johns, T., Pelletier, B. and Galaty, J., 2014. Institutional factors affecting wild edible plant (WEP) harvest and consumption in semi-arid Kenya. Land use policy, 38, pp.48-69. https://doi.org/10.1016/j.landusepol.2013.10.014

Singh Rawat, K.S., Singh, S.K., Bala, A. and Szabó, S., 2019. Estimation of crop evapotranspiration through spatial distributed crop coefficient in a semi-arid environment. Agricultural Water Management, 213, pp.922-933. https://doi.org/10.1016/j.agwat.2018.12.002

Singha, C. and Swain, K.C., 2016. Land suitability evaluation criteria for agricultural crop selection: A review. Agricultural reviews, 37(2). https://doi.org/10.18805/ar.v37i2.10737

Smithers, J.C. and Schulze, R.E., 2000. Long duration design rainfall estimates for South Africa. Pretoria: Water Research Commission.

Sun, H., Wang, S. and Hao, X., 2017. An Improved Analytic Hierarchy Process Method for the evaluation of agricultural water management in irrigation districts of north China. Agricultural Water Management, 179, pp.324-337. https://doi.org/10.1016/j.agwat.2016.08.002

Team, R.C., 2017. A language and environment for statistical computing R Found Stat Comput. Vienna, Austria.

World Bank Group, 2018. Overcoming poverty and inequality in South Africa: An assessment of drivers, constraints and opportunities. World Bank.

Thow, A.M., Greenberg, S., Hara, M., Friel, S., duToit, A. and Sanders, D., 2018. Improving policy coherence for food security and nutrition in South Africa: a qualitative policy analysis. Food Security, 10(4), pp.1105-1130. https://doi.org/10.1007/s12571-018-0813-4

Tibesigwa, B., Visser, M. and Turpie, J., 2017. Climate change and South Africa's commercial farms: an assessment of impacts on specialised horticulture, crop, livestock and mixed farming systems. Environment, Development and Sustainability, 19(2), pp.607-636. https://doi.org/10.1007/s10668-015-9755-6

Tshabalala, T., Ncube, B., Moyo, H.P., Abdel-Rahman, E.M., Mutanga, O. and Ndhlala, A.R., 2020. Predicting the spatial suitability distribution of Moringa oleifera cultivation using analytical hierarchical process modelling. South African Journal of Botany, 129, pp.161-168. https://doi.org/10.1016/j.sajb.2019.04.010

Ugbaje, S.U., Odeh, I.O. and Bishop, T.F., 2019. Fuzzy measure-based multicriteria land assessment for rainfed maize in West Africa for the current and a range of plausible future climates. Computers and Electronics in Agriculture, 158, pp.51-67. https://doi.org/10.1016/j.compag.2019.01.011

Williams, G., 2011. Random forests. In Data Mining with Rattle and R (pp. 245-268). Springer, New York, NY. https://doi.org/10.1007/978-1-4419-9890-3

Wolfert, S., Ge, L., Verdouw, C. and Bogaardt, M.J., 2017. Big data in smart farming – a review. Agricultural systems, 153, pp.69-80. https://doi.org/10.1016/j.agsy.2017.01.023

Yi, X. and Wang, L., 2013. Land suitability assessment on a watershed of Loess Plateau using the analytic hierarchy process. PloS one, 8(7), p.e69498. https://doi.org/10.1371/journal.pone.0069498

Zabel, F., Putzenlechner, B. and Mauser, W., 2014. Global agricultural land resources – a high resolution suitability evaluation and its perspectives until 2100 under climate change conditions. PloS one, 9(9), p.e107522. https://doi.org/10.1371/journal.pone.0107522

Zabihi, H., Ahmad, A., Vogeler, I., Said, M.N., Golmohammadi, M., Golein, B. and Nilashi, M., 2015. Land suitability procedure for sustainable citrus planning using the application of the analytical network process approach and GIS. Computers and Electronics in Agriculture, 117, pp.114-126. https://doi.org/10.1016/j.compag.2015.07.014

Ziadat, F.M., 2007. Land suitability classification using different sources of information: Soil maps and predicted soil attributes in Jordan. Geoderma, 140(1-2), pp.73-80. https://doi.org/10.1016/j.geoderma.2007.03.004

Zhongming, Z., Linong, L., Xiaona, Y., Wangqiang, Z. and Wei, L., 2018. Summary for Policymakers of IPCC Special Report on Global Warming of 1.5° C approved by governments.

5 AGRONOMIC MANAGEMENT OF SELECTED AFRICAN LEAFY VEGETABLES FOR IMPROVED YIELD, WATER USE AND WATER PRODUCTIVITY

Kunene, T., Chimonyo, V.G.P., Mabhaudhi, T, and Modi, A.T.

Abstract

Crop modelling can generate information about the crop's growth, development, water, and nutritional needs. The primary objectives of this study were (i) to assess the growth and productivity of selected ALVs (amaranth (*Amaranth spp*), cowpea (*Vigna unguiculata*), sweet potato (*Ipomoea batatas*) and wild mustard (*Sinapis arvensis*)) under different management practices, and (ii) assess water productivity (WP) and nutritional water productivity (NWP) of the selected ALVs. Desktop-based research was conducted to achieve the mentioned objectives. Here, information on the studied crops' agronomy secondary data was gathered through a careful literature search. This secondary information was then used to model growth and productivity and quantify nutritional water productivity at different management practices. The Agricultural Production systems SImulator (APSIM) was used to simulate growth and productivities under different management scenarios of planting date, plant density, fertiliser application and irrigation. We used the soil, and climatic data from the University of KwaZulu-Natal's research farm (Ukulinga Research Farm) situated in Pietermaritzburg, South Africa (29°37′S; 30°16′E; 775 m a.s.l.) calibrate the model. All data analysis was done using descriptive statistical analysis (R software). All mean values were subjected to a t-test set at $p<0.05$ significance. The results showed that depending on crop species different management practices can be relevant to achieve optimum growth and productivity for various purposes.

5.1 Introduction

Food and nutrient security remain a challenge in South Africa. At a national level, the country is regarded as food secure, but people still experience some constraints to safe, sufficient, and nutritious food at the household level. Contributing to this challenge of food and nutrient insecurities is the lack of land and resources to produce food. Often, the people that have less to access to food come from a poor community, and as much as they may have access to land for farming, they still lack resources such as water and fertilizer (Van Jaarsveld et al., 2014). On the other hand, some of those who have access to food might still fail to access nutritious foods.

South Africa is known as one of the world's driest countries (Water, 2011; Donnenfeld et al., 2018). More than 80% (98 million ha) of South African land surface is defined as arid or semi-arid, and out of that 80%, only 17% (16.8 million ha) is arable (Hardy et al., 2011). Out of the 22% of land classified as having high potential for cultivation, less than 10% is irrigated, and the rest is rainfed. Only 2.5 million ha of the arable land is rainfed agriculture; the rest of the land is abandoned (Hardy et al., 2011). The limited amount of arable land and variable rainfall contributes largely to low crop production, thus failing to meet millions of households' food requirements. Therefore, it is crucial to implement a sustainable agricultural system given these unfavourable and water limiting conditions. One of the coping strategies for this is using African leafy vegetables (ALVs) (Hardy et al., 2011).

African leafy vegetables are best known for their high nutrition potential. Their management requires low water and fertiliser inputs (Senyolo et al., 2018). They can thrive under limiting conditions and are regarded as potential crops to contribute to food and nutrient security (Mavengahama et al., 2013). However, just like any other crop, they eventually give in to unfavourable conditions such as water stress (Mabhaudhi et al., 2018). To encourage their growth, one would have to understand what best management practices these ALVs require. However, based on the available literature on the agronomy of these ALVs, it is difficult to draw conclusions and recommend best management practices for enhanced yields, water use, and water productivity of ALVs. As part of the solution, besides long field experiments, crop modelling provides an accurate, easy, and less time-consuming solution to assess the full potential of ALVS for their best agronomic management practices for better growth and productivity. In this chapter, APSIM was used to determine best management practices for improved yields, water use, and water productivity of selected ALVs (amaranth, cowpea, sweet potato, and wild mustard). This model singled out because of its ability of "Plug in" to specify any logical or required modules and "Plug out" to define any modules that are no longer needed. This was very advantageous for the studied ALVs as they have never been calibrated for specific cultivar and under different environments.

5.2 Materials and methods

The Agricultural Production Systems Simulator (APSIM) model was calibrated using data from Ukulinga Research Farm is the University of KwaZulu-Natal's research farm situated in Pietermaritzburg, South Africa (29°37′S; 30°16′E; 775 m a.s.l.). Ukulinga research farm has a mean annual rainfall of about 790 mm, received between October to April. During the summer, the average temperature goes up to 26.5 °C (Chimonyo et al., 2016a). According to the profile pit description, the Research Farm soils are dominantly clay-loam textures having 0.6 adequate rooting depth. Using the FAO soil classification system, Ukulinga soils can be further categorised as chromic luvisols. These are shallow brown acidic soils having low to moderate fertility.

The soil water movement and availability are affected by the soil physical properties (Chimonyo et al., 2016b; c). The initial C: N ratio calculated from the results of the soil chemical properties. On these results, carbon (%) for the top 0.2 m layer was 2.3%, while N was 0.3%. Four African Leafy Vegetables were simulated for growth and productivity. These included amaranth, cowpea, sweet potato, and wild mustard. Each crop had 15 samples for each treatment modelled for each growing season in a year (from 2014-2019). Yield (fresh biomass) and evapotranspiration observed as variables from the outputs of the simulation were then used to calculate water productivity for each crop. The growth of crops was also studied for different planting date, planting density, fertiliser application and irrigation scenarios.

5.2.1 Brief description of APSIM model

The Agricultural Production SIMulator (APSIM) is a point scale and daily time-step model that allows modules (sub-models) to be associated with simulating agricultural systems over a single homogenous field over a certain period (Ahmed and Fayyaz-Ul-Hassana, 2011; Chimonyo et al., 2016a). Numerous modules grouped as soil, plant, environment, and management are included in the APSIM. This model mimics the mechanistic growth of the crops, a series of management options with regards to cropping systems (e.g. mono-cropping, intercropping, and rotation), and soil processes (additions, losses, transformations (changes), and translocation or movement (Ahmed and Fayyaz-Ul-Hassana, 2011). The APSIM model simulates the growth and development of crops in a daily time-step on an area basis, per square meter, not a single plant (Robertson and Lilley, 2016). The inputs required by the APSIM module include weather, soil, crop data and management options (Ojeda et al., 2017).

The growth and development of this module respond to soil water supply, soil nitrogen, and climate. It then returns the information on the uptake of nitrogen and soil water to its SoilN and SoilWat modules each day for these systems' reset (Keating et al., 2003). Evaporation and runoff rate were calculated using the information on the soil cover provided to the SoilWat module (Ahmed and Fayyaz-Ul-Hassana, 2011). The plant modules simulate a crops' vital physiological processes with a diverse range of produce from early to focus crops such as sorghum to various crop modules available for plants such as canola, cowpea, peanut, etc. The crop species on the APSIM module currently uses the same physiological principles to capture and use growth and development resources. The main difference is the shapes and thresholds of their response functions. The SoilWater is a daily time-step cascading water balance module derived from CERES and PERFECT and is a module. The dynamics of both carbon and nitrogen in the soil are described in the SoilN module (Gaydon et al., 2017). APSIM Met provides daily weather information to all modules within the APSIM simulation (Keating et al., 2003).

5.2.2 Simulation

5.2.2.1 Soil file

The APSIM model soil modules are classified based on the international and African format, and they include generic soil profiles for Africa. The soil properties required in this module have texture, bulk density (BD), total porosity, the drained upper limit (DUL), saturation (SAT), plant available water capacity (PAWC), pH, and crop lower limit (LL), (**Table 5.1**) for the simulation of soil water-related processes and yields. The following table describes the shallow layers of the farm according to their physical characteristics.

Table 5.1: Soil physical characteristics (Chimonyo et al., 2016a)

Depth (cm)	Texture	BD[1] (g cm^{-3})	Airdry[2] (mmmm^{-1})	LL15[3] (mm mm^{-1})	DUL[4] (mm mm^{-1})	SAT[5] (mm mm^{-1})	KS[6] (mm day^{-1})
0-10	Clay loam	1.20	0.20	0.21	0.39	0.44	20.90
10-30	clay loam	1.20	0.23	0.23	0.41	0.467	18.18
30-60	clay	1.20	0.26	0.26	0.415	0.467	13.92

[1]BD – Bulk density; [2]Airdry – Hydroscopic water content; [3]LL15 – Permanent wilting point; [4]DUL – Field capacity; [5]SAT – Saturation; [6]KS – Hydraulic conductivity

The maximum reduction curve number due to cover for the current study cover for maximum curve reduction, slope, discharge width, catchment area, and the maximum pond will be left on default (**Table 5.2**). Each soil depth, soil water condition (SWCON) was given as a fraction at planting. The portion of water that moves to the next layer (above DUL) was set as 0.3 (**Table 5.2**)

Table 5.2: The soil water module description

Parameter	Value
Summer Cona	3.5
Summer U	5
Summer date	1 Nov
Winter Cona	2
Winter U	2
Winter date	1 April
Diffusivity constant	40
Diffusivity slope	16
Soil albedo	0.12
Bare soil runoff curve number	73

5.2.2.2 Soil organic matter

The soil chemical and physical parameters were obtained from the Ukulinga soil results published by (Chimonyo et al., 2016a). After analysing the soil, Soil organic matter was inputted into the model as a percentage of carbon, C and nitrogen, N, which was then used to calculate the C: N ratio. The root C: N ratio was set to 40, root mass as 1000 kg/ha and the soil C: N ratio as 12. The initial nitrogen was measured as 56 kg/ha for both NO3 and NH4 before planting. The initial water was also measured and set before the beginning of the simulation. Where absent, it was interpolated by running the model for two seasons before the actual planting date.

5.2.2.3 MET file

The daily weather data to create the Met file was obtained from the Automatic Weather Station (AWS) situated less than 1 km within Ukulinga Research Farm. The AWS is a division of the Agricultural Research Council − Institute for Soil, Climate and Water (ARC-ISCW) network of automatic weather stations. For the MET file, daily weather data comprising maximum (T_{max}), minimum (T_{min}) air temperature (°C), solar radiation (Rad, MJ m^{-2}), rainfall (mm) was used. The same data was used by Chimonyo et al. (2016a) was extracted from the period between 27 January 2004 and appended to 20 October 2019. It was then converted to XML format. The values of average ambient temperature (TAV) and the annual amplitude in monthly temperature (AMP) were calculated and input into the MET files via "tav amp".

5.2.2.4 Crop file

The crop files found in APSIM do not include leafy vegetable crops except cowpea. Therefore, The APSIM model was adapted for canola, cowpea, and potato varieties. For amaranth and wild mustard, the canola file was used. The potato was adjusted for sweet potato, and the brown mix variety of cowpea was used since it is the most drought-tolerant variety. To achieve this step, describing the growth phenology of these crops using growth degree days (GDD °C) and time of growth (days) is essential (**Table 5.3**-**5.6**).

Table 5.3: The phenological growth stages of amaranth (*Amaranthus spp*)

APSIM stage name (code) – Canola	**Amaranth Phenological growth stages**	**Days**	**GDD °C**
Sowing (1)	-	-	-
Germination (2)	Germination[1,3]	3-4[1,3]	13-16[2,3]
Emergence (3)	Germination[1,3]		
End_of_juveline (4)	Opening of cotyledons[1,3]	4-5[1,3]	16-20[2,3]
End_of_juveline (4)	True leaves (2 leaves) [3]	8-10[1,3]	26-24[3]
-	5-6 Leaves[3]	21-32[1,3]	63-115[3]
Floral_initiation (5)	Apical inflorescence[3]	40-57[1,3]	130-218[3]
Flowering (6)	Anthesis and axillary inflorescence[1,3]	69-79[1,3]	299-377[3]
Start_grain_fill (7)	Seed development and ripening[1,3]	85-113[1-3]	410-644[2,3]
End_grain_fill (8)	-	-	-
Maturity (9)	Ripening[1,3]	120-53[1,3]	709-731[3]
Harvest_ripe (10)	Ripening – Senescence[1,3]	-	-
End_crop (11)	-	-	-

[1]Bello (2013), [2]VeggieHarvest. (2019), [3]Martínez-Núñez et al. (2019)

Table 5.4: The phenological growth stages of cowpea (*Vigna unguiculata*)

APSIM stage name (code)	Phenological growth stages	Days	GDD °C
Sowing (1)	-	-	-
Germination (2)	-	-	-
Emergence (3)	Emergence[2,3]	16[1,2,4]	242[3,4]
End_of_juveline (4)	End of the juvenile stage[2,3]	33[1,4]	514[3,4]
Floral_initiation (5)	Floral initiation[2,3]	52[1,2,4]	787[3,4]
Flowering (6)	Flowering[2,3]	64[1,2,4]	933[3,4]
Start_grain_fill (7)	Start of grain filling[2,3]	83[1,2,4]	1190[3,4]
End_grain_fill (8)	End of grain filling[2,3]	107[1,2,4]	1453[3,4]
Maturity (9)	Maturity[2,3]	125[1,2,4]	1660[3,4]
Harvest_ripe (10)	Harvest[2,3]	125[1,2,4]	1660[3,4]
End_crop (11)	Senescence[2,3]	-	-

[1]Shiringani (2007), [2]Ntombela (2012), [3]International Institute of Tropical Agriculture (2012), [4]Schwartz (2010)

Table 5.5: The phenological growth stages of sweet potato (*Ipomoea batatas*)

APSIM stage name (code) – Potato	Sweet potato phenological growth stages	Days
Sowing (1)	-	-
Germination (2)	Initial phase[1,3]	28[2,3]
Emergence (3)	Initial phase[1,3]	
Floral (4)	Intermediate phase[1,3]	49[2,3]
Tuberin (5)	Intermediate phase[1,3]	-
Flowering (6)	Final phase[1,3]	-
Full senescence (7)	Final phase[1,3]	
Maturity (8)	Final phase[1,3]	

[1]Van de Fliert, E. and Braun (1999), [2]Francesco (2005), [3]Kharzhevska (2019)

5.2.2.5 Manager Folder

The APSIM manager module is used to request any action available to any other module. Here this module was used for the following steps: the resetting of individual modules, sowing, application of fertilisers, irrigation or tilling of the soil, harvesting, or killing off crops, calculating of additional variables, to track the system state, and for the reporting of the system in response to events. The sowing variable rules were adjusted as shown (**Table 5.7**).

5.2.3 Scenario analysis

The major factors affecting plant growth, planting date, plant density, fertilizer application rate and irrigation were used to develop scenarios for modelling the best management practice of the studied ALVs. These growth factors were chosen because of the vital role they play in the growth and productivity. since they are major growth factors in APSIM

Table 5.6: The Phenological growth stages of wild mustard (*Brassica juncea L.)*

APSIM stage name (code) – Canola	Wild mustard phenological Growth stages	Days	GDD °C
Sowing (1)	-	-	-
Germination (2)	Germination[1,2]	0-35[2]	3-4[2]
Emergence (3)	Emergence[1,2]		108-136[2]
End_of_juveline (4)	Leaf stages – two leaf unfolded[1,2]	30-90[2]	214-251[2]
	Four leaves unfolded[1,2]		320-365[2]
Floral_initiation (5)	Flowering – at least one open floret on 50% or more plants[1,2]	90-100[2]	506-567[2]
Flowering (6)	Flowering – flowering 50% complete[1,2]	95-125[2]	679-747[2]
Start_grain_fill (7)	Seed fill – seed filling begins. 10% of seed have reached a final size[1,2]	120-150[2]	886-962[2]
End_grain_fill (8)	Maturity – Seeds begins to mature. 10p% of the seeds has changed the colour[1,2]		1232-1322[2]
Maturity (9)	Maturity -70% of the seeds on the main stem has changed the colour[12]	145-1502	1440-1538[2]
Harvest_ripe (10)	Maturity complete – 90% of seeds has changed colour (ripe) [1,2]		1509-1610[2]
End_crop (11)	Senescence[1,2]		

[1]Kullabas (2019), [2]Canola Council of Canada (2017)

5.2.3.1 Planting dates

The selected African leafy vegetables (amaranth, cowpea, sweet potato, and wild mustard) are known as warm-season crops. Therefore, the selection of planting date began in spring until the end of summer. That is from 1-Septemeber, 1-October, 1-November, 1-December, 1-January, 1-February, 1-March (**Table 5.*8***).

5.2.3.2 Plant density

Simulations were performed at less or more than 50% of the recommended plant population to determine the optimum plant density (or plant population) for each leafy vegetable crop. For amaranth, an optimum plant density of 17.4 plants m^2 was used. For cowpea, 17.4 plants m^2, for sweet potato five plants m^2, and wild mustard, 27 plants m^2. Simulations were done by maintaining the recommended plant population of one component and changing the other, resulting in 8 simulations (**Table 5.8**).

5.2.3.3 Fertiliser application rate

Amaranth requires a minimum of 100 kg ha^{-1} N to produce 40 tons ha^{-1} of leaves and 1 ton ha^{-1} of grain (Sullivan and Specialist, 2003). Cowpea requires 40 kg ha^{-1} N to make 1 ton ha^{-1} of seed and ton ha^{-1} of hay (DAFF, 2013). Sweet potato 100 kg ha^{-1} N (Gupta, 2011), and wild mustards requires 90 kg ha^{-1} N to produce 112 tons ha^{-1} (Government of Saskatchewan, 2017) (***Table 5.8***). Accurate fertiliser recommendations can help farmers correctly apply fertilisers for better yields that meet or exceed food demands. Therefore, improving yields by addressing fertiliser application as one of the limiting factors is desirable.

To model this scenario analysis based on the recommendations made by Sullivan and Specialist (2003), DAFF (2013), Gupta (2011) and Government of Saskatchewan (2017) for amaranth, cowpea, sweet potato and wild mustard, respectively, were used with fertiliser representatives of 0%, 25%, and 50% of the recommended rates (**Table 5.8**). This range represents a scenario whereby the farmer does not have access to fertiliser (0%), somewhat have access (25%) and (50%) only have access to half the fertiliser of the recommended rate (**Table 5.8**).

5.2.3.4 Irrigation

Depending on texture and structure, different soils may differ in water-holding capacity. As one of the management options to improve growth and yield gaps, irrigation can be introduced to growing plants. Irrigation is defined as applying controlled amounts of water to plants at set intervals (Hirota and Satoh, 1988; Zotarelli et al., 2010). However, to be more precise about irrigation and intervals, farmers often develop a schedule using the irrigation calendar based on the crop's previous seasons' water requirements. This is irrigation scheduling, which is merely applying water at the right time and at the correct time (Zotarelli et al., 2010). Irrigation is affected by numerous factors such as root distribution, and soil characteristics and evaporative plant demand. Thus, to establish proper irrigation, these are essential factors to look into. In the present experiment, a drip irrigation method was used to simulate the growth and yields of amaranth, cowpea, sweet potato, and wild mustard at three different Field Capacity (FC) water levels (**Table 5.8**). Here, the idea is to use the irrigation scheduling with crop water requirement by considering the most critical growth stages where the plant requires water and use guidelines for irrigation.

The manager folder was modified for each leafy vegetable, and the sowing variable was set. The above table does not show variables where default settings were used.

5.2.4 Data analysis and visualisation

The simulation output obtained on growth and productivity were subjected to descriptive statistics, t-test analysis and generalized linear mixed analysis (GLMM) on R statistical software (version 1.3.959). The generalized linear mixed and t-test analysis was used at a confidence interval level of 95%. For the output analysis, descriptive values such as means, standard deviations, box and whiskers plots, and graphs were used. The box and whiskers plot were used to show the general trend and steadiness of data. In contrast, the t-test was used to determine any difference among the means of leaf number, leaf mass, leaf area index and water productivity.

Table 5.7: Sowing using the variable rule

Description	**Value**			
Crop properties				
Name of crop	Canola	Cowpea	Potato	Canola
Enter cultivar	Mustard	banjo	Sweet potato	Wild mustard
Method of cropping	Sole	Sole	Sole	Sole
Exclude from rotation sequence	no	no	no	no
Sowing criteria				
Enter sowing window START date (dd-mm)	1-Sep	1-Sep	1-Sep	1-Sep
Enter sowing window END (dd-mm)	1-Apr	1-Apr	1-Apr	1-Apr
Must sow	Yes	Yes	Yes	Yes
Enter amount of cumulative rainfall (mm)	20	20	20	20
Enter number of days to acumulate rainfall (days)	5	5	5	5
Enter amount of soil water (mm)	100	100	200	100
Enter opportunity number to sow on	2	2	2	2
Enter upper limit of soil water in top layer (0-2) (mm esw/mm soil)	2	2	2	2

Enter upper limit of soil water in top layer (0-2) (mm esw/mm soil)	0	0	0	0
Sowing parameter				
Enter name of crop to sow	canola	cowpea	potato	canola
Enter sowing density (plant/m^2)	174	25	1.87	27
Enter sowing depth (mm)	20	20	300	15
Enter cultivar	Amaranth	banjo	russet	Wild_mustard
Enter crop growth class	Plant	plant	plant	plant
Enter row spacing (mm)	300	300	900	100
Harvesting rule				
Harvesting rule				
Enter the name of crop ti harvest when ripe	canola	cowpea	potato	canola
Fertiliser at sowing				
Amount of starter fertiliser at sowing (kg/ha)	72.5	44	100	101
Sowing fertiliser type	urea_N	urea_N	urea_N	urea_N
Fertiliser on days after sowing – top-up				
Aount of N required in top 3 layers (kg/ha)	200	100	0	200
Fertiliser application details				
The module used to apply fertiliser	Fertiliser	Fertiliser	Fertiliser	Fertiliser
Fertiliser type	NO3_N	NO3_N	broadcast_p	urea_N

Table 5.8: A scenario analysis of selected African leafy vegetables

Scenarios	Amaranth	Cowpea	Sweet potato	Wild mustard
1. Nitrogen fertiliser application (kg/ha) (0, 50, 100% of recommended)	72.50	44.00	100.00	73.00
2. Irrigation (mm) 0, 45, 90 of PAW	1000.00	1150.00	1395.00	1000.00
3. Planting dates (trigger season climate method, modelling and fixed date approaches)	For all crops, the planting dates for the sowing of crops began from 1-Septemeber, 1-October, 1-November, 1-December, 1-January, 1-February, 1-March, 1-April			
4. Planting density (plants/m^2) high (-50%) or low (+50%) of the recommended	17.40	18.50	1.85	27.00

5.3 Results

5.3.1 Amaranth

5.3.1.1 Planting date

Different planting date resulted in different responses to leaf number, leaf mass, leaf area index (LAI) and water productivity (WP) (**Figure 5.1**). Early planting 01-September (1) favoured a high number of leaves (123). Contrary to this, late plantings (01-March) resulted in a low leaf number (89). Results for leaf mass, LAI and WP showed an inverse relationship with leaf mass. The general observation was that late planting date gave the highest leaf mass, LAI and WP compared to early planting dates. Planting date 01-March (7) and 01-December (4) gave the highest (1 324 g plant^{-1}) and lowest (1 089 g plant^{-1}) leaf mass, respectively. Planting in March resulted in the highest LAI (2.53) and WP (0.41 g m^{-3}) and while November planting had the lowest simulated values (1.90, 0.21 g m^{-3}, respectively).

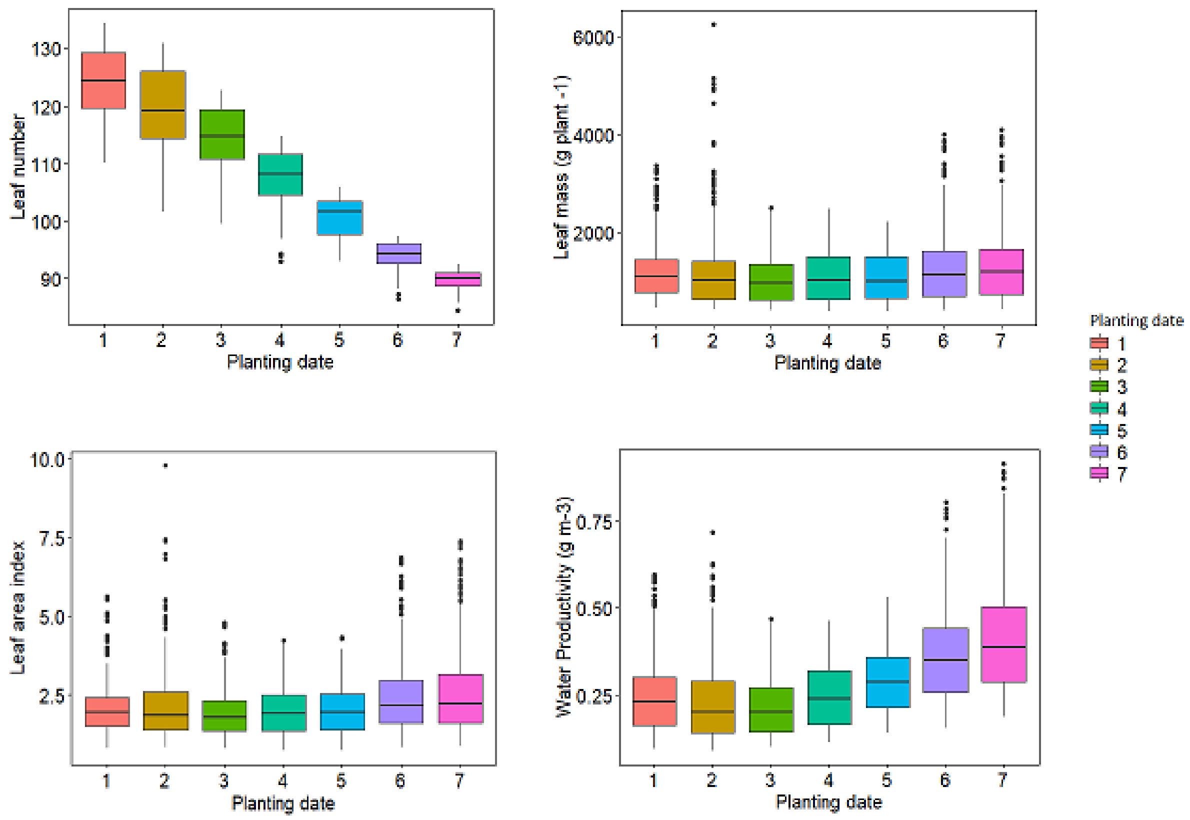


Figure 5.1: The effect of planting dates on leaf number, leaf mass (g plant^{-1}), leaf area index and water productivity (g m^{-3}) on growth and development of amaranth. Planting date 1 through 7 correspond to the 1st of September (1), October (2), November (3), December (4), January (5), February (6) and March (7) respectively.

5.3.1.2 Plant density

There was a significant difference ($P<0.05$) in leaf number and LAI of the amaranth plants (**Figure 5.2**). However, plant density did not affect ($P>0.05$) leaf mass and WP. Overall, the leaf mass, LAI and WP were all optimum under medium plant density, 17.4 plants m^2. On the other hand, leaf number decreased with an increase in plant density. Leaf mass was the highest (1193 kg ha^{-1}) at medium plant density (17.4 plants m^2) and the lowest (1165 g plant^{-1}) at low (8.7 plants m^2) plant density. At plant density, 26.1 plants m^2, the mean leaf mass was 1173 g plant^{-1}. The leaf area index was 2.32, 2.21, and 1.87 at 26.1, 17.4 and 8.7 plants m^2. There were no significant differences for WP across the simulated plant density. There was no significant difference in WP across the different plant densities. Overall, WP was 0.29 g m^{-3} with a standard deviation of 0.13. There were more outliers for the simulated WP under high plant density than under low plant density (Figure 3.2).

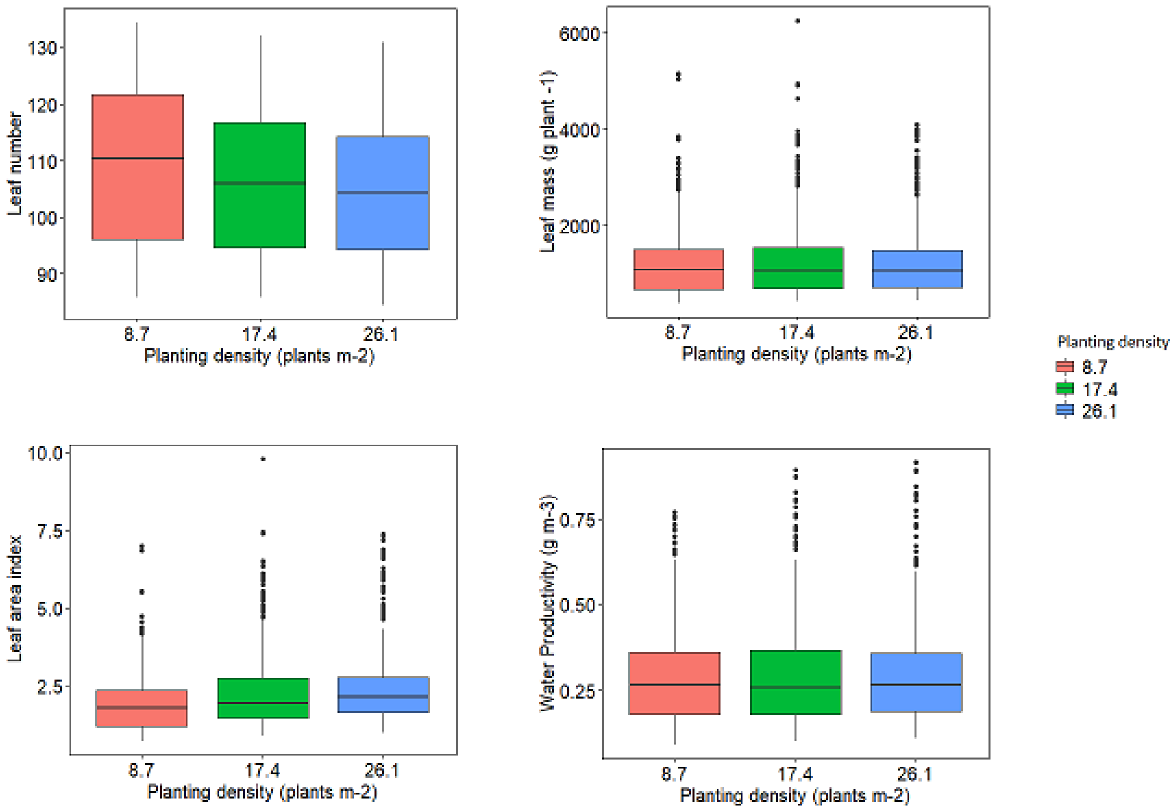


Figure 5.2: The effect of plant density (plants m^2) on leaf number, leaf mass (g $plant^{-1)}$, leaf area index and water productivity (g m^{-3}) on growth and development of amaranth

5.3.1.3 Fertiliser application

In terms of leaf number and leaf mass, the simulated results at different fertiliser applications showed no significant differences. The simulated leaf number was the same (106) at different fertiliser rates, respectively (**Figure 5.3**). An average leaf mass of 1188, 1173 and 1170 g $plant^{-1}$ was obtained at 71, 35.5, and 0 kg ha^{-1} of fertiliser application. The plants simulated with 71 kg ha^{-1} fertiliser had the highest (2.17) LAI, and the ones simulated with 0 and 35.5 kg ha^{-1} gave the lowest (2.14). Water productivity also showed a similar trend with LAI. The highest WP means value (0.29 g m^{-3}) was at 71 kg ha^{-1} and 0 and 35.5 kg ha^{-1} fertiliser application giving the lowest

(0.28 g m^{-3}). Several outliers were observed across the measure variables, and this could have been attributed to different climatic conditions observed.

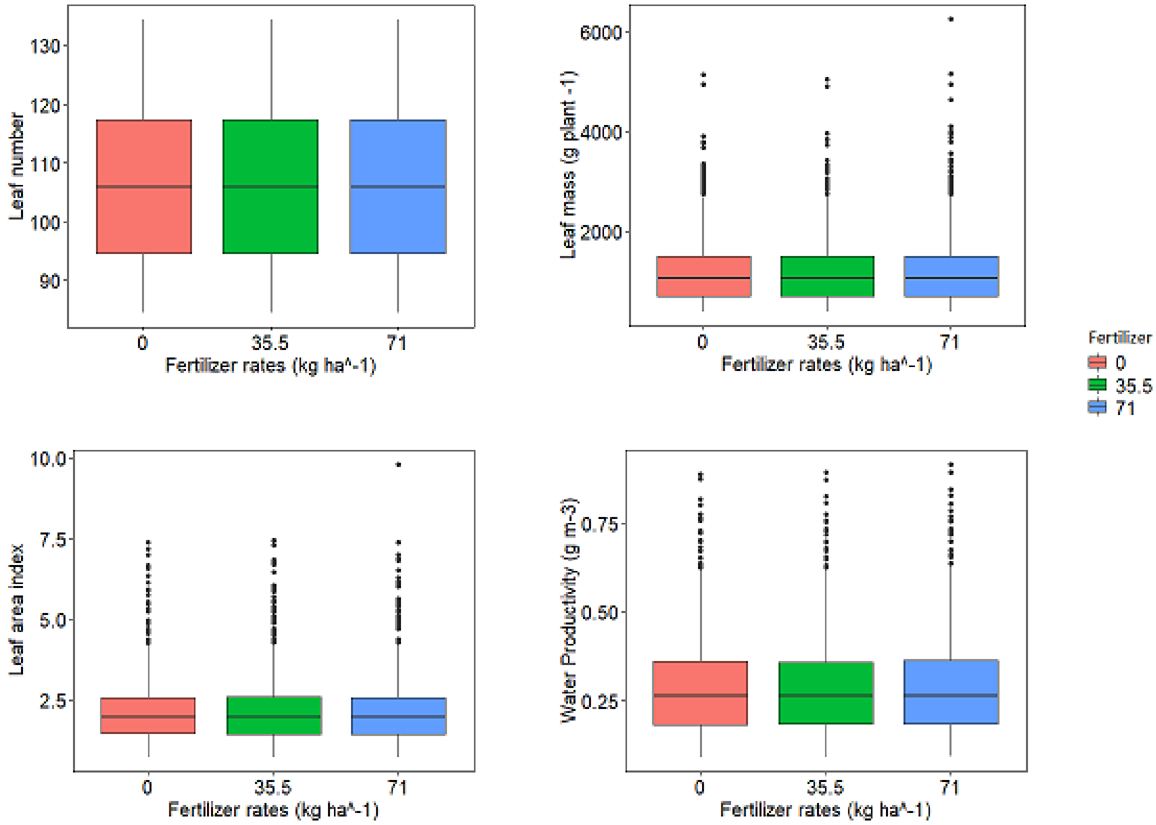


Figure 5.3: The effect of Fertiliser (kg ha^{-1}) on leaf number, leaf mass (g plant^{-1}), leaf area index and water productivity (g m^{-3}) on growth and development of amaranth

5.3.1.4 Irrigation

The different irrigation levels resulted in significant differences ($P<0.05$) in leaf number, leaf mass, LAI, and WP. Increasing water availability through irrigation increased simulated leaf mass (**Figure 5.4**). There were no irrigation, leaf number, leaf mass, LAI, and WP values. Adding 40 mm of water resulted in an increase in leaf number, leaf mass, LAI, and WP by 4.8, 119.2, 89.3, and 85.0%, respectively.

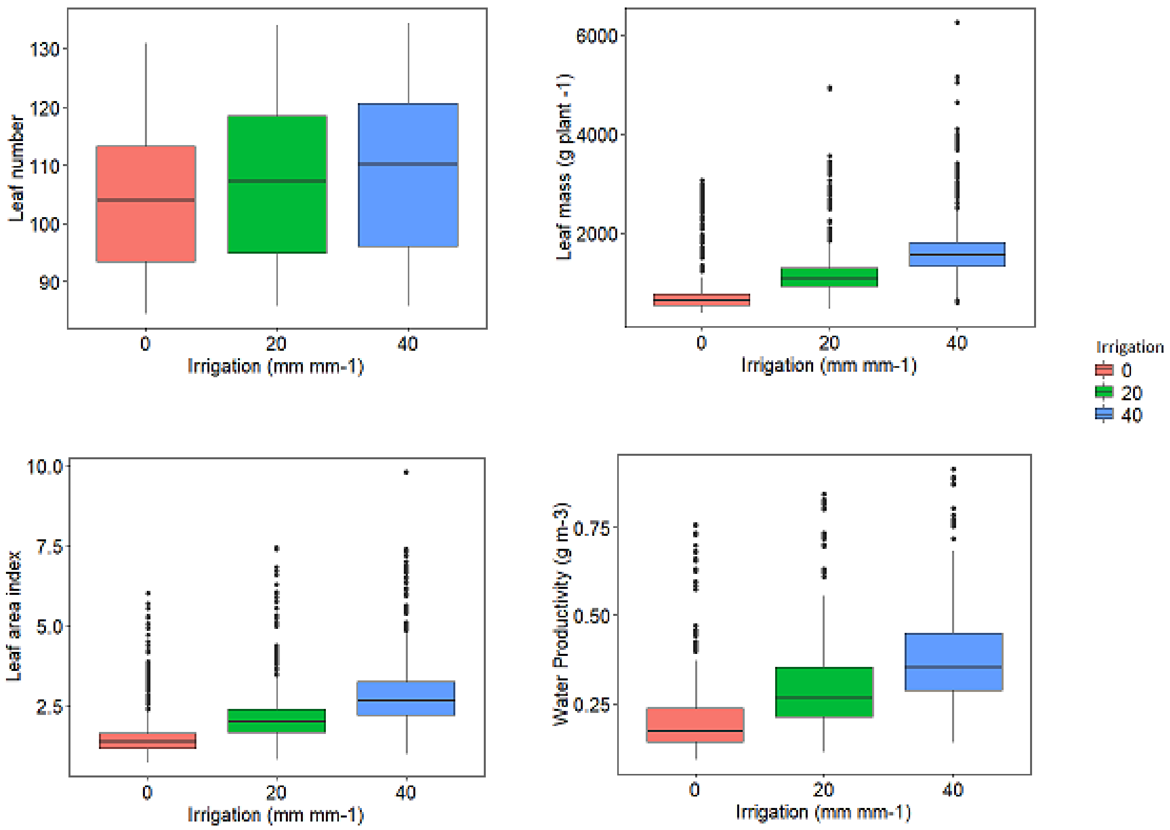


Figure 5.4: The effect of irrigation (mm mm^{-1}) on leaf number, leaf mass (g plant^{-1}), leaf area index and water productivity (g m^{-3}) on growth and development of amaranth

5.3.1.5 Management practice combinations

The best management combination for high leaf number (130) was no fertiliser, 17.4 plants m^2, 40 mm mm^{-1}, planting date 1 (01-September). Leaf mass was the highest (2130 g plant^{-1}) at the combination 71 kg ha^{-1}, 17.4 plants m^2, 40 mm mm^{-1}, 01-October. The planting date 01-March (7), high irrigation (40 mm) and fertilization (71 kg ha^{-1}), and plant density (26.1 plants m^2) resulted in a high leaf area (3.84). Lastly, WP was the highest at the combination of high fertilization (71 kg ha^{-1}) and irrigation (40 mm), plant density (17.4 plants m^2) and when amaranth was sown in March (7). Different management strategies can be applied to promote growth and productivity depending on the overall production objective.

5.3.2 Cowpea

5.3.2.1 Planting date

The effect of planting dates on leaf number, leaf mass, LAI and WP were observed to be pronouncedly different (P<0.05) for each planting date scenario (Figure 3.5). They were planting early increased in leaf number, leaf mass, and LAI, while late planting resulted in a decrease in these variables. To add, simulated growth and productivity decreased on plants simulated in 01-March. 01-October (2) had the highest (53) and 01-March (7) the lowest (24) leaf number. The leaf mass also differed according to planting dates. Observed simulated results showed that plants sown on 01-October (2) had the highest leaf mass (2309 g plant^{-1}), compared to those planted on 01-March (7), which had the lowest mean leaf mass of 998.32 kg ha^{-1}. The LAI was the highest (6.05), and the lowest (2.91) for the planting dates 01-October and 01-March. There was a slight increase in WP from early to late planting. Plants simulated in 01-March, which had the lowest (0.52 g m^{-3}) WP while 01-February (2) had the highest (0.64 g m^{-3}) mean WP (**Figure 5.5**).

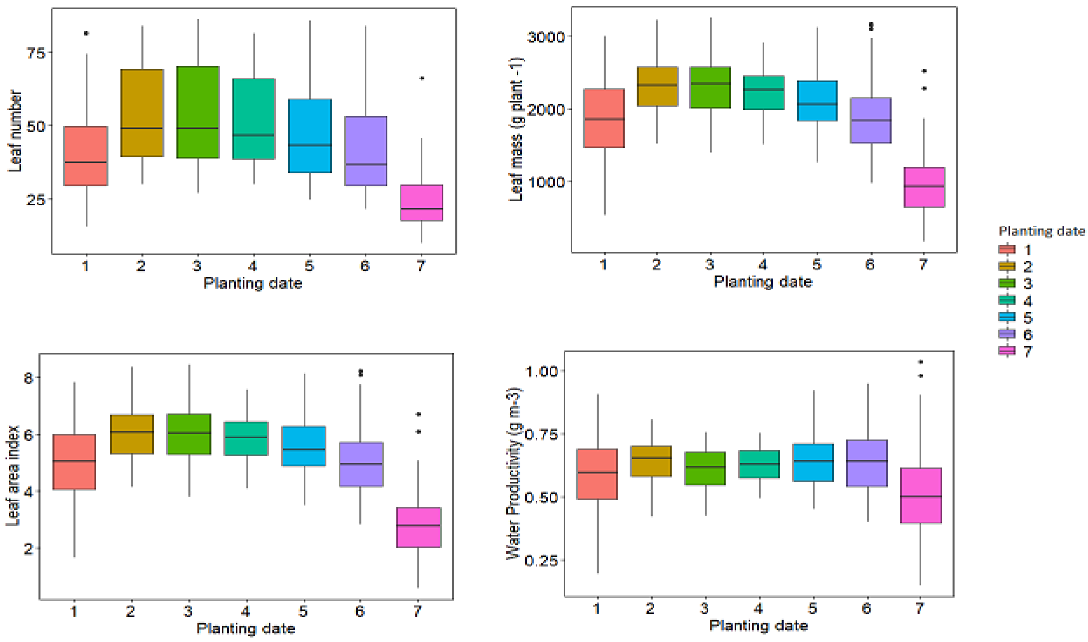


Figure 5.5: The effect of planting dates on leaf number, leaf mass (g plant^{-1}), leaf area index and water productivity (g m^{-3}) on growth and development of cowpea. Planting date 1 through to 7 correspond to the 1st of September (1), October (2), November (3), December (4), January (5), February (6) and March (7), respectively.

5.3.2.2 Plant density

Different plant densities resulted in significantly different (P<0.05 leaf number, leaf mass, LAI and WP. While other growth parameters increased with an increase in plant density, leaf number decreased (**Figure 5.6**), which may have been due to the high competition of resources such as sunlight and nutrients that resulted from the in-between spaces being too small. The mean number was 62 at low plant density (8.7 plants m^2), 40, and 31 at 17.4 plants m^2, the mean number of leaves was 40, and it was lowest (31) at 26.1 plants m^2. Leaf mass, LAI, and WP increased with an increase in plant density.

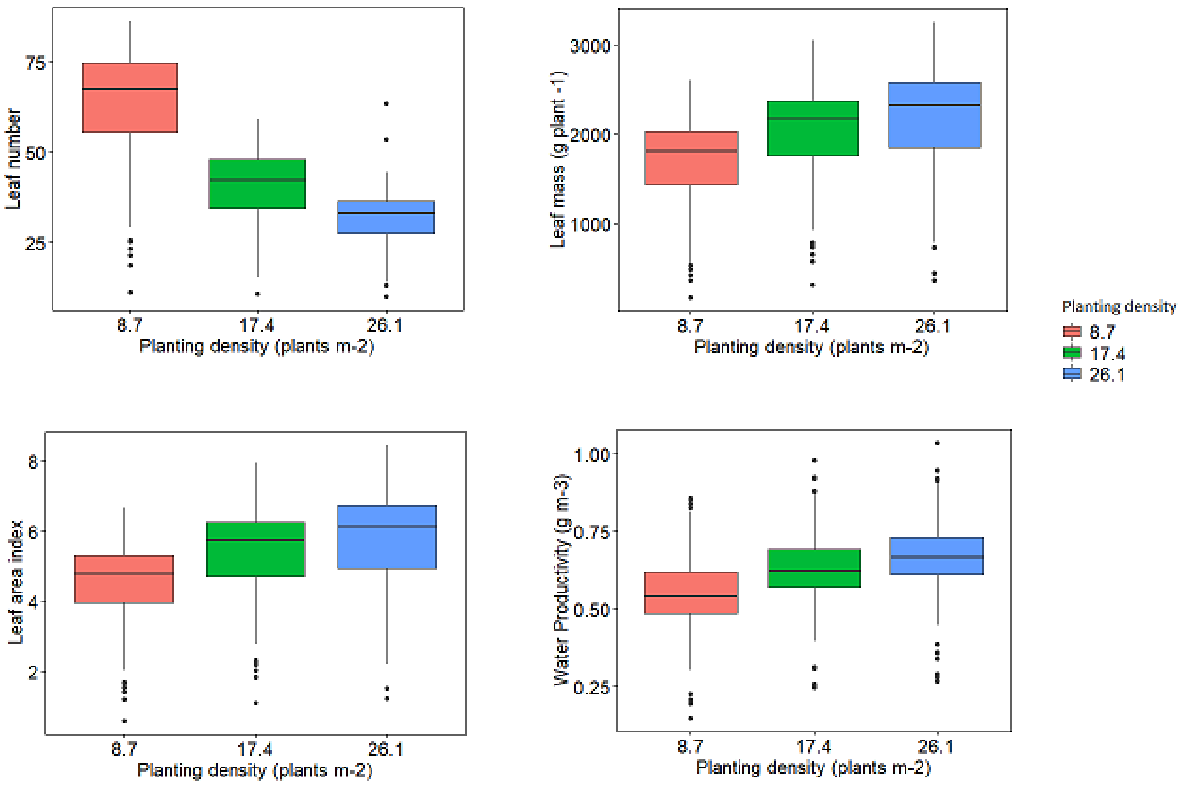


Figure 5.6: The effect of planting density (plants m^2) on leaf mass (g $plant^{-1}$), leaf area index and water productivity (g m^{-3}) on growth, development, and productivity of cowpea

These were the highest at 26.1 plants m^2, (2163 g $plant^{-1}$, 5.75, and 0.66 g m^{-3}), moderate at medium plant density, 17.4 plants m^2, (1993 g $plant^{-1}$, 5.32, and 0.62 g m^{-3}) and lower at low plant density, 8.7 plants m^2 (1673 g $plant^{-1}$, 4.47, and

0.54 g m^{-3}) respectively. Moreover, the plant leaf mass data was fairy legally distributed away around the mean (**Figure 5.6**).

5.3.2.3 Fertiliser application

There was a significant difference ($P<0.05$) in leaf number across different fertiliser application rates. However, the simulated results showed no change in the cowpea plant's growth and productivity (**Figure 5.7**). The mean leaf number was 44 across different fertiliser applications (0, 30, 60 kg ha^{-1}). Leaf mass, LAI and WP were also the same across all fertiliser application rates (0, 30, and 60 kg ha^{-1}). These were 1948 g $plant^{-1}$, 5.19, and 0.61 g m^3, respectively (**Figure 5.7**). These findings were not expected as fertiliser is generally known to affect the growth and development, thus productivity of plants. The cause of cowpea not responding to the applied fertiliser maybe that cowpea can fix its nitrogen and supply it to the soil, thus leaving the inputted fertiliser with no role to play as the soils were already sufficient in nitrogen for the growth of the cowpea plants. The type of fertiliser used on these plants and the time of application may also cause these similarities.

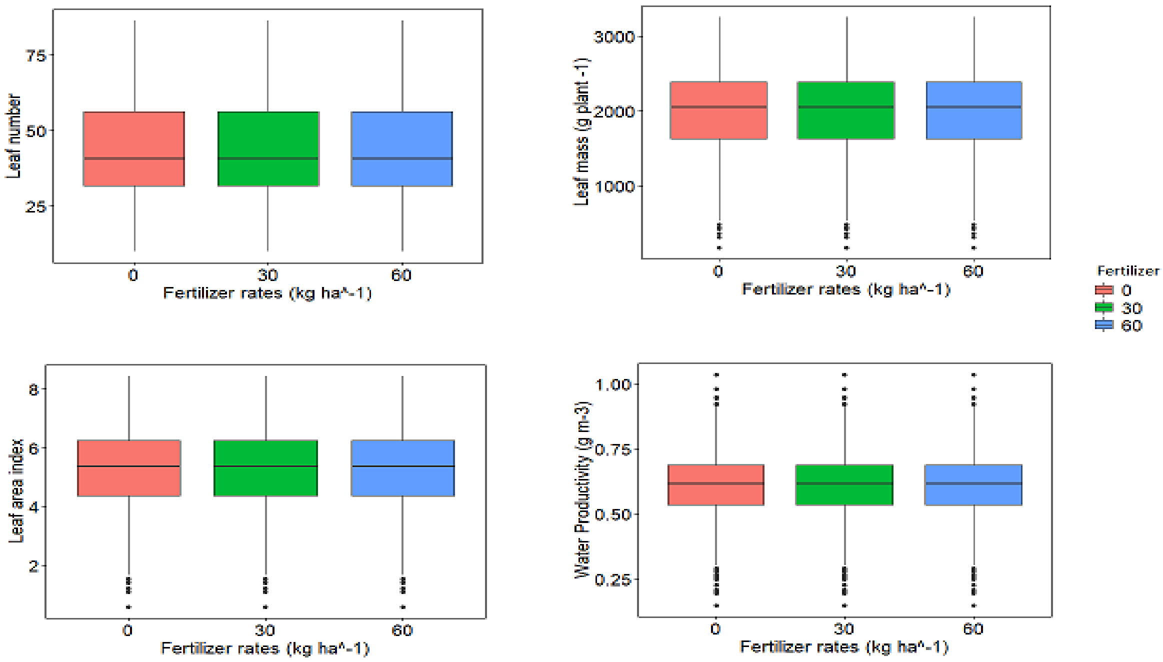


Figure 5.7: The effect of Fertiliser (kg ha^{-1}) on leaf number, leaf mass (g $plant^{1}$), leaf area index and water productivity (g m^3) on growth, development, and productivity of cowpea

5.3.2.4 Irrigation

There was no significant difference in leaf number upon different irrigation levels results. (0, 20 and 40 mm) (Figure 3.8). Across all water application levels, the leaf number was 44. Leaf mass was higher (1963, g plant^{-1}) where no there was no irrigation (0 mm) and lower (1922 g plant^{-1}) at 20 mm. At high water application (40 mm), leaf mass was moderate (1960 g plant^{-1}). LAI was higher (5.23) at no water application and lower (5.13) at 20 mm. High irrigation 40 mm resulted in a moderate (5.22) leaf area index. On the other hand, WP was (0.61 g m^{-3}) at both 0- and 40-mm and lower (0.60 g m^{-3}) at medium irrigation 20 mm mm^{-1} (**Figure 5.8**).

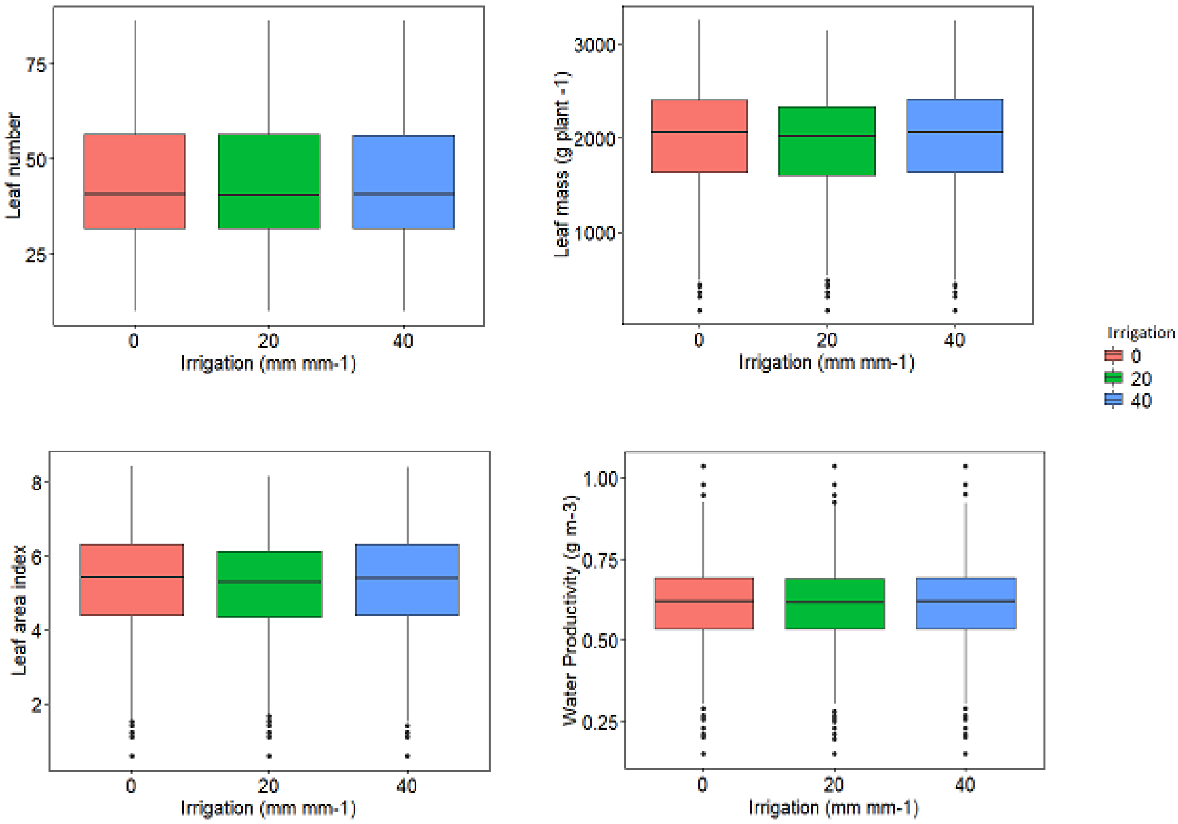


Figure 5.8: The effect of irrigation (mm mm$^{-1)}$ on leaf number, leaf mass (g plant^{-1}), leaf area index and water productivity (g m^{-3}) on growth and development of cowpea

5.3.2.5 Management practice combinations

The interaction of plant density and planting date was significantly different (P<0.05) in leaf number. Leaf number was the highest (74) for plants sown on the 1st of

October (2) at 8.7 plants m^2 for all fertiliser levels (0, 30, 60 kg ha^{-1}) with high (40 mm) or no (0 mm mm^{-1}) water application. The combination (0 mm, 26.1 plant m^{-2} across all fertiliser application levels and planting date 2 (01-October) resulted in high leaf mass, 2587 g $plant^{-1}$. These results were the same for LAI, which was 6.78. A high mean WP of 0.69 g m^{-3} was observed when there was no water applied on cowpea plants, at a plant density of 26.1 plant m^{-2}, in all fertiliser application rates (0, 30, and 60 kg ha^{-1}) on plants simulated on planting date 5 (01-January).

5.3.3 Sweet potato

5.3.3.1 Planting date

Different planting date resulted in varied responses to leaf number, leaf mass, LAI, and WP for sweet potato. The LAI, leaf mass and WP were significantly ($P<0.05$) affected by planting date. Simulated leaf number differed slightly across different planting dates (**Figure 5.9**). Overall, the leaf number was 43 regardless of the planting date. The planting date 01-November (3) and 01-March (7) had the highest (931 g $plant^{-1}$) and lowest (767 g $plant^{-1}$) leaf mass, respectively. There was a general increase in LAI and WP with later planting. Interestingly, planting February (6) and December (4) gave the highest (0.04) and the lowest (0.03) LAI.

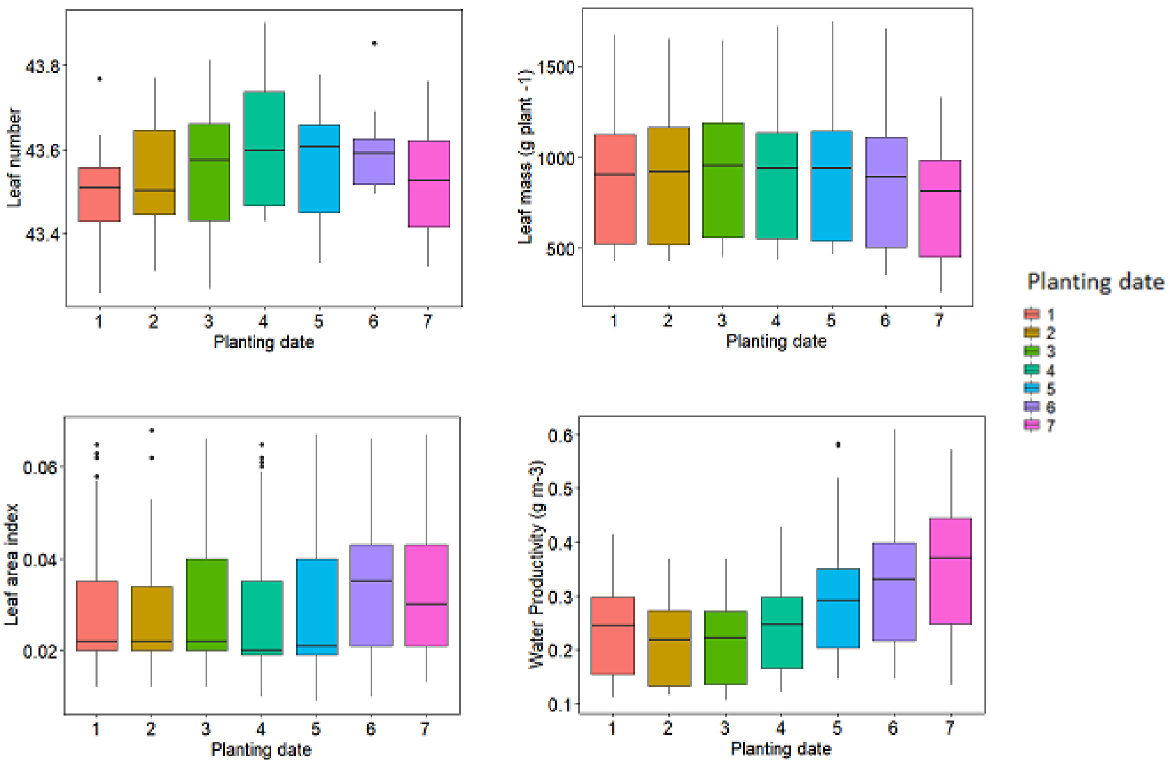


Figure 5.9: The effect of planting dates on leaf number, leaf mass (g plant^{-1}), leaf area index and water productivity (g m^{-3}) of sweet potato. Planting date 1 through to 7 correspond to the 1st of September (1), October (2), November (3), December (4), January (5), February (6) and March (7), respectively.

Growing in March (7) gave the highest (0.35 g m^{-3}), and planting in October (2) gave the lowest (0.21 g m^{-3}) WP, respectively, (**Figure 5.9**). Results suggest that late planting gives optimum results in leaf number, leaf mass, LAI, and WP.

5.3.3.2 Plant density

There was no change in leaf number of sweet potato plants observed across different plant density. However, a significant ($P<0.05$) increases in leaf mass, LAI, and WP, with an increase in plant density (**Figure 5.10**). At high plant density (2.5 plants m^{2}), leaf mass was 491 g plant^{-1}, at 5.0 plants m^{2}, 907 g plant^{-1}, and at a high planting date of 7.5 plants m^{2}, leaf mass was the highest (1234 g plant^{-1}). LAI and WP were high (0.04 and 0.36 g m^{-3}) at high plant density (7.5 plants m^{2}), medium plant density (0.32 and 0.28 g m^{-3}) and at low plant density (2.5 plants m^{2}) was (0.20 and 0.17 g m^{-3}), respectively.

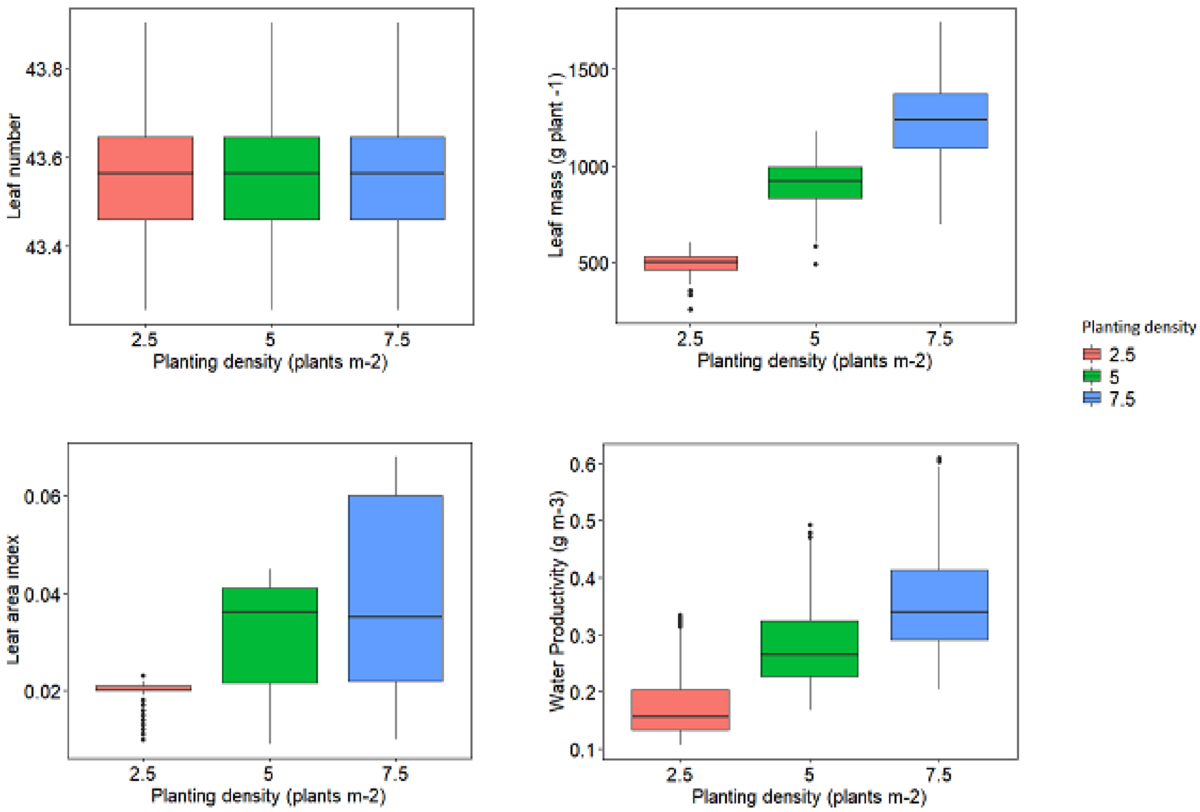


Figure 5.10: The effect of plant density (plants m^2) on leaf number, leaf mass (g plant^{-1}), leaf area index and water productivity (g m^{-3}) on growth and development of sweet potato

The simulated LAI results showed a wider distribution around the mean for sweet potato planted at higher plant density. The reasoning behind this might be that LAI is less stable under tall plant density owing to increased competition for resources such as light and other growth factors.

5.3.3.3 Fertiliser application

Fertiliser application rate did not affect leaf number. However, a pronounced effect on leaf mass, LAI and WP was observed. There was a significant increase ($P<0.05$) in leaf mass, LAI, and WP, increasing fertiliser rates. At high fertiliser application, 60 kg ha^{-1}, the average leaf mass was 933 g plant^{-1} and medium fertiliser application (30 kg ha^{-1}), 901 g plant^{-1} at no fertiliser application, 797 g plant^{-1}. The LAI was 0.04, 0.03, and 0.02 at high, medium and no fertiliser application, respectively. Lastly, at high fertiliser application, the average WP was 0.27 g m^{-3} (**Figure 5.11**). Generally, adding fertiliser improves growth. However, as observed from the simulated results, this was not the case for leaf number. To add, although these results varied (outliers), fertiliser application at a higher (60 kg ha^{-1}) rate resulted in optimum growth and development of sweet potato.

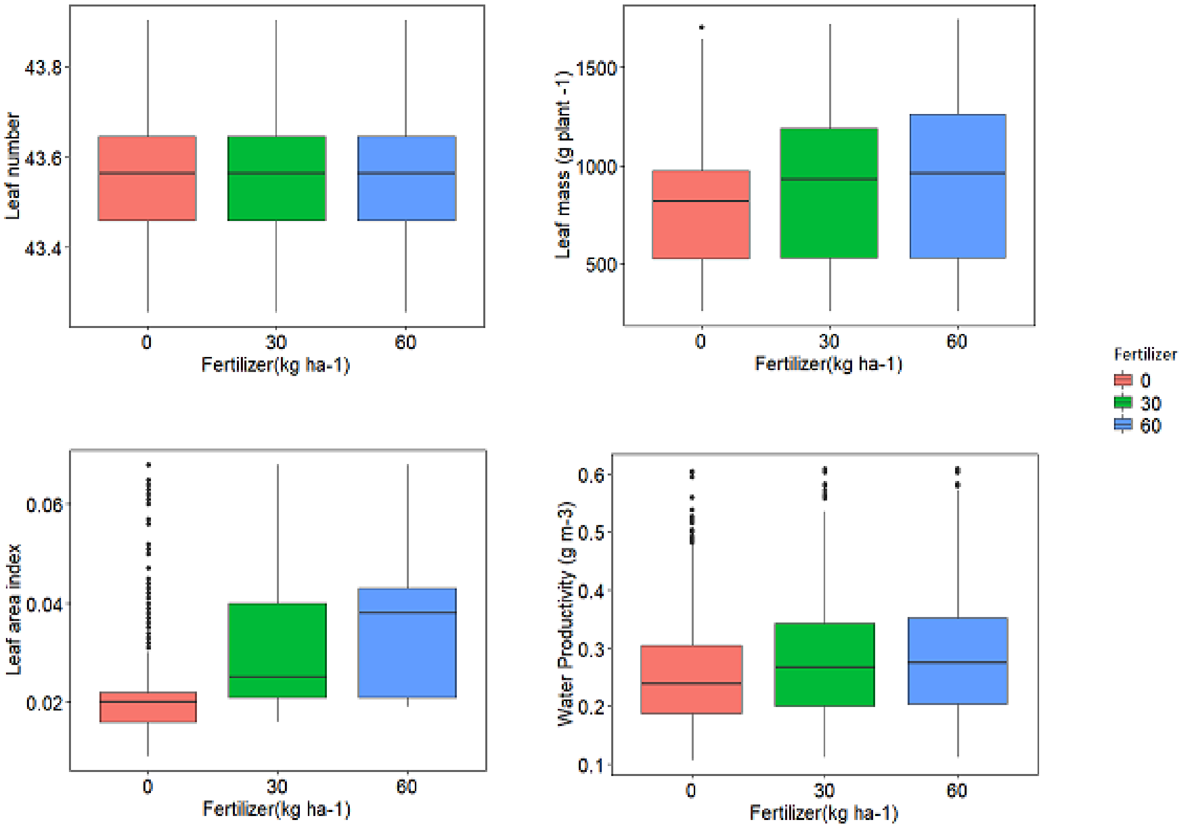


Figure 5.11: The effect of Fertiliser (kg ha^{-1}) on leaf number, leaf mass (kg ha^{-1}), leaf area index and water productivity (g m^{-3}) on growth and development of sweet potato

5.3.3.4 Irrigation

There was no significant difference (P>0.05) across different leaf number, leaf mass, LAI and WP simulated mean results. No change in leaf number observed upon changing the amount of water applied to the sweet potato plants (**Figure 5.12**). However, a slight change was observed for leaf mass, LAI, and WP. Leaf mass was 875 g plant^{-1} at no water application, 882 g plant^{-1} at 40 mm, and 874 g plant^{-1} and 60 mm of irrigation. Overall, the mean LAI was 0.03, and WP was 0.27 g m^{-3} regardless of water applied. It was interesting to note that the simulated results varied widely across the mean. There were outliers in the results for water productivity (**Figure 5.12**).

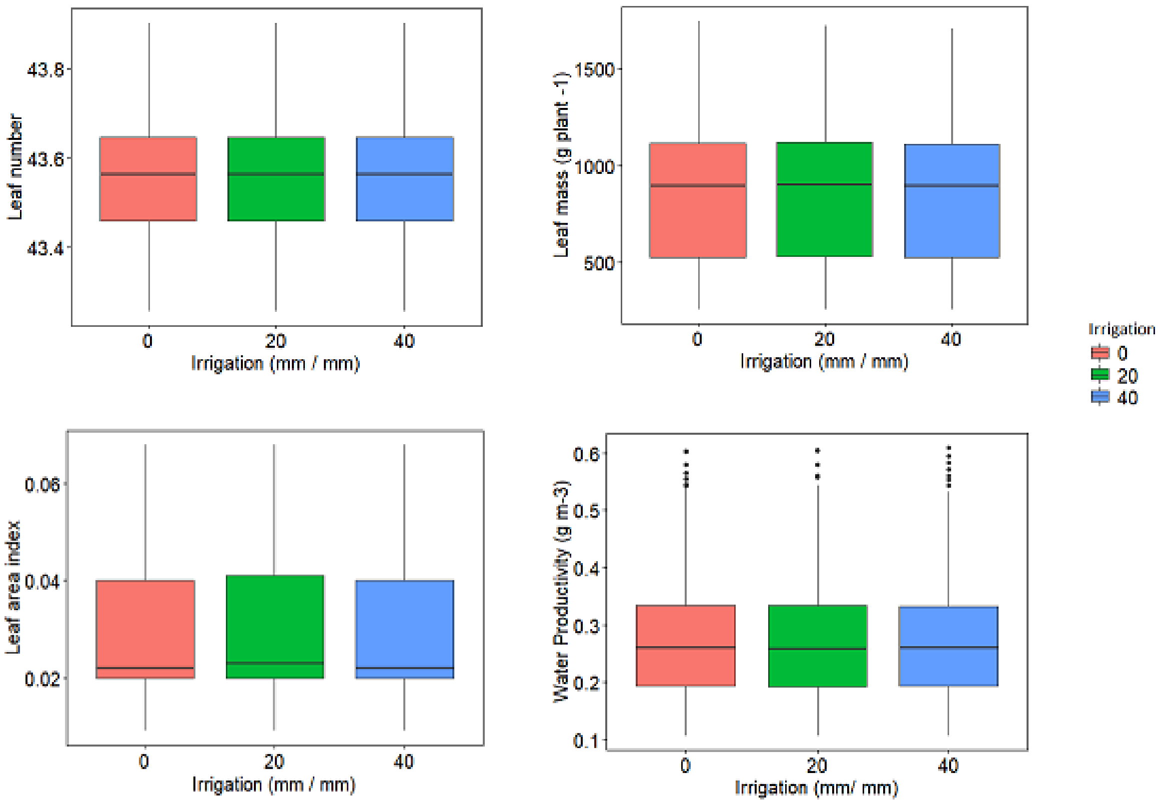


Figure 5.12: The effect of irrigation (mm mm^{-1}) on leaf number, leaf mass (g plant^{-1}), leaf area index and water productivity (g m^{-3}) on growth and development of sweet potato

5.3.3.5 Management practice combinations

The interaction of plant density, fertiliser and planting date was found to be significantly different on leaf mass. The WP results were also significantly different ($P<0.05$) under plant density and fertiliser interaction. The interaction of fertiliser and planting date was also considerably different in terms of leaf mass. A significant difference was observed on LAI where plant density, fertiliser and planting date interacted. In terms of leaf number, there was no significant difference. All combinations of management practices resulted in an average of 43 leaves.

The planting date 4 (01-December) was found to ideal for different plant densities, fertiliser application and irrigation levels. Across all different management practice combinations, leaf number was the same, 43. On the other hand, leaf mass, LAI and WP showed a substantial difference when subjected to different managerial practices changes. The best management practice for leaf mass (1458 g plant^{-1}) was at planting date 4 (01-December), high plant density (7.5 plants m^2), 60 kg ha^{-1} of fertiliser and 20 mm water application. Planting in March, at high density, 30 kg ha^{-1} fertiliser application and high irrigation of 40 mm were the best management practice combination to give a high LAI of 0.06. Lastly, WP was the highest (0.47) in plants sown on 01-March, at 7.5 plants m^2, 30 kg ha^{-1} fertiliser application and irrigation of 40 mm.

5.3.4 Wild mustard

5.3.4.1 Planting date

Different planting dates gave varied results in leaf number, leaf mass, LAI, and WP, and these simulated results were significantly different ($P<0.05$). A general decrease in leaf number, leaf mass, and LAI was observed to progress from early to late planting (**Figure 5.13**). However, planting in 01-November (3) gave more leaves (39) per plant. The mean leaf number was lower (23) on plants sown 01-March (3). Leaf mass, on the other hand, was high (1491 g $plant^{-1}$) and low (903 g $plant^{-1}$) on wild mustard sown on (01-October) and 7 (01-March). Interestingly, LAI was higher, 3.84 and more down, 2.35, on plants sown in 01-October (2) and 01-March (7), respectively. Early planting (01-September) resulted in high (0.33 g m^{-3}) WP and low WP (0.29 g m^{-3}) on wild mustard sown in 01-March (7) (**Figure 5.13**). Given the results, they were planting early resulted in higher yields compared to planting late.

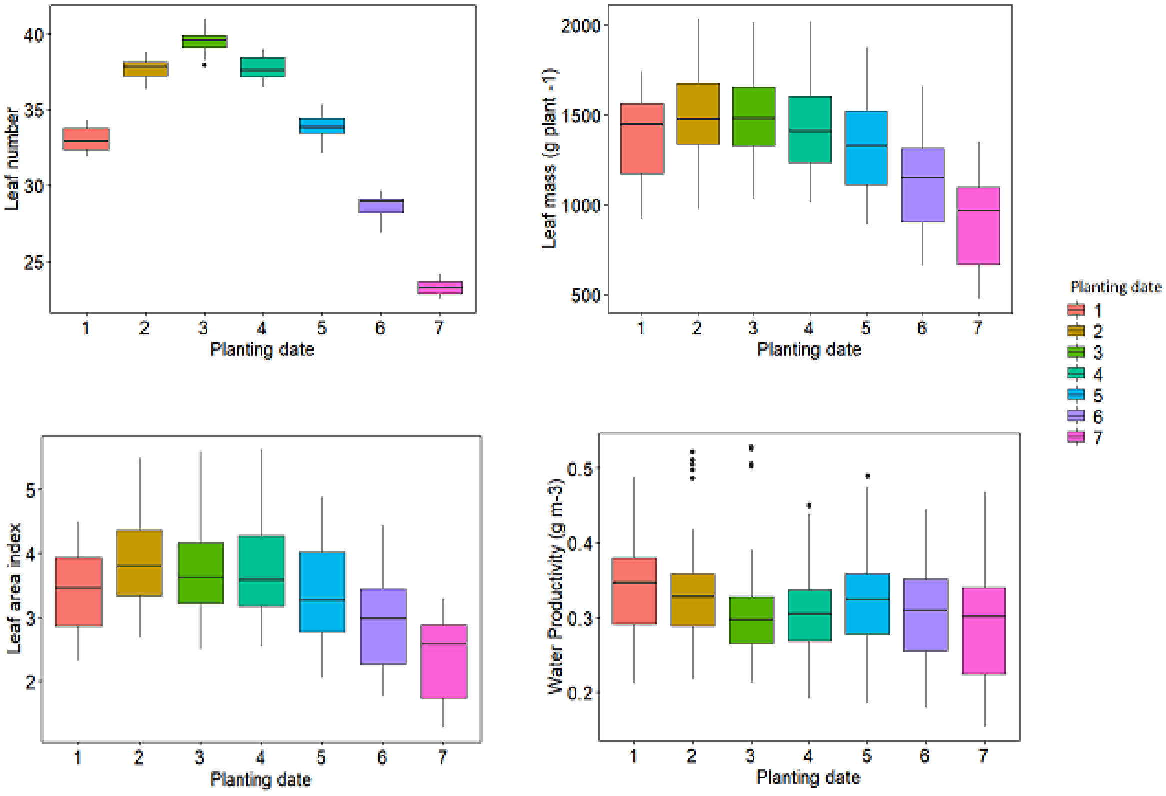


Figure 5.13: The effect of planting dates on leaf number, leaf mass (g plant^{-1}), leaf area index and water productivity (g m^{-3}) on growth and development of wild mustard. Planting date 1 through to 7 correspond to the 1st of September (1), October (2), November (3), December (4), January (5), February (6) and March (7), respectively.

5.3.4.2 Plant density

Different planting densities did not affect leaf number. Leaf mass, LAI and WP increased with an increase in plant, P<0.05 (**Figure 5.14**). At high plant density (30.5 plants m^2) leaf mass, LAI and WP were (1443 g plant^{-1}, 3.67, 0.34 g m^{-3}), at medium plant density (27 plants m^2) it was (1395 g plant^{-1}, 3.58, and 0.33 g m^{-3}) and at low planting (13.5 plants m^2) density it was (1056 g plant^{-1}, 2.72, 0,25 g m^{-3}), respectively. It suggested that planting in high densities is ideal for the growth and development of wild mustard. However, as observed from the simulated results (**Figure 5.14**), the growth parameters' responses were highly distributed and had outliers. This could mean that plants' growth was not even, and resources are more likely to be received by some plants and not others.

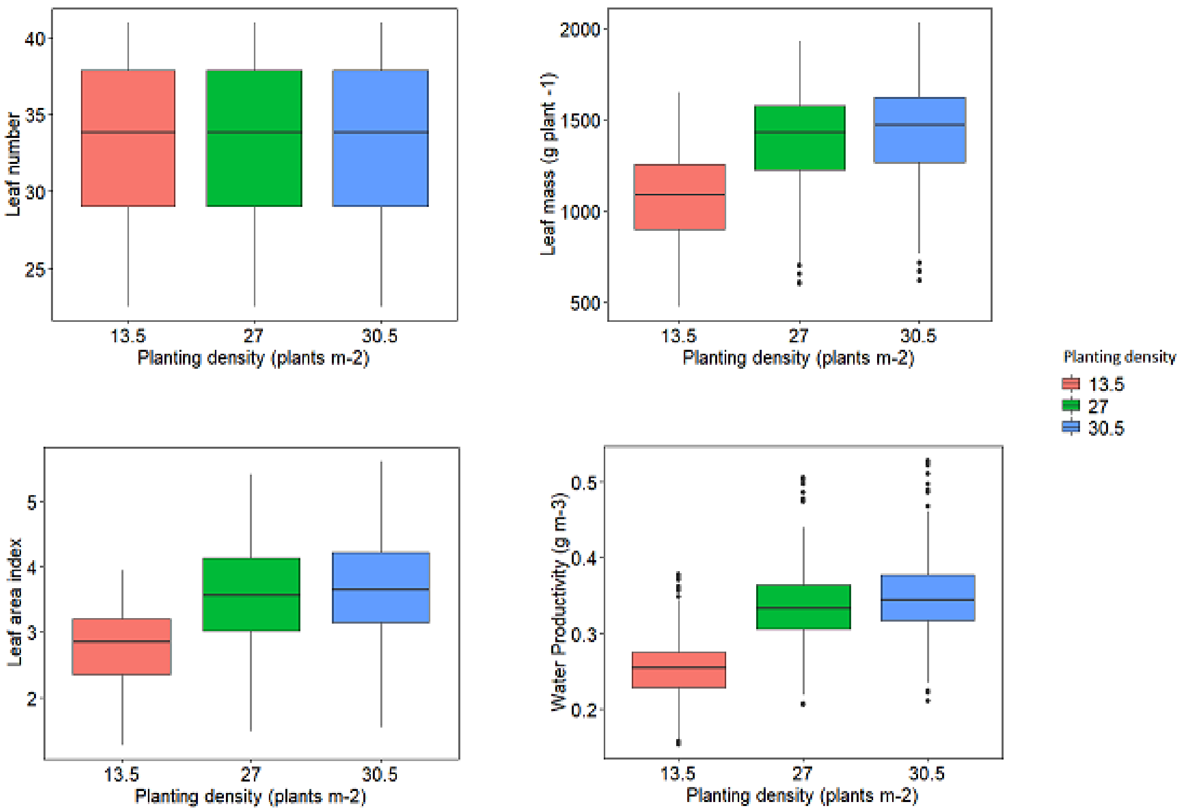


Figure 5.14: The effect of plant density (plants m^2) on leaf mass (g $plant^{-1}$), leaf area index and water productivity (g m^{-3}) on growth and development of wild mustard

5.3.4.3 Fertiliser application

Different fertiliser applications did not affect leaf number. The leaf mass results, LAI and WP, were significantly different ($P<0.05$) (**Figure 5.15**). Across all fertiliser application rates (0, 35.5, 71 kg ha^{-1}), the mean number of leaves was 33. The leaf mass and LAI were higher 1319 g $plant^{-1}$ and 3.38 at medium fertiliser application (35.5 kg ha^{-1}) and lower (1287 g $plant^{-1}$) at 71 kg ha^{-1} fertiliser application. At no fertiliser application, leaf mass was 1288 g $plant^{-1}$, and LAI was 3.32, respectively. On the other, WP did not follow this trend. It increased with an increase in fertiliser application. The crops were more productive (0.33 g m^{-3}) where there 0.30 g m^{-3}, respectively (**Figure 5.15**).

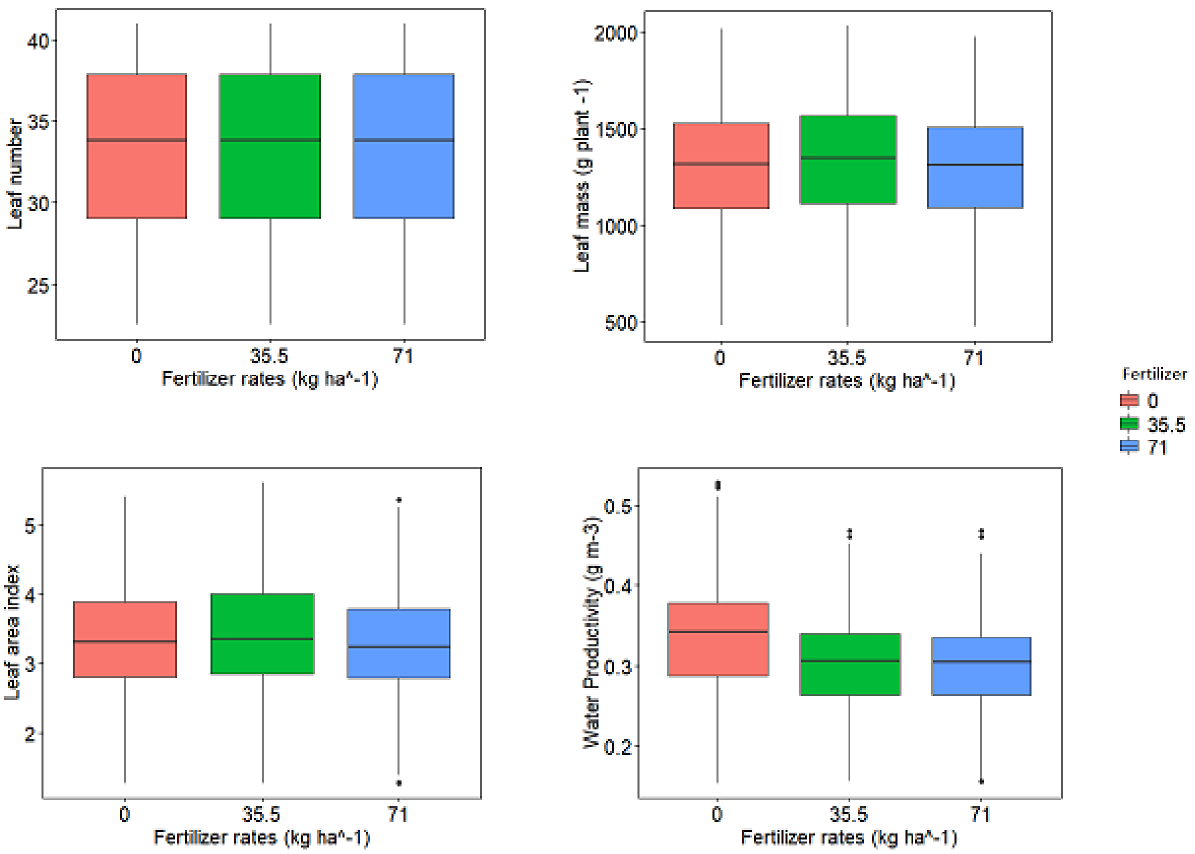


Figure 5.15: The effect of Fertiliser (kg ha^{-1}) on leaf number, leaf mass (g plant^{-1}), leaf area index and water productivity (g m^{3}) on growth and development of wild mustard

5.3.4.4 Irrigation

The simulates results on leaf number, leaf mass, LAI and WP were significantly different (P<0.05) across different irrigation treatments. However, there was no change in leaf number across different irrigation levels 0,40,60 mm, (***Figure 5.16***). The mean number of leaves was 33. On the other hand, leaf mass, LAI and WP had varied results upon increasing water application to crops. At different irrigation levels 0, 40,60 mm, leaf mass and LAI was 1263, 1299 and 1331 g plant^{-1}, and 3.21, 3.33, and 3.34, respectively. Water productivity was 0.30 g m^{-3} at 0 mm, and for both levels 40, 60 mm, it was 0.31 g m^{-3} which was a small difference between different irrigation levels (***Figure 5.16***). The simulated growth and productivity response values were observed to be fairly distributed around the mean and LAI, and WP had outliers.

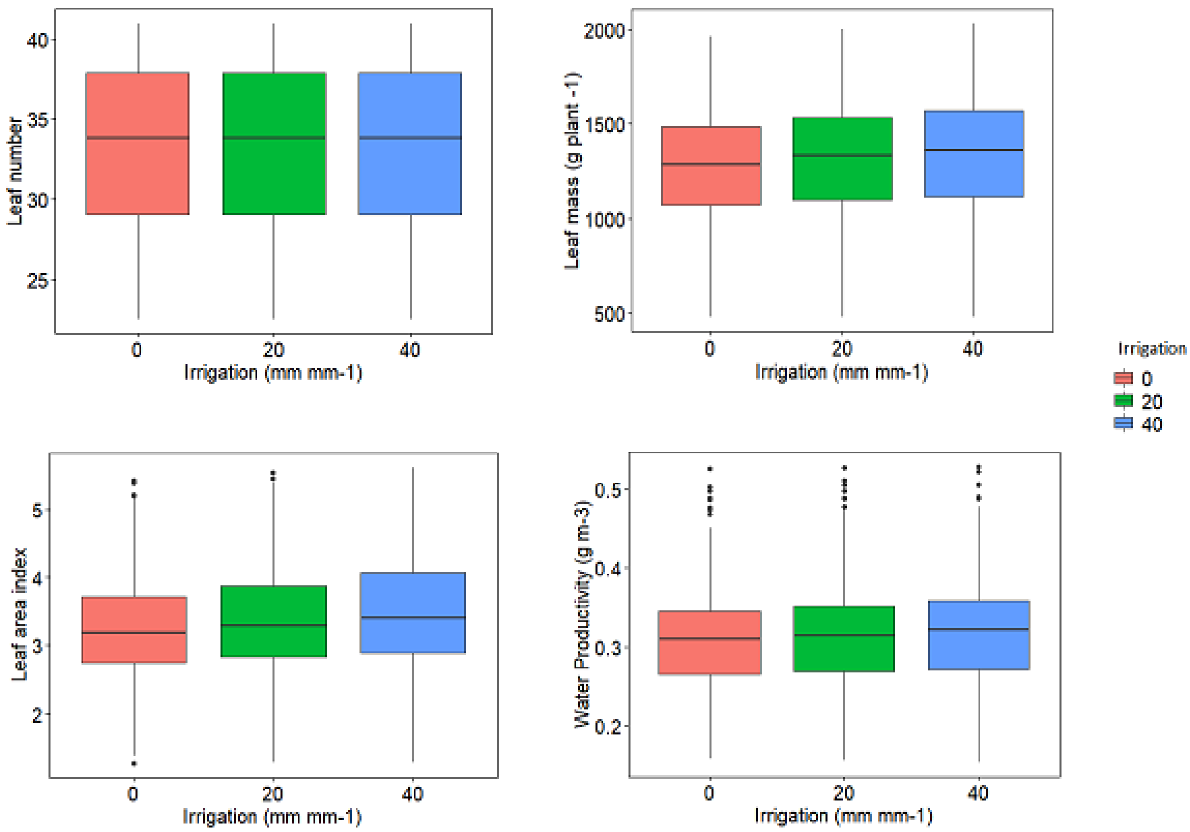


Figure 5.16: The effect of irrigation (mm mm^{-1}) on leaf number, leaf mass (g plant^{-1}), leaf area index and water productivity (g m^{-1}) on growth and development of wild mustard

5.3.4.5 Management practice combinations

Planting date 3 (01-November) at all fertiliser applications, irrigation, and plant density combinations for high leaf number (39) was the best management practice. A high mean leaf mass of 1724 g plant^{-1} was obtained under best management practice combinations of 35.5 kg ha^{-1} of fertiliser, irrigation at 40 mm, increased plant density (30.5 plants m^{2}), and plants' sown planting date (01-October). This was the same for the LAI, which was 4.51. However, for high WP (0.39 g m^{-3}), the ideal management combinations were no fertiliser application, plant density at 30.5 plants m^{2}, 40 mm^{-1} of water and at planting date 01-January (5).

5.4 Discussion

5.4.1 Planting date effect on growth and productivity of ALVs

The optimum planting date gives the highest yields and shows less variation over time (Kucharik, 2008). Overall, and across all the studied crop species, planting late (December to February) results in high leaf mass, LAI, and water productivity. Except for cowpea, planting late resulted in an improvement in growth and productivity for simulated crops. The simulated trend could be because, during February and March, it is assumed that soil has increased water content that supports the early establishment of crops. Also, air temperatures are high, creating a conducive environment for successful establishment. The simulated crops are sub-tropical and thrive in warm-cool climates (Chivenge et al., 2015). With late planting, the vegetative pick period occurs during colder months. Less water was lost through evaporation, meaning more was available for crop uptake and use.

The low temperatures experienced during the vegetative phase also allows for the slow accumulation of heat units, extending the growth duration and time spent accumulating assimilates (Evans and Sadler, 2008). Simulations at the beginning of the summer season may have resulted in less low leaf mass, resulting in low LAI and WP because plants grow more rapidly due to higher temperatures. This also corresponds to higher evaporative demand and overall evapotranspiration resulting in lower WP. Water productivity can be defined as the obtained yield per given water unit (Morison et al., 2008). Therefore, any strategy aimed at improving yield while using the same amount of water or decreasing the amount of water with the same or increasing yield will improve water productivity (Molden et al., 2010).

5.4.2 Plant density effect on growth and productivity of ALVs

Overall, the increase in plant density resulted in leaf number reduction for all simulated crops. However, simulated results showed that increasing plant density resulted in a general rise in leaf mass, LAI, and WP for the crops under investigation. These results are contrary to many studies that have observed a decrease in plant growth and productivity, increasing plant density. For instance, Walp et al. (2010) observed that increasing plant density decreased LAI in cowpea plants. When plant density increases, resource competition among plants arises, resulting in uneven growth or death of some plants (Maseko et al., 2015). With each additional plant, a reduction in individual plants' mass was offset by an increase in plant density.

Another reason may be the development of fewer branches per plant at a high density, leading to high leaf mass (Maseko et al., 2015). To add, an increase in LAI resulted in a reduction in evaporation, which improved water availability, leading to increased transpiration, thus increasing leaf mass. Overall, this was the same amount of water received by the system, but there was an increase in leaf mass, increasing water productivity. A note must be taken that increasing plant density above a certain threshold can result in yield penalties. It was observed on these results that more plants per square metre can still be sown above-recommended planting density, and this may be at the expense of other growth parameters. Different growth variables favoured by different plant densities across all crops. For optimal leaf number, plants must be sown under low plant density and at high plant density for ideal leaf area index. Leaf mass and water productivity differed depending on a crop species type, and these were higher under high or medium plant densities. Therefore, no matter what plant density is used, one or more growth aspects may be compromised.

5.4.3 Fertiliser application effect on growth and productivity of ALVs

Crop growth nutrients are essential for crops as it improves the photosynthetic capacity of crops by enhancing carbon dioxide assimilation and improving enzymic function (Deng et al., 2006). Depending on a crop species, increasing fertiliser application either showed some or no effect on growth and productivity for selected ALVs. Amaranth and cowpea did not respond to the application of fertiliser at different levels. Also, cowpea can fix nitrogen, producing nitrogen that can be useful for its growth and development, suggesting no need for fertiliser addition (DAFF, 2013). Results also suggest that the Ukulinga farm soils are sufficiently fertile to provide optimum growth for these crops. However, sweet potato followed a different trend as the increase in fertiliser application resulted in an improved leaf canopy, thus leaf area index (LAI) and consequently water productivity. These results suggest that sweet potato is a heavy N feeder and requires relatively high N fertiliser amounts. According to Kuzhivilayil et al. (2016), tuber crops that grow under warm to hot summers and cool to mild winters are high nutrient demanding, and proper integrated management helps achieve yield potential. Leaf mass, LAI, and WP decreased with more fertiliser application. Under different fertiliser application rates, no change in leaf number was observed across all crop species.

5.4.4 Irrigation effect on growth and productivity of ALVs

Increasing water application increased the WP of these selected leafy vegetables. Irrigation had no effect on leaf number across all plants. The Ukulinga soils are clay-loam and therefore are suitable for irrigation since they can retain water for more extended periods, attributed to their excellent water-holding, aeration and drainage properties (Chimonyo et al., 2016a). Generally, under semi-arid conditions, irrigation often improves crops' growth by enhancing water availability for transpiration. Depending on the crop's growth stage, one of these processes is more vital than the other. For example, in the early stages of growth, evaporation is more important than transpiration (Brouwer and Heibloem1986). Therefore, it is imperative that irrigation increases during critical growth stages and where water is limited to improve WP. Water productivity increment is achieved where most transpiration result in yield gain (Rockström and Barron, 2007). However, for all crops except amaranth, there was no change in leaf mass upon increasing irrigation. This might have been because the soil in the system already had water from the rainfall, which was above a certain threshold where irrigation could not be initiated.

5.4.5 Effect of factor/treatment combinations on growth and productivity of ALVs

The different treatment combinations resulting in optimum yields for each leafy vegetable was evidence that these crops can be grown under other conditions on different management strategies. It was also evident that multiple planting can is possible when these optimal management practices are observed. The growth in terms of leaf number being not affected for some crops such as amaranth may have been since conditions were already favourable. Thus, changing any managerial practice could not be effective. This was not expected as it disagrees with Kanda et al. (2020), who found irrigation to significantly affect the cowpea plant's growth and development. Different crops species with different architecture require different management practices. Therefore, they utilize and share resources differently.

5.5 Conclusion

ALVs are generally grown under dry environments where they experience water stress, so correct management of these crops may improve productivity. The studied leafy vegetables establish in a short period (4-5 weeks) and are mostly favoured by early planting. Nonetheless, this may compromise their water productivity. As noticed, plant density plays a vital role in the growth and productivity of ALVs; increasing it to a certain threshold may result in growth, yield and productivity are compromised. The unresponsiveness of fertiliser to leaf number was not expected as fertiliser application is thought to improve vegetative growth. In this study, irrigation was shown to have disagreed with some of the previous studies. Therefore, it might be of interest that future studies revisit these sections for validation and correction.

5.6 References

Ahenkora, K., Adu Dapaah, H.K. and Agyemang, A., 1998. Selected nutritional components and sensory attributes of cowpea (Vigna unguiculata [L.] Walp) leaves. Plant Foods for Human Nutrition, 52(3), pp.221-229. doi: 10.1023/A:1008019113245.

Ahmed, M. and Hassan, F.U., 2011, December. APSIM and DSSAT models as decision support tools. In 19th International Congress on Modelling and Simulation, Perth, Australia (pp. 12-16).

Aletor, O.L.U.W.A.T.O.Y.I.N., Oshodi, A.A. and Ipinmoroti, K., 2002. Chemical composition of common leafy vegetables and functional properties of their leaf protein concentrates. Food chemistry, 78(1), pp.63-68. doi: 10.1016/S0308-8146(01)00376-4.

Almazan, A.M., Begum, F. and Johnson, C., 1997. Nutritional quality of sweetpotato greens from greenhouse plants. Journal of food composition and analysis, 10(3), pp.246-253. . doi: 10.1006/jfca.1997.0538.

Amagloh, F.K., Atuna, R.A., McBride, R., Carey, E.E. and Christides, T., 2017. Nutrient and total polyphenol contents of dark green leafy vegetables, and estimation of their iron bioaccessibility using the in vitro digestion/Caco-2 cell model. Foods, 6(7), p.54. doi: 10.3390/foods6070054.

Amisigo, B.A., McCluskey, A. and Swanson, R., 2015. Modeling impact of climate change on water resources and agriculture demand in the Volta Basin and other basin systems in Ghana. Sustainability, 7(6), pp.6957-6975. doi: 10.3390/su706695

Andini, R., Yoshida, S. and Ohsawa, R., 2013. Variation in protein content and amino acids in the leaves of grain, vegetable and weedy types of amaranths. Agronomy, 3(2), pp.391-403. doi: 10.3390/agronomy3020391.

Aroca, R. and Ruiz-Lozano, J.M., 2012. Regulation of root water uptake under drought stress conditions. In Plant responses to drought stress (pp. 113-127). Springer, Berlin, Heidelberg. doi: 10.1093/jxb/err266.

Awoyinka, A.F., Abegunde, V.O. and Adewusi, S.R., 1995. Nutrient content of young cassava leaves and assessment of their acceptance as a green vegetable in Nigeria. Plant Foods for Human Nutrition, 47(1), pp.21-28. doi: 10.1007/BF01088163.

Azais-Braesco, V., Goffi, C. and Labouze, E., 2006. Nutrient profiling: comparison and critical analysis of existing systems. Public health nutrition, 9(5), pp.613-622. doi: 10.1079/PHN2006966.

Baldermann, S., Blagojević, L., Frede, K., Klopsch, R., Neugart, S., Neumann, A., Ngwene, B., Norkeweit, J., Schröter, D., Schröter, A. and Schweigert, F.J., 2016. Are neglected plants the food for the future?. Critical Reviews in Plant Sciences, 35(2), pp.106-119. doi: 10.1080/07352689.2016.1201399.

Beletse, Y.G., Laurie, R., Du Plooy, C.P., Laurie, S.M. and Van den Berg, A., 2012, January. Simulating the yield response of orange fleshed sweet potato 'Isondlo' to water stress using the FAO AquaCrop model. In II All Africa Horticulture Congress 1007 (pp. 935-941).

Bello, Z.A., 2013. Characterization and modelling of water use by amaranthus and pearl millet (Doctoral dissertation, University of the Free State).

Bello, Z.A. and Walker, S., 2017. Evaluating AquaCrop model for simulating production of amaranthus (Amaranthus cruentus) a leafy vegetable, under irrigation and rainfed conditions. Agricultural and Forest Meteorology, 247, pp.300-310. doi: 10.1016/j.agrformet.2017.08.003.

Bengough, A.G., 2012. Root elongation is restricted by axial but not by radial pressures: so what happens in field soil?. Plant and Soil, 360(1), pp.15-18. doi: 10.1007/s11104-012-1428-8.

Berglund, D.R. and Schneiter, A.A., 2003. Tame mustard production.

Brouwer, C. and Heibloem, M., 1986. Irrigation water management: irrigation water needs. Training manual, 3.

Canola Council of Canada., 2017. Canola Encyclopedia. https://www.canolacouncil.org/canola-encyclopedia/crop-development/growth-stages/ (accessed 3 October 2019).

Chadwick, P.M., Crawford, C. and Ly, L., 2013. Human food choice and nutritional interventions. Nutrition Bulletin, 38(1), pp.36-42. doi: 10.1111/nbu.12005.

Chakrabarti, B., 2013. Crop simulation model Types of crop simulation models. Articles from Indian Agricultural Research Institute. New Delhi. p. 4-5

Chibarabada, T.P., Modi, A.T. and Mabhaudhi, T., 2017. Nutrient content and nutritional water productivity of selected grain legumes in response to production environment. International Journal of Environmental Research and Public Health, 14(11), p.1300. doi: 10.3390/ijerph14111300.

Chibarabada, T.P., Modi, A.T. and Mabhaudhi, T., 2017. Expounding the value of grain legumes in the semi-and arid tropics. Sustainability, 9(1), p.60. doi: 10.3390/su9010060.

Chikwendu, J.N., Igbatim, A.C. and Obizoba, I.C., 2014. Chemical composition of processed cowpea tender leaves and husks. International Journal of Scientific and Research Publications, 4(5), pp.1-5.

Chimonyo, V.G.P., Modi, A.T. and Mabhaudhi, T., 2015. Perspective on crop modelling in the management of intercropping systems. Archives of Agronomy and Soil Science, 61(11), pp.1511-1529.

Chimonyo, V.G.P., Modi, A.T. and Mabhaudhi, T., 2016. Simulating yield and water use of a sorghum-cowpea intercrop using APSIM. Agricultural Water Management, 177, pp.317-328. doi: 10.1016/j.agwat.2016.08.021.

Chimonyo, V.G.P., Modi, A.T. and Mabhaudhi, T., 2016. Assessment of sorghum-cowpea intercrop system under water-limited conditions using a decision support tool. Water SA, 42(2), pp.316-327. doi: 10.4314/wsa.v42i2.15.

Chimonyo, V.G.P., Modi, A.T. and Mabhaudhi, T., 2016. Water use and productivity of a sorghum-cowpea-bottle gourd intercrop system. Agricultural Water Management, 165, pp.82-96. doi: 10.1016/j.agwat.2015.11.014.

Chivenge, P., Mabhaudhi, T., Modi, A.T. and Mafongoya, P., 2015. The potential role of neglected and underutilised crop species as future crops under water scarce conditions in Sub-Saharan Africa. International journal of environmental research and public health, 12(6), pp.5685-5711. doi: 10.3390/ijerph120605685.

Cooper, P.J., Dimes, J., Rao, K.P.C., Shapiro, B., Shiferaw, B. and Twomlow, S., 2008. Coping better with current climatic variability in the rain-fed farming systems of sub-Saharan Africa: An essential first step in adapting to future climate change?. Agriculture, ecosystems & environment, 126(1-2), pp.24-35. doi: 10.1016/j.agee.2008.01.007.

DAFF., 2009. Indigenous Food Crops. Department of Forestry, Fisheries and the Environment. doi: 10.1097/WCO.0b013e3283608459.

DAFF., 2011. Sweet potato (Ipomoea batatas L .) production agriculture. Department of Forestry, Fisheries and the Environment

DAFF., 2013. Production guidelines for cowpea. Department of Forestry, Fisheries and the Environment pp1-24.
Deng, F.M., Mu, T.H., Zhang, M. and Abegunde, O.K., 2013. Composition, structure, and physicochemical properties of sweet potato starches isolated by sour liquid processing and centrifugation. Starch-Stärke, 65(1-2), pp.162-171.
Devi, N.S., Sadhan Kumar, P.G., Peter, K.V. and Indira, V., 2006, December. Indigenous leaf vegetables for administering vitamin A and minerals. In I International Conference on Indigenous Vegetables and Legumes. Prospectus for Fighting Poverty, Hunger and Malnutrition 752 (pp. 367-372).
Di Paola, A., Valentini, R. and Santini, M., 2016. An overview of available crop growth and yield models for studies and assessments in agriculture. Journal of the Science of Food and Agriculture, 96(3), pp.709-714.
Donnenfeld, Z., Hedden, S. and Crookes, C., 2018. A delicate balance: Water scarcity in South Africa.
Doorenbos, J., 1977. Crop water requirements. Irrigation and drainage paper, 24.
Drewnowski, A., Dwyer, J., King, J.C. and Weaver, C.M., 2019. A proposed nutrient density score that includes food groups and nutrients to better align with dietary guidance. Nutrition Reviews, 77(6), pp.404-416. doi: 10.1093/nutrit/nuz002.
Ebert, A.W., 2014. Potential of underutilized traditional vegetables and legume crops to contribute to food and nutritional security, income and more sustainable production systems. Sustainability, 6(1), pp.319-335. doi: 10.3390/su6010319.
El Naim, A.M. and A.A. Jabereldar. 2010. Effect of Plant density and Cultivar on Growth and Yield of Cowpea (Vigna Effect of Plant density and Cultivar on Growth and Yield of Cowpea Vigna.) Aust. J. Basic Appl. Sci. (May): 3148-3153.
Enyiukwu, D.N., Amadioha, A. and Ononuju, C., 2018. Nutritional significance of cowpea leaves for human consumption. Greener Trends in Food Science and Nutrition, 1(1), pp.1-10. doi: 10.15580/gtfsn.2018.1.061818085.
Erdem, Y., Arin, L., Erdem, T., Polat, S., Deveci, M., Okursoy, H. and Gültaş, H.T., 2010. Crop water stress index for assessing irrigation scheduling of drip irrigated broccoli (Brassica oleracea L. var. italica). Agricultural Water Management, 98(1), pp.148-156. doi: 10.1016/j.agwat.2010.08.013.
Erpen, L., Streck, N.A., Uhlmann, L.O., Langner, J.A., Winck, J.E. and Gabriel, L.F., 2013. Estimating cardinal temperatures and modeling the vegetative development of sweet potato/Estimativa das temperaturas cardinais e modelagem do desenvolvimento vegetativo em batata-doce. Revista Brasileira de Engenharia Agrícola e Ambiental, 17(11), pp.1230-1239. http://dx.doi.org/10.1590/S1415-43662013001100015.
Escudero, N.L., Albarracin, G., Fernández, S., De Arellano, L.M. and Mucciarelli, S., 1999. Nutrient and antinutrient composition of Amaranthus muricatus. Plant foods for human nutrition, 54(4), pp.327-336. doi: 10.1023/A:1008149721435.

Essack, H., Odhav, B. and Mellem, J.J., 2017. Screening of traditional South African leafy vegetables for specific anti-nutritional factors before and after processing. Food Science and Technology, 37, pp.462-471. doi: 10.1590/1678-457x.20416.

Evans, R.G. and Sadler, E.J., 2008. Methods and technologies to improve efficiency of water use. Water resources research, 44(7). doi: 10.1029/2007WR006200.

Filho, G.X., Barreira, T.F., Santos, R.H., Priore, S.E., Della Lucia, C.M. and Pinheiro-Sant'Ana, H.M., 2018. Chemical composition, carotenoids, vitamins and minerals in wild mustard collected in native areas. Horticultura Brasileira, 36, pp.59-65.

Fiume Francesco., 2005. Sweet Potato. http://sperimentazione.altervista.org/Sweetpotato.html (accessed 2 October 2019).

Fliert, E.V.D. and Braun, A.R., 1999. Farmer field school for integrated crop management of sweetpotato: Field guides and technical manual. International Potato Center (CIP).

FAO, 2009. How to Feed the World in 2050. Insights from an Expert Meet. FAO. doi: 10.1111/j.1728-4457.2009.00312.x.

Franzke, A., Lysak, M.A., Al-Shehbaz, I.A., Koch, M.A. and Mummenhoff, K., 2011. Cabbage family affairs: the evolutionary history of Brassicaceae. Trends in plant science, 16(2), pp.108-116. doi: 10.1016/j.tplants.2010.11.005.

Freiberger, C.E., Vanderjagt, D.J., Pastuszyn, A., Glew, R.S., Mounkaila, G., Millson, M. and Glew, R.H., 1998. Nutrient content of the edible leaves of seven wild plants from Niger. Plant foods for Human nutrition, 53(1), pp.57-69.

Gal, P.Y., Merot, A., Moulin, C.H., Navarrete, M. and Wery, J., 2010. A modelling framework to support farmers in designing agricultural production systems. Environmental Modelling & Software, 25(2), pp.258-268. doi: 10.1016/j.envsoft.2008.12.013.

Gaydon, D.S., Wang, E., Poulton, P.L., Ahmad, B., Ahmed, F., Akhter, S., Ali, I., Amarasingha, R.P.R.K., Chaki, A.K., Chen, C. and Choudhury, B.U., 2017. Evaluation of the APSIM model in cropping systems of Asia. Field Crops Research, 204, pp.52-75. doi: 10.1016/j.fcr.2016.12.015.

Gaydon, D.S., Probert, M.E., Buresh, R.J., Meinke, H., Suriadi, A., Dobermann, A., Bouman, B. and Timsina, J., 2012. Rice in cropping systems – Modelling transitions between flooded and non-flooded soil environments. European journal of agronomy, 39, pp.9-24. doi: 10.1016/j.eja.2012.01.003.

Gockowski, J., Mbazo'o, J., Mbah, G. and Moulende, T.F., 2003. African traditional leafy vegetables and the urban and peri-urban poor. Food policy, 28(3), pp.221-235. doi: 10.1016/S0306-9192(03)00029-0.

Gomez Carlos, P., 2004. COWPEA Post-harvest Operations.

Govender, L., Pillay, K., Siwela, M., Modi, A. and Mabhaudhi, T., 2017. Food and nutrition insecurity in selected rural communities of KwaZulu-Natal, South Africa – Linking human nutrition and agriculture. International Journal of Environmental Research and Public Health, 14(1), p.17. doi: 10.3390/ijerph14010017.

Government of Saskatchewan., 2017. Mustard Production Manual.

Graeub, B.E., Chappell, M.J. and H. Wittman. 2016., The State of Family Farms in the World. World Dev. 87: 1-15. doi: 10.1016/j.worlddev.2015.05.012.

Grain SA., 2020. Boost grain production with legumes.

Grove, I. and Monaghan, J., 2018. Drought Risk and YOU.

Gupta, U., 2011. Sweet Potato [Ipomoea batatas (L.) Lam.]. What's New About Crop Plants. doi: 10.1201/b10736-14.

H.F. Schwartz. 2010. Cowpea Growth Stages. Bean IPM https://beanipm.pbgworks.org/cowpea.

Hardy, M., Dziba, L., Kilian, W. and Tolmay, J., 2011. Rainfed farming systems in South Africa. In Rainfed farming systems(pp. 395-432). Springer, Dordrecht. doi: 10.1080/07900628808722366.

Holzworth, D.P., Huth, N.I., deVoil, P.G., Zurcher, E.J., Herrmann, N.I., McLean, G., Chenu, K., Van Oosterom, E.J., Snow, V., Murphy, C. and Moore, A.D., 2014. APSIM-evolution towards a new generation of agricultural systems simulation. Environmental Modelling & Software, 62, pp.327-350. . doi: 10.1016/j.envsoft.2014.07.009.

Hu, J., Wu, W., Cao, Z., Wen, J., Shu, Q.L. and Fu, S.L., 2016. Morphological, physiological and biochemical responses of Camellia oleifera to low-temperature stress. Pak J Bot, 48, pp.899-905.

Imungi, J.K. and Potter, N.N., 1983. Nutrient contents of raw and cooked cowpea leaves. Journal of food science, 48(4), pp.1252-1254. doi: 10.1111/j.1365-2621.1983.tb09204.x.

International Institute of Tropical Agriculture's., 2012. Cowpea at Different Growth Stages. Flickr. https://www.flickr.com/photos/iita-media-library/7170925132.

IPGRI, 2002. Neglected and underutilized plant species: strategic action plan of the International Plant Genetic Resources Institute. . International Plant Genetic Resources Institute, Rome, Italy. (February): 1-20.

Jiao, Y., Jiang, Y., Zhai, W. and Yang, Z., 2012. Studies on antioxidant capacity of anthocyanin extract from purple sweet potato (Ipomoea batatas L.). African Journal of Biotechnology, 11(27), pp.7046-7054. . doi: 10.5897/AJB11.3859.

Kabas, O., Yilmaz, E., Ozmerzi, A. and Akinci, İ., 2007. Some physical and nutritional properties of cowpea seed (Vigna sinensis L.). Journal of food engineering, 79(4), pp.1405-1409. doi: 10.1016/j.jfoodeng.2006.04.022.

Kala, A. and Prakash, J., 2004. Nutrient composition and sensory profile of differently cooked green leafy vegetables. International Journal of Food Properties, 7(3), pp.659-669. doi: 10.1081/JFP-200033079.

Kanda, E.K., Senzanje, A., Mabhaudhi, T. and Mubanga, S.C., 2020. Nutritional yield and nutritional water productivity of cowpea (Vigna unguiculata L. Walp) under varying irrigation water regimes. Water SA, 46(3), pp.410-418.

Kant, S., Bi, Y.M. and Rothstein, S.J., 2011. Understanding plant response to nitrogen limitation for the improvement of crop nitrogen use efficiency. Journal of Experimental Botany, 62(4): 1499-1509. doi: 10.1093/jxb/erq297.

Keating, B.A., Carberry, P.S., Hammer, G.L., Probert, M.E., Robertson, M.J., Holzworth, D., Huth, N.I., Hargreaves, J.N., Meinke, H., Hochman, Z. and McLean, G., 2003. An overview of APSIM, a model designed for farming systems simulation. European journal of agronomy, 18(3-4), pp.267-288.

Kolb, L.N. and Gallandt, E.R., 2013. Modelling population dynamics of Sinapis arvensis in organically grown spring wheat production systems. Weed Research, 53(3), pp.201-212. . doi: 10.1111/wre.12018.

Kucharik, C.J., 2008. Contribution of planting date trends to increased maize yields in the central United States. Agronomy Journal, 100(2), pp.328-336. doi: 10.2134/agronj2007.0145.

Kullabas., 2019. Lifecycle of A Mustard Plant. https://www.kullabs.com/classes/subjects/units/lessons/notes/note-detail/759.

Lewu, F.B. and Mavengahama, S., 2010. Wild vegetables in Northern KwaZulu Natal, South Africa: Current status of production and research needs. Scientific Research and Essays, 5(20), pp.3044-3048.

Li, S.X., Wang, Z.H., Malhi, S.S., Li, S.Q., Gao, Y.J. and Tian, X.H., 2009. Nutrient and water management effects on crop production, and nutrient and water use efficiency in dryland areas of China. Advances in agronomy, 102, pp.223-265. doi: 10.1016/S0065-2113(09)01007-4.

Love, J.H., 2014. Effects of fertilizer application and pinching on the yield of grain amaranth (Amaranthus hypochondriacus)(Doctoral dissertation).

Lowenberg-Deboer, J., Krause, M., Deuson, R. and Reddy, K.C., 1991. Simulation of yield distributions in millet-cowpea intercropping. Agricultural Systems, 36(4), pp.471-487. doi: 10.1016/0308-521X(91)90072-I.

Ma, L., Ahuja, L.R., Saseendran, S.A., Malone, R.W., Green, T.R., Nolan, B.T., Bartling, P.N.S., Flerchinger, G.N., Boote, K.J. and Hoogenboom, G., 2011. A protocol for parameterization and calibration of RZWQM2 in field research. Methods of introducing system models into agricultural research, 2, pp.1-64. doi: 10.2134/advagricsystmodel2.c1.

Mabhaudhi, T., Chibarabada, T.P., Chimonyo, V.G.P., Murugani, V.G., Pereira, L.M., Sobratee, N., Govender, L., Slotow, R. and Modi, A.T., 2018. Mainstreaming underutilized indigenous and traditional crops into food systems: A South African perspective. Sustainability, 11(1), p.172.

Mabhaudhi, T., Chibarabada, T. and Modi, A., 2016. Water-food-nutrition-health nexus: Linking water to improving food, nutrition and health in Sub-Saharan Africa. International journal of environmental research and public health, 13(1), p.107. doi: 10.3390/ijerph13010107.

Mabhaudhi, T., Chimonyo, V.G.P., Hlahla, S., Massawe, F., Mayes, S., Nhamo, L. and Modi, A.T., 2019. Prospects of orphan crops in climate change. Planta, 250(3), pp.695-708. doi: 10.1007/s00425-019-03129-y.

Mabhaudhi, T., Chimonyo, V.G. and Modi, A.T., 2017. Status of underutilised crops in South Africa: Opportunities for developing research capacity. Sustainability, 9(9), p.1569. doi: 10.3390/su9091569.

Madodé, Y.E., Linnemann, A.R., Nout, M.J., Vosman, B., Hounhouigan, D.J. and Van Boekel, M.A., 2012. Nutrients, technological properties and genetic relationships among twenty cowpea landraces cultivated in West Africa. International journal of food science & technology, 47(12), pp.2636-2647. doi: 10.1111/j.1365-2621.2012.03146.x.

Martínez-Núñez, M., Ruiz-Rivas, M., Vera-Hernández, P.F., Bernal-Muñoz, R., Luna-Suárez, S. and Rosas-Cárdenas, F.F., 2019. The phenological growth stages of different amaranth species grown in restricted spaces based in BBCH code. South African Journal of Botany, 124, pp.436-443. doi: 10.1016/j.sajb.2019.05.035.

Maseko, I., Nogemane, N., Beletse, Y.G. and Du Plooy, C.P., 2015. Growth, physiology and yield responses of Amaranthus cruentus, Corchorus olitorius and Vigna unguiculata to plant density under drip-irrigated commercial production. South African Journal of Plant and Soil, 32(2), pp.87-94. doi: 10.1080/02571862.2014.994142.

Maseko, I., Mabhaudhi, T., Tesfay, S., Araya, H.T., Fezzehazion, M. and Plooy, C.P.D., 2017. African leafy vegetables: A review of status, production and utilization in South Africa. Sustainability, 10(1), p.16.

Maseko, I., Mabhaudhi, T., Tesfay, S., Araya, H.T., Fezzehazion, M. and Plooy, C.P.D., 2017. African leafy vegetables: A review of status, production and utilization in South Africa. Sustainability, 10(1), p.16. doi: 10.3390/su10010016.

Mavengahama, S., McLachlan, M. and De Clercq, W., 2013. The role of wild vegetable species in household food security in maize based subsistence cropping systems. Food Security, 5(2), pp.227-233. doi: 10.1007/s12571-013-0243-2.

Mayes, S., Massawe, P.G., Alderson, J.A. and Roberts, S.N., Azam-Ali and Hermann, M. 2011. The potential for underutilized crops to improve security of food production. J. Exp. Bot, pp.1-5. doi: 10.1093/jxb/err396.

Mduma, I., Msuya, J., Mwanri, A.W. and Yang, R.Y., 2012. Carotenoids retention and in vitro iron bioavailability of traditional cowpea leaf dishes of rural Tanzania. International Journal of Food Sciences and Nutrition, 63(3), pp.267-272. doi: 10.3109/09637486.2011.620947.

Micheni, A.N., Kihanda, F.M., Warren, G.P. and Probert, M.E., 2004. Testing the APSIM Model with Experimental Data from the Long-term Manure Experiment at Machang's (Embu), Kenya. In ACIAR PROCEEDINGS (pp. 110-117). ACIAR; 1998.

Mohanraj, R. and Sivasankar, S., 2014. Sweet Potato (Ipomoea batatas [L.] Lam)-A valuable medicinal food: A review. Journal of medicinal food, 17(7), pp.733-741. . doi: 10.1089/jmf.2013.2818.

Molden, D., Oweis, T., Steduto, P., Bindraban, P., Hanjra, M.A. and Kijne, J., 2010. Improving agricultural water productivity: Between optimism and caution. Agricultural water management, 97(4), pp.528-535. doi: 10.1016/j.agwat.2009.03.023.

Morison, J.I.L., Baker, N.R., Mullineaux, P.M. and Davies, W.J., 2008. Improving water use in crop production. Philosophical Transactions of the Royal Society B: Biological Sciences, 363(1491), pp.639-658. doi: 10.1098/rstb.2007.2175.

Morison, J.I.L., Baker, N.R., Mullineaux, P.M. and Davies, W.J., 2008. Improving water use in crop production. Philosophical Transactions of the Royal Society B: Biological Sciences, 363(1491), pp.639-658. doi: 10.1098/rstb.2007.2175.

Mosha, T.C., Pace, R.D., Adeyeye, S., Laswai, H.S. and Mtebe, K., 1997. Effect of traditional processing practices on the content of total carotenoid, β-carotene, α-carotene and vitamin A activity of selected Tanzanian vegetables. Plant foods for human nutrition, 50(3), pp.189-201.

Mosha, T.C. and Gaga, H.E., 1999. Nutritive value and effect of blanching on the trypsin and chymotrypsin inhibitor activities of selected leafy vegetables. Plant foods for human nutrition, 54(3), pp.271-283. doi: 10.1023/A:1008157508445.

Motsa, N.M., Modi, A.T. and Mabhaudhi, T., 2015. Sweet potato (Ipomoea batatas L.) as a drought tolerant and food security crop. South African Journal of Science, 111(11-12), pp.1-8.

Mziray, R.S., Imungi, J.K. and Karuri, E.G., 2001. Nutrient and antinutrient in contents of raw and cooked Amaranthus hybridus. Ecology of food and nutrition, 40(1), pp.53-65. doi: 10.1080/03670244.2001.9991637.

Nadiia Havryliuk Kharzhevska., 2019. Lifecycle of Sweet Potato on A White Background. Dreamstime. https://www.dreamstime.com/life-cycle-sweet-potato-plant-white-background-life-cycle-sweet-potato-plant-white-background-beautiful-image144137998.

Uusiku, N.P., Oelofse, A., Duodu, K.G., Bester, M.J. and Faber, M., 2010. Nutritional value of leafy vegetables of sub-Saharan Africa and their potential contribution to human health: A review. Journal of food composition and analysis, 23(6), pp.499-509. doi: 10.1016/j.jfca.2010.05.002.

Njeme, C., Goduka, N.I. and George, G., 2014. Indigenous leafy vegetables (imifino, morogo, muhuro) in South Africa: A rich and unexplored source of nutrients and antioxidants. African Journal of Biotechnology, 13(19), pp.1933-1942. doi: 10.5897/ajb2013.13320.

Nordeide, M.B., Hatløy, A., Følling, M., Lied, E. and Oshaug, A., 1996. Nutrient composition and nutritional importance of green leaves and wild food resources in an agricultural district, Koutiala, in southern Mali. International journal of food sciences and nutrition, 47(6), pp.455-468. doi: 10.3109/09637489609031874.

NRC., 2006. Lost Crops of AFRICA: volume II Vegetables.

Ntatsi, G., Gutiérrez-Cortines, M.E., Karapanos, I., Barros, A., Weiss, J., Balliu, A., dos Santos Rosa, E.A. and Savvas, D., 2018. The quality of leguminous vegetables as influenced by preharvest factors. Scientia Horticulturae, 232, pp.191-205. doi: 10.1016/j.scienta.2017.12.058.

Ntombela, Z., 2012. Growth and yield responses of cowpeas (Vigna unguiculata L.) to water stress and defoliation (Doctoral dissertation).

Nyadanu, D. and Lowor, S.T., 2015. Promoting competitiveness of neglected and underutilized crop species: comparative analysis of nutritional composition of indigenous and exotic leafy and fruit vegetables in Ghana. Genetic resources and crop evolution, 62(1), pp.131-140. . doi: 10.1007/s10722-014-0162-x.

Nyathi, M.K., 2019. Assessment of nutritional water productivity and improvement strategies for traditional vegetables in South Africa (Doctoral dissertation, Wageningen University and Research).

Nyathi, M.K., Van Halsema, G.E., Beletse, Y.G., Annandale, J.G. and Struik, P.C., 2018. Nutritional water productivity of selected leafy vegetables. Agricultural Water Management, 209, pp.111-122. doi: 10.1016/j.agwat.2018.07.025.

Nyathi, M.K., Van Halsema, G.E., Beletse, Y.G., Annandale, J.G. and Struik, P.C., 2018. Nutritional water productivity of selected leafy vegetables. Agricultural Water Management, 209, pp.111-122. doi: 10.1016/j.agwat.2018.07.025.

Nyathi, M.K., Van Halsema, G.E., Annandale, J.G. and Struik, P.C., 2018. Calibration and validation of the AquaCrop model for repeatedly harvested leafy vegetables grown under different irrigation regimes. Agricultural water management, 208, pp.107-119. doi: 10.1016/j.agwat.2018.06.012.

Okamoto, M., Satoh, M. and Hirota, J., 1988. Irrigation. International Journal of Water Resources Development, 4(1), pp.27-29.

Obidiegwu, J.E., Bryan, G.J., Jones, H.G. and Prashar, A., 2015. Coping with drought: stress and adaptive responses in potato and perspectives for improvement. Frontiers in plant science, 6, p.542. doi: 10.3389/fpls.2015.00542.

Odhav, B., Beekrum, S., Akula, U.S. and Baijnath, H., 2007. Preliminary assessment of nutritional value of traditional leafy vegetables in KwaZulu-Natal, South Africa. Journal of Food Composition and Analysis, 20(5), pp.430-435. doi: 10.1016/j.jfca.2006.04.015.

Ogunlela, A.O. and Sadiku, I.B.S., 2017. Yield and water use efficiency of Amaranthus cruentus grown under SMS-based irrigation system. Journal of Research in Forestry, Wildlife and Environment, 9(3), pp.32-42.

Ojeda, J.J., Volenec, J.J., Brouder, S.M., Caviglia, O.P. and Agnusdei, M.G., 2017. Evaluation of Agricultural Production Systems Simulator as yield predictor of Panicum virgatum and Miscanthus x giganteus in several US environments. Gcb Bioenergy, 9(4), pp.796-816. doi: 10.1111/gcbb.12384.

Ojo, J.A., Olowoake, A.A. and Obembe, A., 2014. Efficacy of organomineral fertilizer and un-amended compost on the growth and yield of watermelon (Citrullus lanatus Thumb) in Ilorin Southern Guinea Savanna zone of Nigeria. International Journal of Recycling of Organic Waste in Agriculture, 3(4), pp.121-125. doi: 10.1007/s40093-014-0073-z.

Okamoto, M., Satoh, M. and Hirota, J., 1988. Irrigation. *International Journal of Water Resources Development*, *4*(1), pp.27-29.

Oke, M.O. and Workneh, T.S., 2013. A review on sweet potato postharvest processing and preservation technology. African Journal of Agricultural Research, 8(40), pp.4990-5003. doi: 10.5897/ajar2013.6841.

Olayiwola, I.O., Abubakar, H.N., Adebayo, G.B. and Oladipo, F.O., 2009. Study of sweet potato (Ipomea batatas lam) foods for indigenous consumption through chemical and anti-nutritive analysis in Kwara state, Nigeria. Pakistan Journal of Nutrition, 8(12), pp.1894-1897. doi: 10.3923/pjn.2009.1894.1897.

Onwonga, R.N., Mbuvi, J.P., Kironchi, G. and Githinji, M., 2010. Modelling the potential impact of climate change on sorghum and cowpea production in semi-arid areas of Kenya using the agricultural production systems simulator (APSIM). In Second RUFORUM Biennial Meeting, Research Application Summary (pp. 47-55).

Onyango, C.M., Shibairo, S.I., Imungi, J.K. and Harbinson, J., 2008. The physico-chemical characteristics and some nutritional values of vegetable amaranth sold in Nairobi-Kenya. Ecology of food and nutrition, 47(4), pp.382-398. doi: 10.1080/03670240802003926.

Owade, J.O., Abong', G., Okoth, M. and Mwang'ombe, A.W., 2020. A review of the contribution of cowpea leaves to food and nutrition security in East Africa. Food Science & Nutrition, 8(1), pp.36-47. doi: 10.1002/fsn3.1337.

Owade, J.O., Gachuiri, C.K. and Abong, G.O., 2019. Utilization of croton seed as a possible animal feed: a review.

Pace, R.D., Dull, G.G., Phills, B.R., Bonsi, C. and Forrester, I.T., 1988. The effect of topping frequency on nutrient content of sweet potato green tips. Journal of Food Composition and Analysis, 1(4), pp.326-333. doi: 10.1016/0889-1575(88)90032-4.

Padulosi, S., Hodgkin, T., Williams, J. and Haq, N., 2002. 30 underutilized crops: trends, challenges and opportunities in the 21st century. Managing plant genetic diversity, p.323.

Padulosi, S., Thompson, J. and Rudebjer, P.G., 2013. Fighting poverty, hunger and malnutrition with neglected and underutilized species: needs, challenges and the way forward.

Paranamana, N., Radampola, K. and Bulugahapitiya, V.P., 2015. Nutritional and anti-nutritional contents of alternative plant feed ingredients for fish feed formulation. Indian Journal of Animal Sciences, 85(2), pp.212-215.

Pearce, F., 2011. Can 'climate-smart' agriculture help both Africa and the planet. Yale Environment, 360, p.2012.

Pennington, J.A. and Fisher, R.A., 2010. Food component profiles for fruit and vegetable subgroups. Journal of Food Composition and Analysis, 23(5), pp.411-418. doi: 10.1016/j.jfca.2010.01.008.

Perry, C., Steduto, P., Allen, R.G. and Burt, C.M., 2009. Increasing productivity in irrigated agriculture: Agronomic constraints and hydrological realities. Agricultural water management, 96(11), pp.1517-1524. doi: 10.1016/j.agwat.2009.05.005.

Pisarikova, B., J. Peterka, M., Trčková, J., Moudrý, Z., Zralý, Z. and Herzig, I., 2006. Chemical composition of the above-ground biomass of Amaranthus cruentus and A. hypochondriacus. Acta Veterinaria Brunensis, 75(1): 133-138. doi: 10.2754/avb200675010133.

Powell, B., Thilsted, S.H., Ickowitz, A., Termote, C., Sunderland, T. and Herforth, A., 2015. Improving diets with wild and cultivated biodiversity from across the landscape. Food security, 7(3), pp.535-554. doi: 10.1007/s12571-015-0466-5.

Pretorius, B., 2014. Nutritional water productivity of orange fleshed sweet potato.

Raihana, A.N., Marikkar, J.M.N., Amin, I. and Shuhaimi, M., 2015. A review on food values of selected tropical fruits' seeds. International Journal of Food Properties, 18(11), pp.2380-2392. doi: 10.1080/10942912.2014.980946.

Rankine, D.R., Cohen, J.E., Taylor, M.A., Coy, A.D., Simpson, L.A., Stephenson, T. and Lawrence, J.L., 2015. Parameterizing the FAO AquaCrop Model for Rainfed and Irrigated Field-Grown Sweet Potato. Agronomy Journal, 107(1), pp.375-387. doi: 10.2134/agronj14.0287.

Raymundo, R., Asseng, S., Cammarano, D. and Quiroz, R., 2014. Potato, sweet potato, and yam models for climate change: A review. Field Crops Research, 166, pp.173-185. doi: 10.1016/j.fcr.2014.06.017.

Renault, D. and Wallender, W.W., 2000. Nutritional water productivity and diets. Agricultural water management, 45(3), pp.275-296. doi: 10.1016/S0378-3774(99)00107-9.

Rhandzu S., 2007. Yield and Yield Components Among Selected Cowpea. (August).

Kurata, R., Kobayashi, T., Ishii, T., Niimi, H., Niisaka, S., Kubo, M. and Kishimoto, M., 2017. Influence of sweet potato (Ipomoea batatas L.) leaf consumption on rat lipid metabolism. Food Science and Technology Research, 23(1), pp.57-62. doi: 10.3136/fstr.23.57.

Robertson, M.J. and Lilley, J.M., 2016. Simulation of growth, development and yield of canola (Brassica napus) in APSIM. Crop and Pasture Science, 67(4), pp.332-344. doi: 10.1071/cp15267.

Rockström, J. and Barron, J., 2007. Water productivity in rainfed systems: overview of challenges and analysis of opportunities in water scarcity prone savannahs. Irrigation Science, 25(3), pp.299-311. doi: 10.1007/s00271-007-0062-3.

Sahrawat, K.L., 2006. Plant nutrients: sufficiency and requirements. Encyclopedia of soil science, 1, pp.1306-1310. doi: 10.1081/e-ess3-120042731

Santhosh Mithra, V.S. and Somasundaram, K., 2008. A model to simulate sweet potato growth. World applied sciences journal, 4(4), pp.568-577.

Santhosh Mithra, V.S., Pushpalatha, R., Sunitha, S., George, J., Singh, P.P., Singh, R.S., Tarafdar, J., Mitra, S., Deo, C., Pareek, S. and Lakshmi, B.K.M., 2019. Evaluation of a crop growth model for sweet potato over a set of agro-climatic conditions in India. Current Science (00113891), 117(1).

Schönfeldt, H.C. and Pretorius, B., 2011. The nutrient content of five traditional South African dark green leafy vegetables – A preliminary study. Journal of food composition and analysis, 24(8), pp.1141-1146. doi: 10.1016/j.jfca.2011.04.004.

Schreinemachers, P., Berger, T. and Aune, J.B., 2007. Simulating soil fertility and poverty dynamics in Uganda: A bio-economic multi-agent systems approach. Ecological economics, 64(2), pp.387-401. doi: 10.1016/j.ecolecon.2007.07.018.

Sebetha, E.T., Ayodele, V.I., Kutu, F.R. and Mariga, I.K., 2010. Yields and protein content of two cowpea varieties grown under different production practices in Limpopo province, South Africa. African Journal of Biotechnology, 9(5). doi: 10.5897/ajb09.1132.

Sekeroglu, N., Ozkutlu, F., Deveci, M., Dede, O. and Yilmaz, N., 2006. Evaluation of some wild plants aspect of their nutritional values used as vegetable in Eastern Black Sea Region of Turkey. Asian Journal of Plant Sciences.

Sena, L.P., Vanderjagt, D.J., Rivera, C., Tsin, A.T., Muhamadu, I., Mahamadou, O., Millson, M., Pastuszyn, A. and Glew, R.H., 1998. Analysis of nutritional components of eight famine foods of the Republic of Niger. Plant foods for human nutrition, 52(1), pp.17-30.

Senyolo, G.M., Wale, E. and Ortmann, G.F., 2018. The determinants of farmers' decision to produce African leafy vegetables in the Limpopo province, South Africa. African Journal of Science, Technology, Innovation and Development, 10(7), pp.771-778. doi: 10.1080/20421338.2018.1513894.

Shackleton, S.E. and Shackleton, C.M., 2012. Linking poverty, HIV/AIDS and climate change to human and ecosystem vulnerability in southern Africa: consequences for livelihoods and sustainable ecosystem management. International Journal of Sustainable Development & World Ecology, 19(3), pp.275-286. doi: 10.1080/13504509.2011.641039.

Shekhawat, R.S., Singh, V. and Garg, B., 2009. Intelligent Image Processing For Feature Extraction from Digital Images. 89: 1704-1709. doi: 10.3945/ajcn.2009.26736AA.1704S.

Shukla, S. and Rastogi, A., 2013. Amaranth : A New Millennium Crop of Nutraceutical Values Critical Reviews in Food Science and Nutrition Amaranth : A New Millennium Crop of Nutraceutical Values. (January). doi: 10.1080/10408398.2010.517876.

Šimůnek, J. and Hopmans, J.W., 2009. Modeling compensated root water and nutrient uptake. Ecological modelling, 220(4), pp.505-521. doi: 10.1016/j.ecolmodel.2008.11.004.

Singh, G., Kawatra, A. and Sehgal, S., 2001. Nutritional composition of selected green leafy vegetables, herbs and carrots. Plant Foods for Human Nutrition, 56(4), pp.359-364.

Snapp, S.S., Blackie, M.J., Gilbert, R.A., Bezner-Kerr, R. and Kanyama-Phiri, G.Y., 2010. Biodiversity can support a greener revolution in Africa. Proceedings of the National Academy of Sciences, 107(48), pp.20840-20845. doi: 10.1073/pnas.1007199107.

Speek, A.J., Temalilwa, C.R. and Schrijver, J., 1986. Determination of β-carotene content of vegetables by high performance liquid chromatography and spectrophotometry. Food Chemistry, 19, pp.65-74. doi: 10.1016/0308-8146(86)90128-7.

Suárez, S., Mu, T., Sun, H. and Añón, M.C., 2020. Antioxidant activity, nutritional, and phenolic composition of sweet potato leaves as affected by harvesting period. International Journal of Food Properties, 23(1), pp.178-188. doi: 10.1080/10942912.2020.1716796.

Suarta, M., Suaria, I.N. and Sulistiawati, N.P.A., 2018. Build Recommendations Nitrogen Fertilization with the Development of the Period of Durian Crop Replanting. International Journal of Life Sciences, 2(1), pp.1-11. doi: 10.29332/ijls.v2n1.73.

Sun, H., Mu, T., Xi, L., Zhang, M. and Chen, J., 2014. Sweet potato (Ipomoea batatas L.) leaves as nutritional and functional foods. Food chemistry, 156, pp.380-389. doi: 10.1016/j.foodchem.2014.01.079.

Timsina, J., De Vries, F.P. and Garrity, D.P., 1993. Cowpea production in rice-based cropping systems of the Philippines – extrapolation by simulation. Agricultural Systems, 42(4), pp.383-405.

Van Jaarsveld, P., Faber, M., Van Heerden, I., Wenhold, F., Van Rensburg, W.J. and Van Averbeke, W., 2014. Nutrient content of eight African leafy vegetables and their potential contribution to dietary reference intakes. Journal of food composition and analysis, 33(1), pp.77-84. doi: 10.1016/j.jfca.2013.11.003.

Van Rensburg, W.J., Van Averbeke, W., Slabbert, R., Faber, M., Van Jaarsveld, P., Van Heerden, I., Wenhold, F. and Oelofse, A., 2007. African leafy vegetables in South Africa. Water SA, 33(3), pp.317-326. doi: 10.4314/wsa.v33i3.49110.

VeggieHarvest., 2019. Amaranth Growing and Harvest Information. https://veggieharvest.com/vegetables/amaranth.html.

Vishwakarma, K.L. and Dubey, V., 2011. Nutritional analysis of indigenous wild edible herbs used in eastern Chhattisgarh, India. Emirates Journal of Food and Agriculture, pp.554-560.

Wang, G., McGiffen Jr, M.E., Lindquist, J.L., Ehlers, J.D. and Sartorato, I., 2007. Simulation study of the competitive ability of erect, semi-erect and prostrate cowpea (Vigna unguiculata) genotypes. Weed research, 47(2), pp.129-139.

Water., 2011. South Africa: a water scarce country. World Cup Leg. Rep. 6: 58-73. https://www.environment.gov.za/sites/default/files/docs/water.pdf.

Whisler, F.D., Acock, B., Baker, D.N., Fye, R.E., Hodges, H.F., Lambert, J.R., Lemmon, J.E., McKinion, J.M. and Reddy, V.R., 1986. Crop simulation models and types of models. Journal of Advances in agronomy 40, pp.141-208. doi: 10.1016/S0065-2113(08)60282-5.

Wysocki, D., 2002. Edible Mustard. (July).

Yadav, S.K. and Sehgal, S., 1995. Effect of home processing on ascorbic acid and β-carotene content of spinach (Spinacia oleracia) and amaranth (Amaranthus tricolor) leaves. Plant foods for human nutrition, 47(2), pp.125-131.

Zhang, L., Zhao, L., Bian, X., Guo, K., Zhou, L. and Wei, C., 2018. Characterization and comparative study of starches from seven purple sweet potatoes. Food hydrocolloids, 80, pp.168-176.

Zotarelli, L., Dukes, M.D. and Morgan, K.T., 2010. Interpretation of soil moisture content to determine soil field capacity and avoid over-irrigating sandy soils using soil moisture sensors. EDIS, 2010(2).

6 CALIBRATION OF AQUACROP, DSSAT AND THE SIMPLE MODEL

Nzimande, TNM., Chimonyo, V.G.P., Mabhaudhi, T, and Modi, A.T.

Abstract

The AquaCrop, DSSAT and SIMPLE model were used as a research tool to estimate climatically driven yield, biomass, and water use for selected NUS in different irrigation scheduling conditions for the Ukulinga Research Farm. Applying a higher amount of irrigation and irrigating more frequently resulted in higher yield, biomass and water use for maize, millet and yield generated by AquaCrop, DSSAT and the SIMPLE model. Thus, the hypothesis is accepted, and it can be concluded that the AquaCrop, DSSAT and SIMPLE model can be a useful decision support system to assist farmers in irrigation scheduling and applying an optimum amount of irrigation water. This can eventually help increase WP and make efficient use of variable rainfalls in South Africa. AquaCrop generated high yields for maize and millet, and the SIMPLE model for sorghum when irrigated and implies that these models are better suited for modelling the effects of irrigation management for the selected species.

6.1 Introduction

Neglected and underutilised species (NUS) play a crucial role in food security and nutrition. Furthermore, NUS also plays a major role in income generation for the rural resource-poor households, and sustainable production in marginal environments (Magbagbeola et al., 2010; Mal, 2007). However, due to the lack of data on growth and yield responses to the environment and different management strategies, current efforts for mainstreaming NUS have not matched those for commercially important crops. To bridge the gap in NUS research, numerous computer-based tools such as crop simulation models (CSMs) are presently being used in generating the much-needed data in crop research (Ewert et al., 2011). These tools are effective since they minimize the need for expensive and time-consuming field experiments. While crop simulation models as decision support tools offer users and policymakers data for best management practices, their uptake and use are low. One major reason for this is that there are huge uncertainties related to model structure and parameters (Palosuo et al., 2011), such as various models requiring large data input and complexity. Further to this, it is uncertain whether the current ensemble of models is suited for modelling NUS. Due to the lack of data on NUS to parameterize and calibrate, many researchers have been calling for the development and use of simpler but equally robust models (Babel et al., 2019; Mabhaudhi et al., 2014a, 2019; Roberts et al., 2017; Zhao et al., 2019).

Currently, the most common crop models implemented in NUS studies are DSSAT (Jones et al., 2003) and AquaCrop (Steduto et al., 2009), which differ in their degree of complexity. In comparison to AquaCrop, DSSAT is regarded as a more complex model due to its relative input requirement of more site-specific and crop variety-associated data (Babel et al., 2019). There are simpler models, such as the SIMPLE Model (Zhao et al., 2019). Although the SIMPLE model has been described as simple by several researchers (Manschadi et al., 2021; Soltani et al., 2020; Zhao et al., 2019), no published studies on predicting the growth, yield and resource use of any NUS. However, there is an ongoing debate on whether a model's simplicity may be appropriate to depict crop responses under observed climate and management options (Palosuo et al., 2011; Zhao et al., 2019). Now the argument is between using simple models to simulate crop growth and yield or focusing on the use of complex models that require a high level of expertise and data. This is important with the current drive for sustainable intensification in the wake of climate change using neglected and underutilised crops. As such, there is a need to assess the appropriateness of using models with varying degree of complexity. Thus, this study compares the performance of three crop simulation models, namely, AquaCrop, DSSAT, and the SIMPLE model, in predicting yield, biomass, and water use of neglected and underutilized cereal crops. It is hypothesised that there is no significant difference in the performance of AquaCrop, DSSAT and the SIMPLE model in estimating/predicting yield, biomass and water use of neglected and underutilized cereal crops regardless of model complexity. It was hypothesised that by AquaCrop, DSSAT and the SIMPLE model would predict the impacts of climate change and irrigation on yield, biomass and water use of selected cereal NUS.

6.2 Materials and methods

6.2.1 Overview of the AquaCrop, DSSAT and the SIMPLE model

6.2.1.1 AquaCrop Model

AquaCrop is defined as an engineering type, a canopy-level model that (Raes et al., 2009; Steduto et al., 2009) simulates crop yield as a function of water consumption under conditions of being rainfed and irrigated (Mabhaudhi et al., 2014b). Also, the model is an adopted framework of Doorenbos & Kassam's (1979) initiative, which was published in the FAO's Irrigation and Drainage Paper No.33. Crops grow in a soil-crop-atmosphere environment, usually described by the relatively trivial input data (Greaves & Wang, 2016). The AquaCrop model requires 29 input parameters. Similarly to other models, the AquaCrop's model component structure consists of a plantation, atmosphere, and soil (soil water balance) (Steduto et al., 2009). Furthermore, the similarity of the AquaCrop model is most prevalent in the constituents of the atmosphere and soil. Thus, the difference of the AquaCrop model, compared to other cereal crop development models, exists based on soil and plant components (Mabhaudhi et al., 2014c). Essentially, when the AquaCrop executes the simulation functionality, four files are used. These files are namely soil, crop, climate and management file. According to Farahani et al. (2009) and Geerts et al. (2009), it is recommended that the AquaCrop retains an accepted and consistent equilibrium between its accuracy and robustness.

6.2.1.2 DSSAT model

The Decision Support System for Agrotechnology Transfer (DSSAT) is a software application program of crop simulation models for over 42 crops as of Version 4.7. DSSAT is a cropping system simulation model that has been continuously improved over the years (Corbeels et al., 2016). The DSSAT is a crop model that helps decision-makers by reducing the time and human resources required for analysing complex alternative decisions (Tsuji et al., 1998). DSSAT model simulates crop yield under different management strategies, optimizing resource use, yield trend simulation under different soil and climate scenarios, and crop risk analysis (Jeffrey et al., 2010;

Jones et al., 2003; Sarkar, 2009). Thus, DSSAT is said to be useful for estimating short-, medium- and long-term impacts of specific land management practices on crop yield, soil water storage, nitrate-N leaching losses, etc. (Boote et al., 2010). The DSSAT primary modules include weather, soil, plant (cultivar/genotype coefficients), soil-plant-atmosphere interface, and management components. DSSAT was first released (v2.1) in 1989 and has been utilised by more than 16,500 researchers, educators, consultants, extension agents, growers, and policy and decision-makers in over 174 countries all over the globe (DSSAT, 2021).

6.2.1.3 SIMPLE model

The SIMPLE model can be defined as simulating crop growth, development, and yield utilising a daily time step, with equations that consider the impact of daily temperature, heat stress, rainfall, and atmospheric CO_2 concentration. The SIMPLE model incorporates nine species parameters for the specification of crop types and four cultivar parameters characterizing cultivar differences (Zhao et al., 2019). In order to run the SIMPLE model, input variables required include weather, atmospheric CO_2 concentration, sowing/harvesting date, irrigation, initial variables (biomass/ cumulative temperature/fraction of solar radiation interception if different from zero), and four variables characterizing the soil, including fraction of plant-available water-holding capacity, runoff curve number, deep drainage coefficient, and root zone depth (Zhao et al., 2019).

These models required inputs of climate data, crop characteristics, soil characteristics, and description of management practices to run simulations. Data was sourced from the Ukulinga Research Farm. Maize was used as a base crop since it is a commercially important crop compared to millet and sorghum, which are identified as generally underutilised.

6.2.2 Study site

This study was conducted using climate and soil data from the Ukulinga Research Farm to create input data files for AquaCrop, DSSAT and SIMPLE model. Ukulinga Research Farm is situated in Pietermaritzburg in the subtropical hinterland of

KwaZulu-Natal Province, South Africa (**Figure 6.1**) and represents a semi-arid environment. The farm is mainly used for training and research by the University of KwaZulu-Natal (UKZN) (Everson et al., 2012). The farm lies 29°37′ S, 30°16′ E with an elevation of approximately 775 m above sea level. Ukulinga is located within quaternary catchment U30D and quinary sub-catchment 4718. Briefly, a quaternary is a fourth level division of a primary catchment. Each quaternary catchment is then further subdivided into three quinary sub-catchments based on altitude. For detailed explanations, the reader is referred to Schulze et al. (2011). Rain falls mostly in summer, between September and April. Rainfall distribution varies during the growing season (Swemmer et al., 2007), with the bulk of the rain falling in November, December, early January, and March (Figure 3.2). Occasionally light to moderate frost occurs in winter (May-July). Chibarabada et al. (2020) reported that Ukulinga receives an average annual rainfall of 694 mm, mainly during the summer months (mid-October to mid-February). During the summer months, average maximum temperatures are between 26 °C and 28 °C while minimum temperatures can be as low as 10 °C. The landform at Ukulinga is colluvial fan, and soils are derived from marine shales.

Figure 6.1: Geographical view of Ukulinga Research Farm (Everson et al., 2012)

6.2.3 Climate description

The daily climate data were obtained from an automatic weather station (AWS) located at the Ukulinga Research farm. The AWS is part of the Agricultural Research Council-Institute for Soil, Climate and Water (ARC-ISCW) network of automatic weather stations. The climate data for all models comprised of rainfall (mm), minimum and maximum air temperature (°C), solar radiation (MJ day^{-1}) and reference evapotranspiration (ET_0) (**Figure 6.3**. ET_0 was based on the FAO Penman-Monteith equation from full daily weather datasets described by (Allen et al., 1998). ET0 was calculated using FAO's ET0 calculator (Raes, 2009) using air temperature, solar radiation, wind speed and relative humidity from the meteo-station. For DSSAT and the SIMPLE model, ET0 was calculated by using the Priestley & Taylor (1972) approach. This approach was used because it is simple and requires less data. For AquaCrop, a default file of the mean annual CO_2 concentration of 369.41 ppm as a reference in 2000 and 390 ppm in 2020, measured at the Mauna Loa Observatory in Hawaii, was used. DSSAT and the SIMPLE model also used this atmospheric CO_2 concentration as input data for simulations. To calculate growing degree days (GDD), AquaCrop used daily minimum and maximum temperature. Temperature is equally important in both DSSAT and the SIMPLE model for phenological development and crop growth.

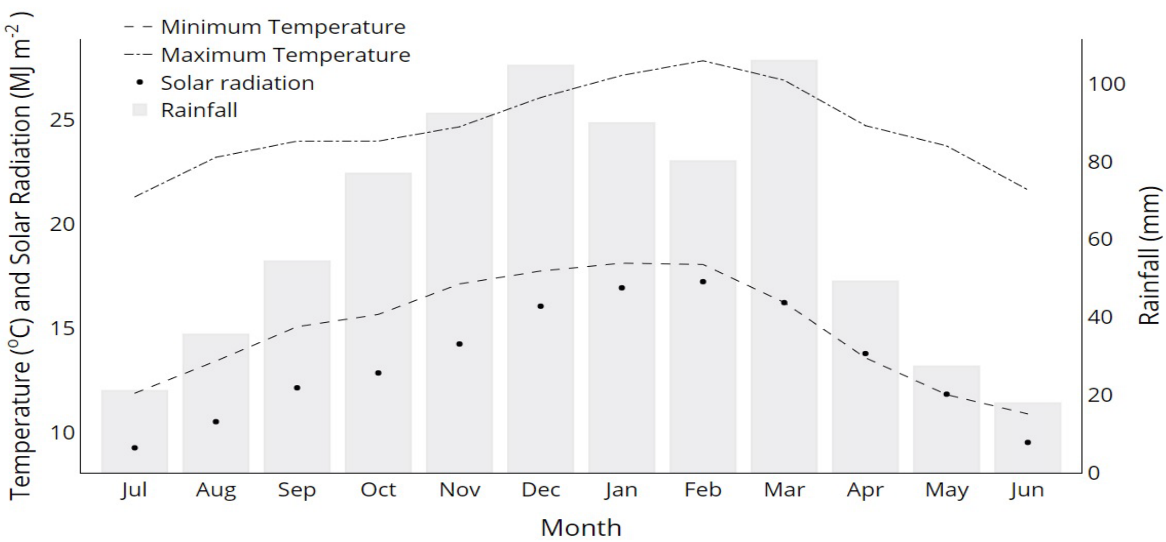


Figure 6.2: Long-term climate data for Ukulinga Research Farm from 2004-2019 obtained from a nearby weather station

6.2.4 Soil description

According to Chimonyo et al. (2016), the dominant soils at Ukulinga are chromic luvisols (FAO soil classification), and these are generally characterised as shallow brown acidic soils with low to moderate fertility. The soil textural class of the Ukulinga Research farm soil profile was classified as clay to clay-loam (USDA Taxonomic System) with an effective rooting depth of 0.6 m and three horizons (**Table 6.1**). In the creation of the soil file, there were no stresses (water, soil fertility, and soil salinity) being considered. The Soil file (.SOL) for AquaCrop and SIMPLE model was created using Ukulinga Research farm soil data. In DSSAT, the clay loam soil file embedded in the model was selected to best resemble the Ukulinga soils. Details of the actual soil parameters used in each model were presented in **Table 6.1** and **Table 6.2.**

Table 6.1: Soil water properties from the experimental site at Ukulinga Research Farm (Mabhaudhi, 2012)

Depth (m)	Bulk density (g cm^{-3})	Permanent wilting point (mm mm^{-1})	Field capacity (mm mm^{-1})	Total available water (mm mm^{-1})	Saturation (mm mm^{-1})	Saturated hydraulic conductivity (mm day^{-1})
0.60	1.20	283.00	406.00	123.00	481.00	25

The soil physical characteristics such as the soil texture, bulk density and porosity are considered.

Table 6.2: The soil file from Ukulinga Research Farm

Parameters	Units	Values	AquaCrop	DSSAT	SIMPLE
Upper horizon depth	cm	30	X	X	
Lower horizon depth	cm	10	X	X	
Number of soil horizons	-	3	X		
Sand content	%	33	X	X	
Silt content	%	33	X	X	
Clay content	%	34	X	X	
Bulk density	g/ cm^3	1.20	X	X	
Organic carbon	%	2.90		X	
Organic nitrogen	%	0.24		X	
pH	-	4.51		X	
Saturated water content	%	46.73	X	X	
Field capacity	mm	46.32	X	X	
Wilting point	mm	23.03	X	X	
Plant available water-holding capacity	mm‡	233	X		X
Runoff-curve number	-	75	X	X	X
Deep drainage	-	0.27	X	X	X
Total pore space	mm	36	X	X	
Saturated hydraulic conductivity	cm/h*	25	X	X	
Maximum rooting depth	mm	1	X	X	X

X denotes that the input was used in the model; *For AquaCrop, units are mm/d; ‡ For SIMPLE, units are mm/m

The creation of crop files entailed matching phenology (GDD) and yield potential on pre-existing cultivars across the models. The study used cultivars described by Akumaga et al. (2017), Hadebe et al. (2017) and Bello & Walker (2016) for maize, sorghum and pearl millet, respectively (**Table 6.3**). The cultivars' characteristics are described below (**Table 6.3**) and in the sections below.

Table 6.3: Provincial potential, observed and mean simulated yield for maize, millet, and sorghum

Crops	Crop type (maturity)	Provincial potential yield (t/ha)	Observed yield (t/ha)
Maize	early to medium	[1]8-11 (9.50)	[4]5.51
Sorghum	medium to late	[2]4	[5]5.31
Pearl millet	early to medium	[3]4.3-5.6 (4.95)	[6]6.83

[1] Arathoon & Mtumtum (2013) [2] GAIN Report (2019) [3] GRAINSA (2021) [4] Akumaga et al. (2017) [5] Hadebe et al. (2017) [6] Bello & Walker (2016)

6.2.5 Crop file description

6.2.5.1 AquaCrop model crop file

The AquaCrop model comprises two types of crop parameters: conservative and non-conservative (cultivar specific) parameters (Raes et al., 2009). Conservative parameters were used as presented in the model because they do not change substantially with time, management practices, geographic location or climate (Raes et al., 2009). Additionally, conservative parameters are assumed not to change with cultivars unless shown otherwise. In this study, the tuning of non-conservative parameters was not required because maize, sorghum, and pearl millet were calibrated in the AquaCrop model. Hence, crop parameters used in this study are similar to those used to calibrate the crops in the selected studies where they were obtained (**Table 6.4**).

6.2.5.2 DSSAT model crop file

In the DSSAT model, the coefficients for a specific crop species are stored in three different files, namely cultivar (.CUL), ecotype (.ECO) and species (.SPE). Cultivar coefficients are for a single cultivar (traits differ among cultivars), ecotype coefficients are common to a group of cultivars and species coefficients are common to all cultivars (crop specific traits) (Jones et al., 2003). Hence, maize, sorghum and millet cultivars were selected in DSSAT. Cultivars chosen for maize, sorghum and millet were 2500-2600 GDD, PIONEER 8333 and BJ104, respectively (**Table 6.5**), as they best described the cultivars used by (Akumaga et al., 2017), (Hadebe et al., 2017) and

(Bello & Walker, 2016). The cultivars were selected based on their similarity with the GDD of crops used in the AquaCrop model.

6.2.5.3 SIMPLE model crop file

The SIMPLE model included nine species parameters to specify crop types and four cultivar parameters characterizing cultivar differences. Species parameters were derived from accepted values in the literature (Zhao et al., 2019). Only cultivar parameters were calibrated within a reasonable range, but cultivar parameters are kept constant for the same cultivar when grown in different years or locations. The SIMPLE model calibrated only maize; however, it is not the cultivar used in this study (**Table 6.6**).

Table 6.4: Crop parameters of maize, sorghum, and pearl millet for AquaCrop model

Crop parameters	Pearl millet	Sorghum	Maize
Base temperature (°C) below which crop development does not progress	8	8	8
Upper temperature (°C) above which crop development no longer increases with an increase in temperature	32	30	30
Soil water depletion factor for canopy expansion (p-exp) – Upper threshold	0.30	0.15	0.14
Soil water depletion factor for canopy expansion (p-exp) – Lower threshold	0.65	0.70	0.72
Shape factor for water stress coefficient for canopy expansion (0.0 = straight line)	3	3	2.9
Soil water depletion fraction for stomatal control (p – sto) – Upper threshold	0.70	0.70	0.69
Shape factor for water stress coefficient for stomatal control (0.0 = straight line)	3	6	6
Soil water depletion factor for canopy senescence (p – sen) – Upper threshold	0.75	0.70	0.69
Shape factor for water stress coefficient for canopy senescence (0.0 = straight line)	3	3	2.70
Sum (ET_o) during stress period to be exceeded before senescence is triggered	0	0	0
Soil water depletion factor for pollination (p – pol) – Upper threshold	0.92	0.80	0.80
Vol% for Anaerobiotic point (* (SAT – [vol%]) at which deficient aeration occurs *)	10	5	5
Soil fertility stress at calibration (%)	50	50	50
Crop coefficient when canopy is complete but prior to senescence (Kcb,x)	1.10	1.07	1.03
Decline of crop coefficient (%/day) as a result of ageing, nitrogen deficiency, etc.	0.15	0.30	0.30
Minimum effective rooting depth (m)	0.30	0.30	0.30
Maximum effective rooting depth (m)	1.75	0.60	1
Shape factor describing root zone expansion	18	13	13
Maximum root water extraction (m^3 water/m^3 soil.day) in top quarter of root zone	0.05	0.03	0.08
Maximum root water extraction (m^3 water/m^3 soil.day) in bottom quarter of root zone	0.01	0.01	0.02
Effect of canopy cover in reducing soil evaporation in late season stage	60	50	50
Soil surface covered by an individual seedling at 90% emergence (cm^2)	5	3	6.50

Crop parameters	Pearl millet	Sorghum	Maize
Number of plants per hectare	55556	44444	53333
Canopy growth coefficient (CGC): Increase in canopy cover (fraction soil cover per day)	0.24	0.13	1.30
Maximum canopy cover (CCx) in fraction soil cover	0.95	0.89	0.96
Canopy decline coefficient (CDC): Decrease in canopy cover (in fraction per day)	0.10	1.70	1.06
Calendar Days: from sowing to emergence	4	14	7
Calendar Days: from sowing to maximum rooting depth	45	97	65
Calendar Days: from sowing to start senescence	80	98	91
Calendar Days: from sowing to maturity (length of crop cycle)	120	140	120
Calendar Days: from sowing to flowering	39	70	67
Length of the flowering stage (days)	20	77	30
Crop determinancy linked with flowering	1	1	1
Excess of potential fruits (%)	50	50	50
Building up of Harvest Index starting at flowering (days)	50	70	56
Water Productivity normalized for ET_o and CO_2 (WP*) (gram/m^2)	32	33.70	33.70
Water Productivity normalized for ET_o and CO_2 during yield formation (as% WP*)	100	100	100
Reference Harvest Index (HIo) (%)	30	45	40
Possible increase (%) of HI due to water stress before flowering	10	4	0
Coefficient describing positive impact on HI of restricted vegetative growth during yield formation	10	1	7
Coefficient describing negative impact on HI of stomatal closure during yield formation	8	3	3
Allowable maximum increase (%) of specified HI	15	25	15

Table 6.5: Cultivar coefficients of maize, sorghum, and millet for the DSSAT model

Cultivar coefficients		Maize (2500-2600 GDD)	Sorghum (PIONEER 8333)	Millet (BJ104)
P1	Thermal time from seedling emergence to the end of the juvenile phase (expressed in degree days above a base temperature of 8øC) during which the plant is not responsive to changes in photoperiod.	160.00	325.00	120.00
P2	Extent to which development (expressed as days) is delayed for each hour increase in photoperiod above the longest photoperiod at which development proceeds at a maximum rate (which is considered to be 12.5 hours).	0.75		
P2O	Critical photoperiod or the longest day length (in hours) at which development occurs at a maximum rate. At values greater than P2O, the rate of development is reduced.		15.50	13.40
P2R	Extent to which phasic development leading to panicle initiation (expressed in degree days) is delayed for each hour increase in photoperiod above P2O.		30.00	145.09
PANTH	Thermal time from the end of tassel initiation to anthesis (degree days above TBASE)			
P3	Thermal time from to end of flag leaf expansion to anthesis (degree days above TBASE)		152.50	
P4	Thermal time from anthesis to beginning grain filling (degree days above TBASE)		81.50	
P5	Thermal time (degree days above a base temperature of 8øC) from beginning of grain filling (3-4 days after flowering) to physiological maturity.	780.00	540.00	340.00
G1	Scaler for relative leaf size.		11.00	0.60
G2	Maximum possible number of kernels per plant.	750.00	6.00	
G3	Kernel filling rate during the linear grain filling stage and under optimum conditions (mg/day).	8.50		
G4	Scaler for partitioning of assimilates to the panicle (head).			1.00
PHINT	Phylochron interval; the interval in thermal time (degree days) between successive leaf tip appearances.	49.00	49.00	43.00

Cultivar coefficients	**Maize (2500-2600 GDD)**	**Sorghum (PIONEER 8333)**	**Millet (BJ104)**	
GT	Tillering coefficient, equivalent to G1, but on tillers			
G5	Potential grain size, mg			
AX	Leaf surface area (cm^2/leaf) of largest leaf.			
ALL	Leaf longevity (degree days) of the most longevous leaf.			

Table 6.6: Crop parameters of maize, sorghum, and pearl millet for SIMPLE model

	Crop parameters	**Maize**	**Sorghum**	**Millet**
Tsum	Cumulative temperature requirement from sowing to maturity (°C d)	1419	1648	1337
HI	Potential harvest index.	0.40	0.45	0.30
I50A	Cumulative temperature requirement for leaf area development to intercept 50% of radiation (°C d)	402	420	234
I50B	Cumulative temperature till maturity to reach 50% radiation interception due to leaf senescence (°C d)	546	588	480
Tbase	Base temperature for phenology development and growth (^oC)	8	8	8
Topt	Optimal temperature for biomass growth (^oC)	30	30	32
RUE	Radiation use efficiency (above ground only and without respiration) (g MJ^{-1} m^{-2}).	4.20	3.20	4
I50maxH	The maximum daily reduction in I50B due to heat stress (°C d)	100	100	100
I50maxW	The maximum daily reduction in I50B due to drought stress (°C d)	12	12	12
MaxT	Threshold temperature to start accelerating senescence from heat stress (^oC)	44	44	48
ExtremeT	The extreme temperature threshold when RUE becomes 0 due to heat stress (^oC)	50	50	50
CO_2_RUE	Relative increase in RUE per ppm elevated CO_2 above 350 ppm.	0.01	0.01	0.01
S_Water	Sensitivity of RUE (or harvest index) to drought stress (ARID index).	1.50	1.50	1.50

Maize is one of the crops used in this study, and it is a cereal crop like sorghum and millet. Thus, calibrated maize values for species parameters (CO2_RUE and S_Water) were used to simulate results for maize, millet, and sorghum. I50A and I50B were not readily available for cultivar parameters; hence, these were calculated as I50A (thermal time for flowering*50%) and I50B (thermal time for the start of senescence*50%)

6.2.6 Management file

In AquaCrop, DSSAT and SIMPLE model, the three crops were sown as a direct planting method. The planting period for simulation in all three models ranged from 10/2004-04/2019, and the planting dates chosen were 25 October for maize, 15 October for sorghum and 01 October for pearl millet. These dates represented the recommended planting dates for KZN for the different cereal crops. However, AquaCrop started simulation one day after planting. The optimal planting date was based on Department of Agriculture, Forestry and Fisheries (DAFF) recommendations and historical weather data at Ukulinga. The plant population for maize, sorghum and pearl millet were 53333, 44444 and 55556 plants ha^{-1}, respectively, in all the models. Management practices undertaken were made similar for AquaCrop, DSSAT and SIMPLE model. Due to the SIMPLE model having only irrigation as a management variable, all three models are considered irrigation solely as a management practice, which is investigated in chapter five. The assumption made was that all the models were weed and stress (water, soil fertility, and soil salinity) free.

6.2.7 Climate scenarios

A quaternary catchment represents a fourth-level division of a primary drainage basin. There are 1946 quaternary catchments in southern Africa, 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 et al., 2010; Schulze & Horan, 2007), which produced a total of 5838 quinaries. 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 & Horan, 2007, 2010).

The Ukulinga climate files for AquaCrop, DSSAT and SIMPLE were developed using the historical quinary climate database for South Africa (Schulze et al., 2011). Ukulinga research farm is located within quinary sub-catchment 4697 of quaternary catchment U30J (Schulze et al., 2011). In addition to historical data, the study also used downscaled future climate projections for the Ukulinga quinary. The climate projections were developed by the Council for Scientific and Industrial Research (CSIR) (***Table 6.7***) using output from six global climate models (GCMs) from the CMIP5 archive that was forced by Representative Concentration Pathway 8.5 (RCP 8.5). The climates produced under RCP 8.5 were used as they represent the most extreme scenarios. The selection of these six GCMs was based on their ability to provide a reasonable representation of the El Nino-Southern Oscillation (ENSO) phenomenon for the region.

Table 6.7: Global climate models used in this study (Chimonyo et al., 2020)

Abbreviation	Earth System Models	Institute	Horizontal resolution
ACC	ACCESS1-0	Commonwealth Scientific and Industrial Research Organisation, Australia (CSIRO), and Bureau of Meteorology, Australia (BOM)	1.250 × 1.875°
CCS	CCSM4	National Centre for Atmospheric Research (NCAR), USA	0.9424 × 1.250°
CNR	CNRM-CM5	Centre National de Recherches Meteorologiques, Meteo-France, France	1.4005 × 1.4065°
NOR	NorESM1-M	NorESM (Norwegian Earth System)	1.250 × 0.940°
GFD	GFDL-CM3	Geophysical Fluid Dynamics Laboratory, USA	2.000 × 2.500°
MPI	MPI-ESM-LR	Max Planck Institute for Meteorology, Germany	1.8653 × 1.875°

Various downscaling approaches can be applied, and dynamical downscaling was applied in this study. The climate projections were dynamically downscaled to improve spatial resolution to 0.5° (~50 km) using the CCAM regional climate model developed by the Commonwealth Scientific and Industrial Research Organisation, CSIRO (McGregor, 2005; McGregor & Dix, 2001, 2008). After that, a multiple-nudging strategy was followed to obtain a downscaling to 0.1° (~10 km) resolution using CCAM in stretched-grid mode over South Africa (see Mabhaudhi et al., 2018a). Climate scenarios were then extracted for the gridded pixel that overlapped quinary sub-catchment 4697. For application in crop modelling at a local scale, it is necessary to correct systematic and localised biases in rainfall and temperature projections produced by the climate models. Compared to observed rainfall data from the historical quinary climate database for sub-catchment 4697, the downscaled climate projections were found to have a substantially larger number of rain days, with many rain days having minimal rainfall depths (i.e. < 0.10 mm). Therefore, as described and assessed by Cannon et al. (2015), a quantile delta mapping method was applied to bias correct the climate scenarios using a multiplicative factor for rainfall and an additive factor for temperature.

The bias-corrected climate data provide daily rainfall and temperature scenarios for a continuous period from 1961 to 2100. Daily reference crop evaporation (ETo) estimates were then computed as described for the historical data set (Schulze et al., 2011). Solar radiation for each GCM for Ukulinga was then calculated as described by Schulze and Chapman (2007). The climate database, therefore, satisfied climate file input requirements for AquaCrop, DSSAT and the SIMPLE model and was used to develop projections (as climate files – CLI) for the past (1961-1991), present (1995-2025), mid-century (2030-2060) and late-century (2065-2095) periods. Throughout the analysis, the 'present' timescale was regarded as the baseline.

6.2.7.1 Climate trends

Based on results from Chimonyo et al. (2020), Ukulinga is projected to have a warmer future (mid-and late-century) with the mean maximum temperature increasing by 4.5°C relatives to the baseline maximum temperature of 24 °C (**Figure 6.3**). The six GCMs project an increase in mean minimum temperatures in the future (mid-and late-century) that ranges from 2.0-4.8°C from a minimum baseline temperature of 13°C (Figure 4.1). In general, all GCMs showed that the mean annual precipitation (MAP) across the periods was fairly constant relative to the baseline. Variations were, however, observed across the simulated periods (**Figure 6.3**). For the late-century period, data showed that ACC and CCS predict a 10.6 and 8.3% increase in MAP, respectively, while slight reductions of 3.5 and 2.5% are predicted by CNR and NOR, respectively. However, the more extended box and whisper plots for ACC predict an increase in the inter-annual variability of mean rainfall (750 mm) (**Figure 6.4**). In all instances, projected ET_o was observed to be higher (35%) than projected rainfall and is set to increase in the future (mid and late century) (**Figure 6.4**). In this regard, the rainfall: ET_o ratio is projected to decrease in the near future.

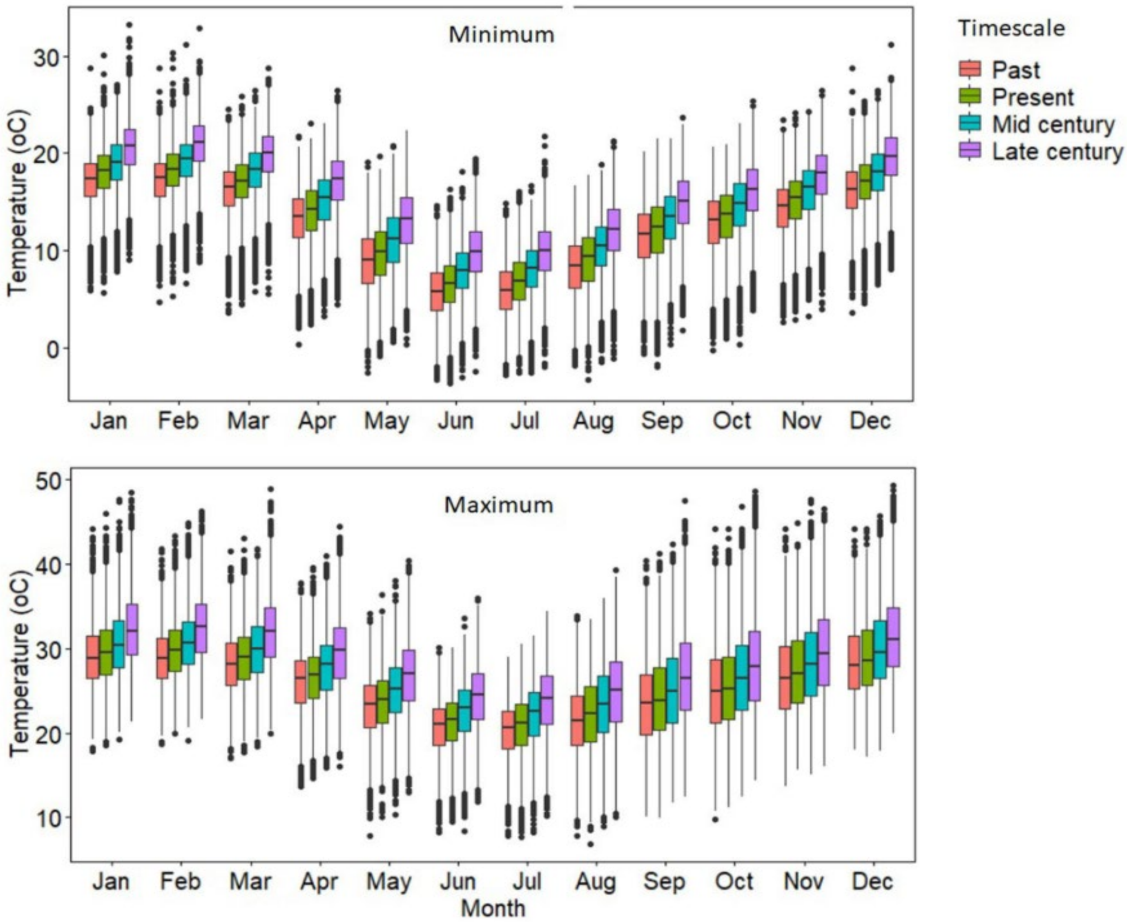


Figure 6.3: Distribution of average monthly minimum (a) and maximum (b) temperature data for the different timescales (past, present, mid-and late-century) from the combined six GCMs (ACC, CCS, CNR, GFD, NOR and MPI) used in this study (Chimonyo et al., 2020)

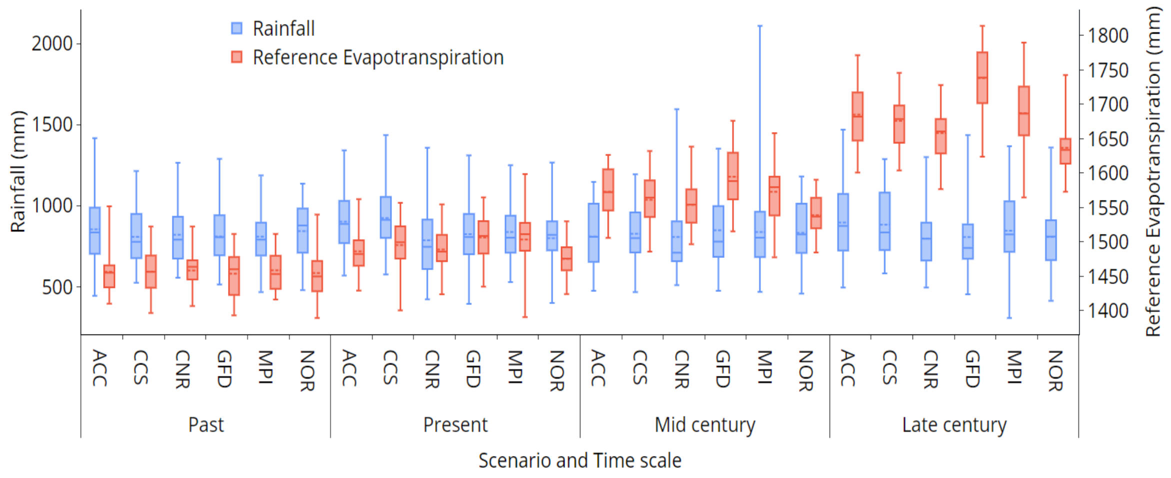


Figure 6.4: Rainfall data represents four different timescales (past, present, mid-and late-century) as simulated by the six GCMs (ACC, CCS, CNR, GFD, NOR and MPI) used in the study. The mean annual rainfall represents the average yearly rainfall calculated from observed rainfall data between 2004 and 2019 (Chimonyo et al., 2020)

6.2.8 Irrigation scenario

Firstly, crops were grown under rainfed conditions, then under irrigation as a management practice. AquaCrop, DSSAT and the SIMPLE model takes into consideration the aspect of irrigation.

The SIMPLE model only requires the irrigation date and amount to simulate crop response to irrigation as a management practice (Zhao et al., 2019). Meanwhile, in DSSAT, irrigation can be applied on specific dates with specified irrigation amounts and methods or controlled by the plant's available water (Jones et al., 2003). AquaCrop can run simulations in different irrigation modes. The default mode is 'rainfed cropping', in which irrigation is not considered. In the other modes, (i) the irrigation water requirement can be determined, (ii) an existing irrigation schedule can be assessed, or (iii) an irrigation schedule can be automatically generated (FAO, 2017a). The methods chosen for use was irrigation scheduling in AquaCrop and the one in which irrigation can be applied on specific dates with specified irrigation amount and methods in DSSAT. These methods made it possible to have similar irrigation inputs used across the three models; hence, they were chosen for this study. In

AquaCrop, when generating irrigation schedules, the irrigation method needs to be specified since it affects the simulation of the soil water balance (FAO, 2017a). Thus, a sprinkler was selected as an irrigation method. It was not a requirement to select the irrigation method in DSSAT, and the SIMPLE model does not have the irrigation method as a parameter under its inputs. Irrigation amounts of 10 and 20 mm were frequented every 7 and 14 days until maturity in AquaCrop, DSSAT and the SIMPLE model for maize, millet, and sorghum.

6.2.9 Model evaluation statistics

The methods of assessing and comparing the performance of models have been discussed widely (Bellocchi & Rivington, 2009; Kobayashi & Salam, 2000; Wallach et al., 2006; Willmott, 1981). There is provision for an indication of uncertainties in model simulations attributable to using various crop models (representing different complexity) and model user groups (representing different application skills) by showing outcomes from the three individual models. Comparing observed data (from the individual studies) with those of model outputs aids in evaluating the reliability and accuracy of simulations. As such, we extracted data for observed yield from the articles used for model calibration. Arathoon & Mtumtum, (2013), GAIN Report (2019) and GRAINSA (2021) were also used for the provision of provincial potential yield for the three crops. The provincial data was used to benchmark the yield potentials for each crop and each model's performance. The calibrated parameters were used to simulate outputs of the three models, including grain yield, aboveground biomass, and evapotranspiration (water use). Since AquaCrop, DSSAT, and the SIMPLE model does not calculate WP directly, simulated outputs of water use (WU in mm) and yield (Y in kg ha^{-1}) were used to determine water productivity (WP in kg mm^{-1} ha^{-1}) as follows:

$$WP_s = \frac{Y\ (kg/ha)}{WU\ (mm)} \qquad \text{Equation 6.1}$$

(Molden, 1997) defined water productivity as ‘crop production’ per unit ‘amount of water used’. Various statistical indicators used in assessing and comparing the performance of models were used in this study. Descriptive statistics such as means, standard deviations, line graphs, and box and whisker plots were used to analyse outputs. Box and whisker plot can show stability and general distribution of the sets of data. A Mann-Kendall trend test was also used to test whether there was statistically significant decreasing or increasing data trends. A P-value < 0.05 indicates a trend, and if τ is +ve, increasing trend, and if τ is -ve, decreasing trend. Additionally, other statistical indicators used were root mean square error (RMSE; Eq. 6.2), normalized root mean square error (NRMSE; Eq. 6.3), coefficient of determination (R2; Eq. 6.4), mean bias error (MBE; Eq. 6.5), and index of agreement (IA; Eq. 6.6) developed by Willmott (1981). The RMSE was taken to measure the relative average difference between the model estimates and measurements: it describes the average absolute deviations between the simulated and observed values.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Pi - Oi)(1)^2} \qquad \text{Equation 6.2}$$

where N is the number of estimate-observation pairs, P_i is the model prediction and O_i is the observed value of the model i.

$$NRMSE = \frac{RMSE}{\bar{O}} \qquad \text{Equation 6.3}$$

where Obar is the average of observation value

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} \qquad \text{Equation 6.4}$$

MBE was taken as an indicator of under- or over-estimation, i.e. the direction and magnitude of bias.

$$MBE = N^{-1}\sum_{i=1}^{N}(Pi - Oi) \qquad \text{Equation 6.5}$$

IA was used as a more general indicator of model efficiency.

$$IA = 1 - \frac{NxMSE}{PE} \qquad \text{Equation 6.6}$$

Where $PE = \sum_{i=1}^{N}(|\dot{P}| + |\dot{O}|)(1^2)$ and where $\dot{P} = P_i - \bar{O}$ and $\dot{O} = O_i - \bar{O}_i$ and $\bar{O}$ is the mean of the observed variable. The main objective of the study was to evaluate model performance. Also were there was a limited number of data points to run all statistic tests; hence statistical analysis was not done for the individual crops but considered maize, millet and sorghum as sub-factors. However, in this study, all the three models were compared against each other (i.e. AquaCrop vs DSSAT, SIMPLE vs DSSAT and AquaCrop vs SIMPLE) because observed data was not available.

The six GCMs were used as climate input data by the three models in simulating the impacts of climate change on selected NUS. Simulation outputs for yield, biomass, WU and WP [yield (kg) per water evapotranspired (m^3)] were then subjected to t-test analysis using the R software (version 4.0.2). The t-test analysis was used to determine if there is a significant difference in outputs for maize, millet and sorghum across models, GCMs, timescale. Descriptive statistics such as means, standard deviations, and box and whisker plots were used to evaluate climate change impacts on yield, biomass, WU and WP for maize, sorghum, and millet. Box and whisker plots, coupled with standard deviations, can show stability and general distribution of data sets. A wider box indicates more variations across the median value of the dataset.

Additionally, a Mann-Kendall trend test was used to perceive statistically significant decreasing or increasing trend in data. A P-value < 0.05 indicates a trend, and if τ is +ve, increasing trend, and if τ is -ve decreasing trend. The present (1995-2025) was used to describe the baseline to compare climate change impacts. The performance of individual GCMs was also evaluated using a similar statistical approach

6.3 Results

6.3.1 Model performance

Provincial potential observed and mean simulated yield were compared (**Table 6.8**) using statistical indicators. Based on MBE, AquaCrop underestimated the yield by 0.22 t/ha, whereas in the case of DSSAT, the underestimation is observed to be 0.24 t/ha and 0.69 t/ha for SIMPLE when comparing the observed yield and simulated yield. Moreover, higher coefficient of determination (R^2) is observed in AquaCrop (0.99) compared to DSSAT (0.92) and the SIMPLE (0.51) model (**Table 6.8**). Taking into consideration the provincial potential yield as a comparative factor, the three models underestimated yield. The statistical comparison of observed and provincial potential yield showed that the provincial potential yield overestimated yield by 0.27 (**Table 6.8**).

Table 6.8: Provincial potential, observed and mean simulated yield for maize, millet, and sorghum

Crops	Crop type (maturity)	Provincial potential yield (t/ha)	Observed yield (t/ha)	Simulated yield ($t\ ha^{-1}$)		
				Aqua Crop	DSSAT	SIMPLE
Maize	early to medium	[1]8-11 (9.50)	[4]5.51	6.55 (1.49)	5.75 (0.70)	5.52 (1.24)
Sorghum	medium to late	[2]4	[5]5.31	7.47 (0.57)	6.45 (1.21)	4.33 (1.16)
Pearl millet	early to medium	[3]4.3-5.6 (4.95)	[6]6.83	2.97 (1.47)	4.72 (0.77)	5.74 (1.59)

[1] Arathoon & Mtumtum (2013) [2] GAIN Report (2019) [3] GRAINSA (2021) [4] Akumaga et al. (2017) [5] Hadebe et al. (2017) [6] Bello & Walker (2016)

Table 6.9: Statistical comparison of the observed, provincial potential and simulated yield for AquaCrop, DSSAT and the SIMPLE model

Model performance	R^2	D-index	RMSE	NRMSE	MBE
Observed vs AquaCrop	0.99	-3.15	2.62	0.45	-0.22
Observed vs DSSAT	0.92	-18.13	1.39	0.24	-0.24
Observed vs SIMPLE	0.51	0.62	0.85	0.14	-0.69
Potential vs AquaCrop	0.03	0.27	2.87	0.47	-0.49
Potential vs DSSAT	0.003	-0.06	2.59	0.42	-0.51
Potential vs SIMPLE	0.27	0.36	2.35	0.38	-0.95
Observed vs Potential	0.06	-0.28	2.66	0.45	0.27

Except for NRMSE and according to the rest of the statistical indicators for yield, results suggested that there was a satisfactory agreement between AquaCrop-DSSAT and DSSAT-SIMPLE. There was a positive correlation for all the three models being compared against each other. The correlations (R^2) between AquaCrop-DSSAT, AquaCrop-SIMPLE and DSSAT-SIMPLE were 0.95, 0.58 and 0.78, respectively.

There were slight differences in model agreement across the different statistical indicators. For instance, good agreement was observed for yield simulated by AquaCrop-DSSAT (R^2 = 0.77). RMSE and NRMSE of 2.48 t/ha and 0.44 t/ha, respectively, for the comparison of AquaCrop and SIMPLE showed a higher deviation in this combination when compared with other comparisons in this study (**Table 6.9**).

There was a positive correlation in biomass for all the three models compared against each other. The comparison between AquaCrop and the SIMPLE model showed the highest R^2 of 0.98 and the comparison between DSSAT and SIMPLE had the lowest R^2 of 0.07. Biomass was simulated well in agreement of 0.42 for AquaCrop-DSSAT, 0.31 for AquaCrop-SIMPLE and 0.22 for DSSAT-SIMPLE. However, due to the high value of AI for AquaCrop and DSSAT, it was evident that this comparison was in more agreement of simulating biomass. Biomass was overestimated in AquaCrop comparison to SIMPLE by 1.03 t/ha, similarly with the comparison between DSSAT and SIMPLE by 0.80 t/ha. Meanwhile, AquaCrop underestimated biomass in comparison to DSSAT by 0.80 t/ha. RMSE and NRMSE of 6.14 t/ha and 0.37 t/ha, respectively, for the comparison of AquaCrop and SIMPLE, showed that there was a higher deviation in this combination when compared with other comparisons in this study (**Table 6.9**).

The results showed that there was a perfect coefficient (R^2 = 1) in water use simulated by AquaCrop-SIMPLE. The same positive relationship of R2 = 0.99 was observed for the comparison of AquaCrop-DSSAT and DSSAT-SIMPLE. AI as a statistical indicator showed that there was agreement for water use simulated by AquaCrop-DSSAT (0.27), AquaCrop-SIMPLE (0.14) and DSSAT-SIMPLE (0.54). There was an underestimation of water use for AquaCrop-DSSAT (-96.61 t/ha), AquaCrop-SIMPLE (-132.87 t/ha) and DSSAT-SIMPLE (-36.26 t/ha). RMSE and NRMSE of 146.59 t/ha and 0.26 t/ha, respectively, for the comparison of AquaCrop and SIMPLE, showed that there was a higher deviation in this combination when compared with other comparisons in this study. The least deviations (RMSE = 40.95 and NRMSE = 0.09) for water use were observed for the DSSAT-SIMPLE comparison (**Table 6.9**).

6.3.2 Yield

The highest mean yield was simulated by the AquaCrop model for maize (6.55 t/ha) and millet (7.47 t/ha). Meanwhile, for sorghum, SIMPLE simulated the highest mean yield of 5.74 t/ha. Yield simulations in AquaCrop had wider box plots for maize and sorghum, suggesting more yield variability. This was in line with the large standard deviation (±1.48 t/ha) observed for maize under AquaCrop. DSSAT had the shorter box plots suggesting less yield variability for both these crops. Contrary to this, for millet, greater yield variability was observed under DSSAT while the least variability was observed under the SIMPLE model (**Figure 6.5**). The DSSAT yield simulation for millet showed the most deviation from the mean by ±1.21 t/ha than other models. For sorghum yield simulated by the SIMPLE model, the highest standard deviation was ±1.59 t/ha (**Figure 6.6**). Across the simulation years, the Mann-Kendall trend analysis showed a significant ($P<0.05$) and positive trend (0.30) in yield for sorghum and a negative trend (-0.40 and -0.63) for maize and millet, respectively.

Coupled with AquaCrop 6.1, DSSAT 4.7.5 and SIMPLE 1.1, dynamically downscaled and bias-corrected climate projections for six GCMs forced by RCP 8.5 were used to simulate maize, millet and sorghum yields over the past, present, mid-, and late-centuries. The aim was to evaluate AquaCrop, DSSAT and SIMPLE's performance in simulating the impacts of climate change on yield, biomass, WU and WP of maize, millet, and sorghum.

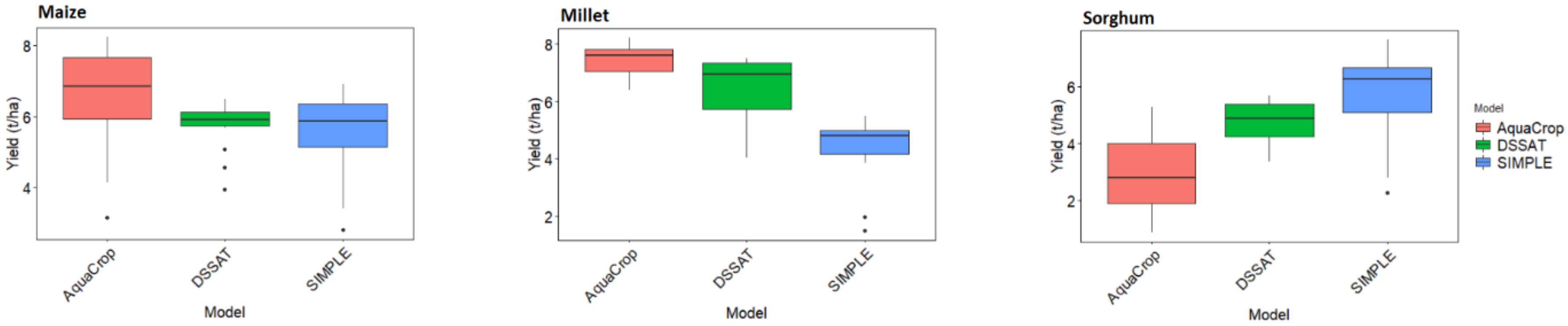


***Figure 6.5**: Yield for maize, millet and sorghum simulated by AquaCrop, DSSAT and SIMPLE*

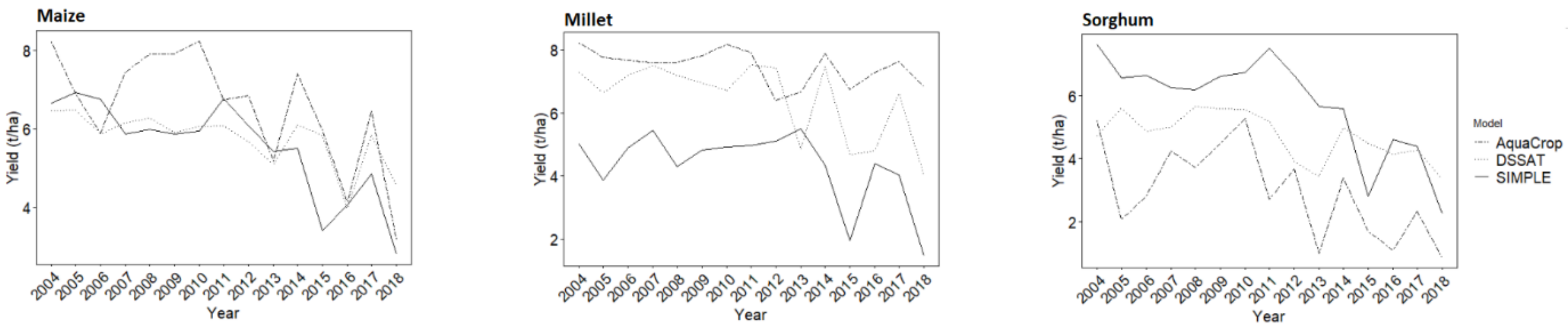


***Figure 6.6:** Yield for maize, millet and sorghum simulated by AquaCrop, DSSAT and SIMPLE from 2004-2018*

Across models, there were highly significant ($P<0.05$) differences for maize, millet, and sorghum yield. Yield simulations across all the crops under the SIMPLE model had wider box plots suggesting more yield variability. Contrary to this, DSSAT had the shorter box plots suggesting less yield variability, however only for millet and sorghum. Maize yield was less variable in AquaCrop (**Figure 6.7**). AquaCrop showed the highest simulated mean yield for maize (8.34 t/ha), millet (6.86 t/ha) and sorghum (5.28 t/ha) (Figure 4.3). SIMPLE simulated the lowest mean yield for maize (4.50 t/ha). Meanwhile, DSSAT simulated the lowest mean yield for millet (2.68 t/ha) and sorghum (3.84 t/ha). Across all the time scales, it was observed that AquaCrop simulated the highest yield, the SIMPLE model and DSSAT simulated the lowest yield across the GCMs, which were inconsistent. This highest value of 8.88 t/ha was observed in the late-century period for ACC in maize, and the lowest value of 2.45 t/ha was observed in the present-century period for GFD in millet.

The results showed no significant ($P>0.05$) differences across the GCMs for maize yield; an average of 6.04 t/ha with a standard deviation of 2.33 t/ha was observed. Highly significant differences ($P<0.05$) across GCMs were observed for millet (4.52 ± 2.12 t/ha) and sorghum (4.59 ± 1.82 t/ha). Across the time scale, there were significant differences ($P<0.05$) in maize and sorghum yield and no significant ($P>0.05$) differences in millet yield. The observed trend for simulated maize yield was past (5.76 ± 2.25) < present (6.02 ± 2.37) < late (6.17 ± 2.33) < mid-century (6.21 ± 2.35 t/ha). The observed trend for simulated millet yield was past (4.37 ± 2) < present (4.55 ± 2.08) < mid (4.56 ± 2.22) < late-century (4.60 ± 2.29 t/ha). The observed trend for simulated sorghum yield was past (4.38 ± 1.82) < late (4.62 ± 1.80) < present (4.69 ± 1.85) < mid-century (4.70 ± 1.88 t/ha). Across the past, present, mid-, and late-century period, the Mann-Kendall trend analysis showed a significant ($P<0.05$) and positive ($\tau = 0.05$) trend in yield for maize. On the other hand, no trend was detected in millet and sorghum yield.

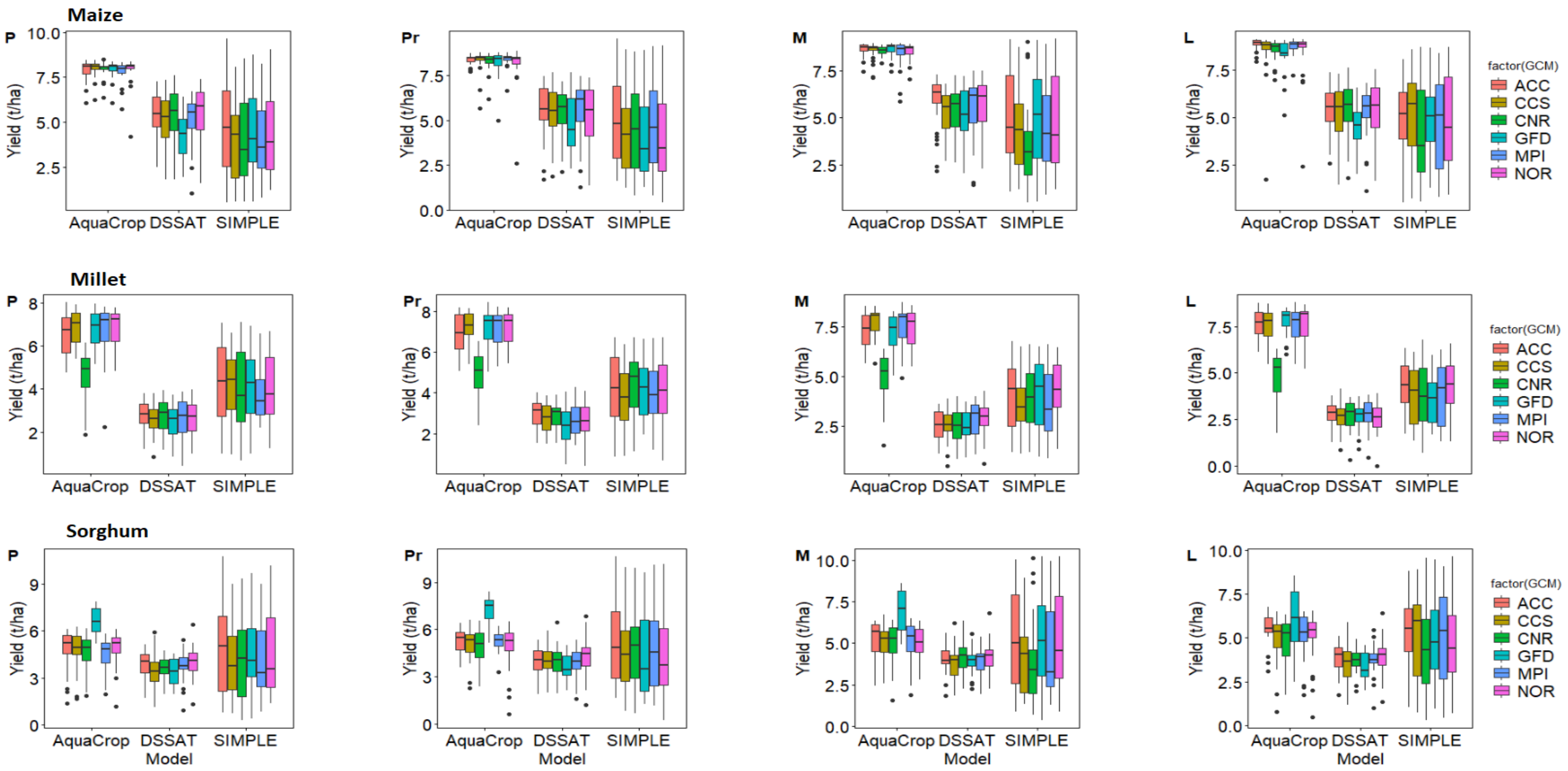


Figure 6.7: Simulated yield (t ha^{-1}) by AquaCrop, DSSAT and SIMPLE for maize, millet, and sorghum during four different time scales (past (P), present (Pr), mid-century (M) and late-century (L)) obtained from the six GCMs (ACC, CSS, CNR, GFD, NOR and MPI)

Across models, there were highly significant ($P<0.05$) differences for maize, millet, and sorghum yield (results not presented). Regardless of the irrigation intervals, yield simulations across all the crops under the SIMPLE model had wider box plots suggesting more yield variability. Contrary to this, DSSAT had the shorter box plots suggesting less yield variability, however only for millet and sorghum. Maize yield was less variable in AquaCrop (Figure 6.7). AquaCrop showed the highest simulated mean yield for maize (8.57 t/ha) and millet (6.10 t/ha). Meanwhile, the SIMPLE model simulated the highest mean yield for sorghum (7.15 t/ha). Across time, there were no significant ($P>0.05$) differences in millet yield. On the contrary, significant ($P<0.05$) differences in maize and sorghum yield were observed (results not presented). Throughout the 2030-2060 period, the Mann-Kendall trend analysis did not detect a maize and millet yield trend. However, a significant ($P<0.05$) and positive ($\tau = 0.04$) trend was observed for sorghum. The results showed no significant ($P>0.05$) differences across the GCMs for maize and millet yield (results not presented). For sorghum yield, a significant difference was observed across GCMs (results not presented).

When compared with the rainfed simulations, the results showed an increase in yield for all the crops due to irrigation. Further increases in yield were observed because of an increase in irrigation amount from 10 to 20 mm. It was observed that yield for maize was 6.21, 7.07 and 7.63 t/ha for rainfed, 10 mm and 20 mm of irrigation, respectively. Yield for millet was observed as 4.56, 4.91, and 4.93 t/ha for rainfed, 10 mm and 20 mm of irrigation, respectively. Yield for sorghum was observed as 4.70, 5.62, and 6.20 t/ha for rainfed, 10 mm and 20 mm of irrigation, respectively. Overall, there was a reduction in crop yield for all species when irrigation frequency was changed from 7 to 14 days. The highest reduction was observed for sorghum [0.61 t/ha (10.9%)] followed by maize [0.58 t/ha (8.21%)] and then millet [0.02 t/ha (4.07%)]. **Figure 6.8** depicts that the greatest improvements in maize and sorghum yield were observed under the SIMPLE model when an irrigation amount of 20 mm was applied every seven days. Indifferent to maize and sorghum, the highest yield was observed under AquaCrop when millet was rainfed.

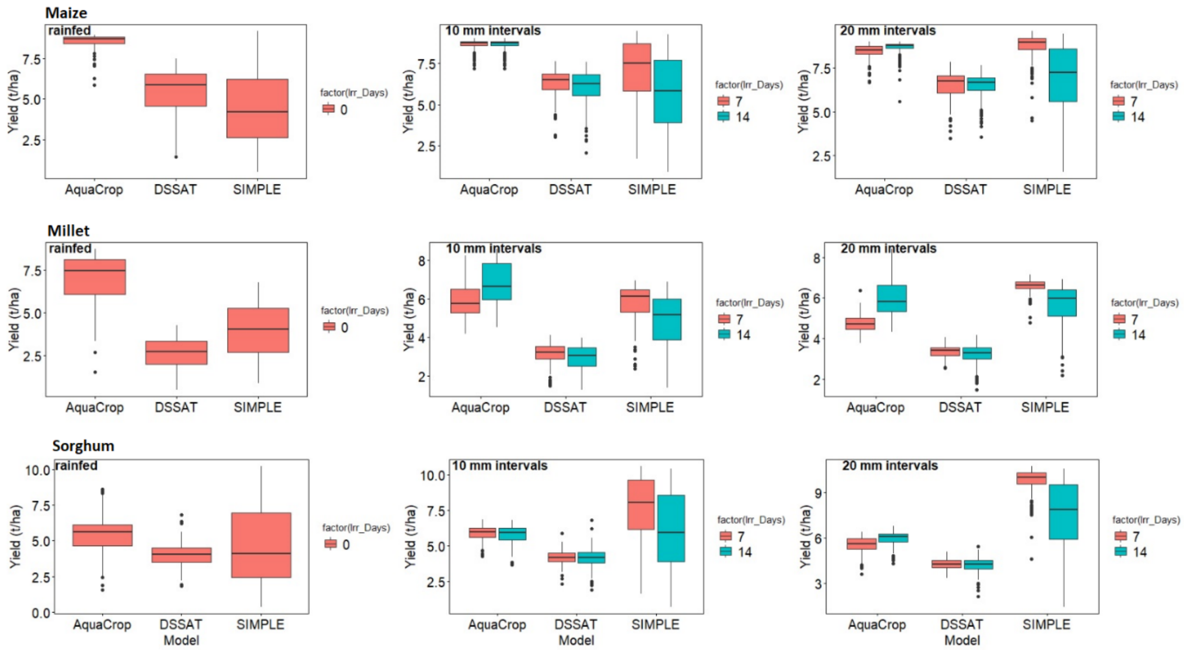


Figure 6.8: Yield for maize, millet and sorghum simulated by AquaCrop, DSSAT and the SIMPLE model under rainfed and irrigation (10 and 20 mm)

6.3.3 Biomass

The calculated mean for biomass showed that AquaCrop simulations attained the highest value for maize (16.78 t/ha) and millet (24.08 t/ha) and DSSAT for sorghum (14.69 t/ha). In Figure 3.5 the wider box plots shown by the AquaCrop model across maize and sorghum indicated that there was more variation in biomass. For millet, the variation in biomass was similar across the three models. Compared to other models, DSSAT showed less variability in biomass for maize and sorghum, as shown by thinner box plots. Analysing simulated biomass results showed large standard deviations for maize (3.11) and millet in SIMPLE (3.87) and for sorghum (4.03) in AquaCrop (Figure 3.5). Overall, the Mann-Kendall trend analysis did not detect a trend in biomass for sorghum. Overall significant ($P<0.05$) and negative trend was observed in simulated biomass for maize (τ = -0.66) and millet (τ = -0.37). For maize, the AquaCrop model depicted a negative trend for biomass from the year 2007-2011, while no clear trend was observed with biomass simulated with DSSAT and SIMPLE (Figure 6.9).

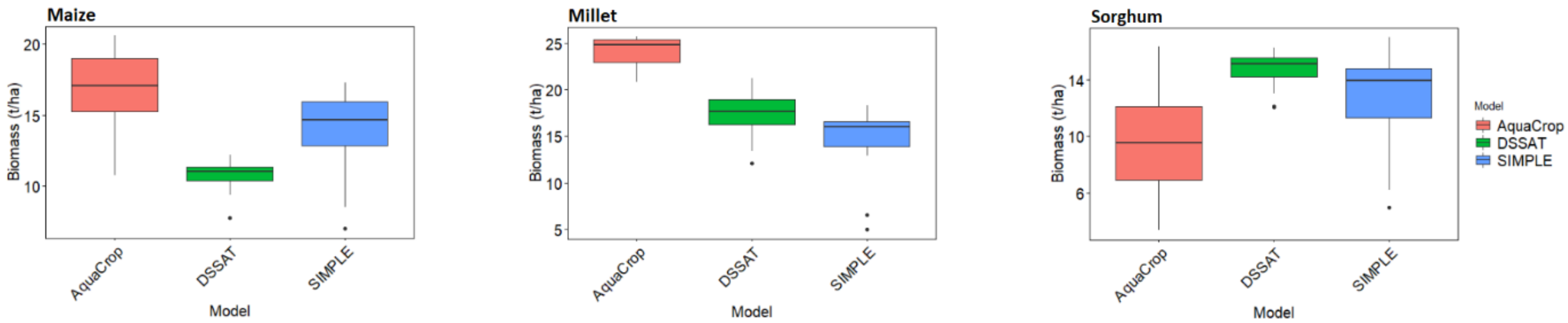


Figure 6.9: Biomass for maize, millet and sorghum simulated by AquaCrop, DSSAT and SIMPLE

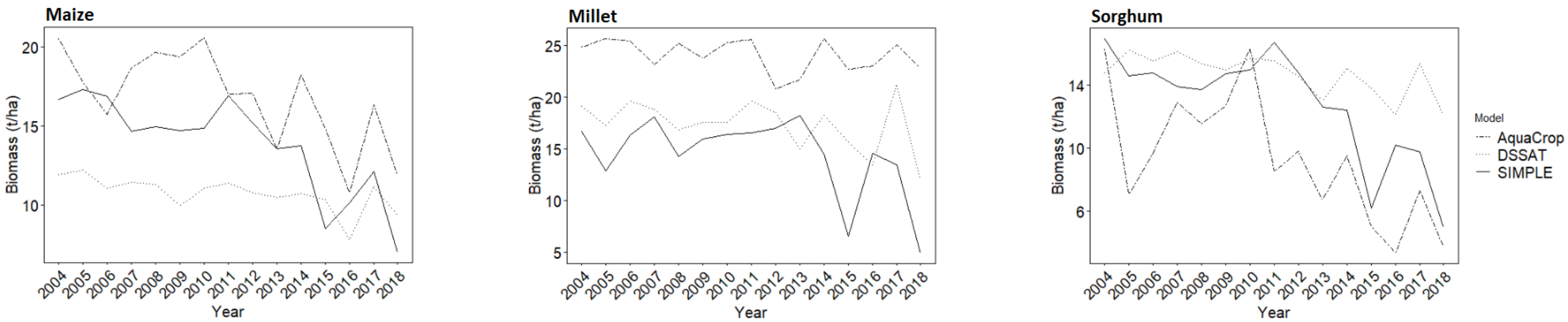


Figure 6.10: Biomass for maize, millet and sorghum simulated by AquaCrop, DSSAT and SIMPLE from 2004-2018Across models, there were highly significant (P<0.05) differences for maize, millet and sorghum biomass (Figure 4.4).

In **Figure 6.10**, the wider box plots shown by the SIMPLE model across maize, millet and sorghum deduced more variation in biomass. Compared to other models, DSSAT showed less variability in biomass for millet and sorghum as shown by thinner box plots. Meanwhile, less variations in maize biomass were observed in simulations by AquaCrop. AquaCrop showed the highest simulated mean biomass for maize (20.84 t/ha), millet (21.68 t/ha) and sorghum (16.04 t/ha). SIMPLE simulated the lowest mean biomass for sorghum (10.38 t/ha). Meanwhile, DSSAT simulated the lowest mean biomass for millet (12.63 t/ha) and maize (10.67 t/ha). Across the GCMs and time scales. it was observed that AquaCrop simulated the highest yield, the SIMPLE model and mostly DSSAT simulated the lowest yield for maize, millet and sorghum. The highest value of 24.83 t/ha was observed in the late-century period for GFD in millet, and the lowest value of 8.46 t/ha was observed in the mid-century period for CNR in sorghum.

There were no significant (P>0.05) differences across the GCMs for maize biomass. However, highly significant (P<0.05) differences were observed for millet and sorghum biomass. Across the GCMs, biomass trends for maize showed a gradual increase towards the late century when compared to the baseline. The observed trend for simulated maize biomass was late (14.72) > mid (14.53) > present (14.10) > past-century (13.66 t/ha). The observed trend for simulated millet biomass was mid-century (16.16) > late (16.11) > present (15.97) > past-century (15.35 t/ha). The observed trend for simulated sorghum biomass was mid (13.80) > present (13.73) > late (13.52) > past-century (12.86 t/ha). The observed trend was consistent with the observed increase in future yield. The Mann-Kendall trend analysis did not detect a trend in biomass for millet and sorghum. A significant (P<0.05) and positive (τ = 0.05) trend was observed in biomass for maize.

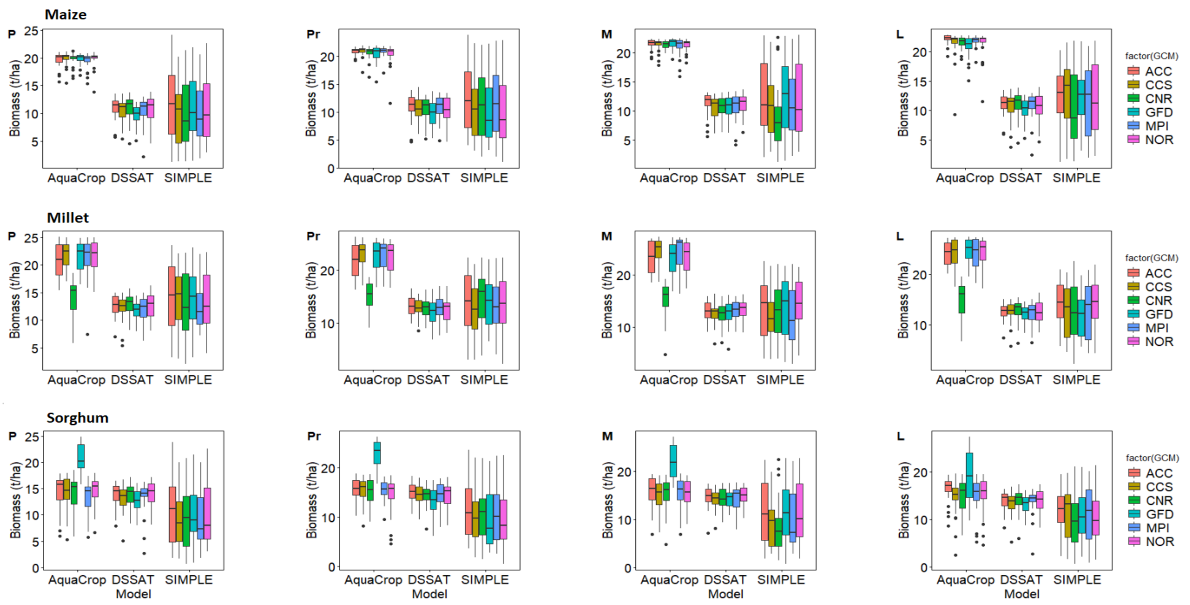


Figure 6.11: Simulated biomass (t ha^{-1}) by AquaCrop, DSSAT and SIMPLE for maize, millet, and sorghum during four different time scales (past (P), present (Pr), mid-century (M) and late-century (L)) obtained from the six GCMs (ACC, CSS, CNR, GFD, NOR and MPI)

Highly significant (P<0.05) differences were observed for maize, millet, and sorghum biomass across the models (results not presented). In **Figure 6.11**, the wider box plots shown by the SIMPLE model across maize, millet and sorghum shows that there was more variation in biomass. Compared to other models, DSSAT showed less variability in biomass for millet and sorghum, as shown by thinner box plots. Meanwhile, fewer variations in maize biomass were observed in simulations based on AquaCrop. The results showed no significant (P>0.05) differences across the GCMs for maize and significant differences for millet and sorghum biomass (results not presented). The average biomass for the GCMs ranged from 16.12-16.88 t/ha for maize with ACC yielding the highest results, 16.61-17.50 t/ha for millet with NOR yielding the highest results and 15.81-16.83 t/ha for sorghum with NOR yielding the highest results. Across time, there were no significant differences (P>0.05) in maize and millet biomass. Contrary to this, highly significant (P<0.05) differences in sorghum biomass over time were observed (results not presented). Across the 2030-2060 period, Mann Kendall trend analysis showed a significant (P<0.05) and positive trend for millet (τ = 0.02) and sorghum (τ = 0.04) biomass. Then, for maize, no trend in biomass was detected.

Similar to yield results, there were inconsistencies observed in biomass across time for all the crops.

An increase in biomass for all the species is observed due to irrigation (). Further increases in maize, millet and sorghum yield were observed because of an increase in irrigation amount from 10 to 20 mm. The biomass for maize was observed to be 14.53, 16.49 and 17.78 t/ha for rainfed, 10 and 20 mm in irrigation, respectively. The most significant increase of 9% in biomass was with sorghum, and the least significant increase of 0.63% was with millet for 10 and 20 mm, respectively. A reduction in biomass across all crop species for irrigation frequency increased from 7 to 14 days. Results showed that the reductions were, 8.33% (1.37 t/ha) in maize, 0.87% (0.15 t/ha) in millet and 9.26% (1.5 t/ha) in sorghum. Figure 5.2 depicts that the SIMPLE model biomass output showed the highest maize (21.88 t/ha), millet (22 t/ha) and sorghum (21.71 t/ha) for the irrigation amount of 20 mm frequented every after 7 days. Nonetheless, results further showed that high millet biomass was attained when the crop was rainfed (no irrigation) in AquaCrop.

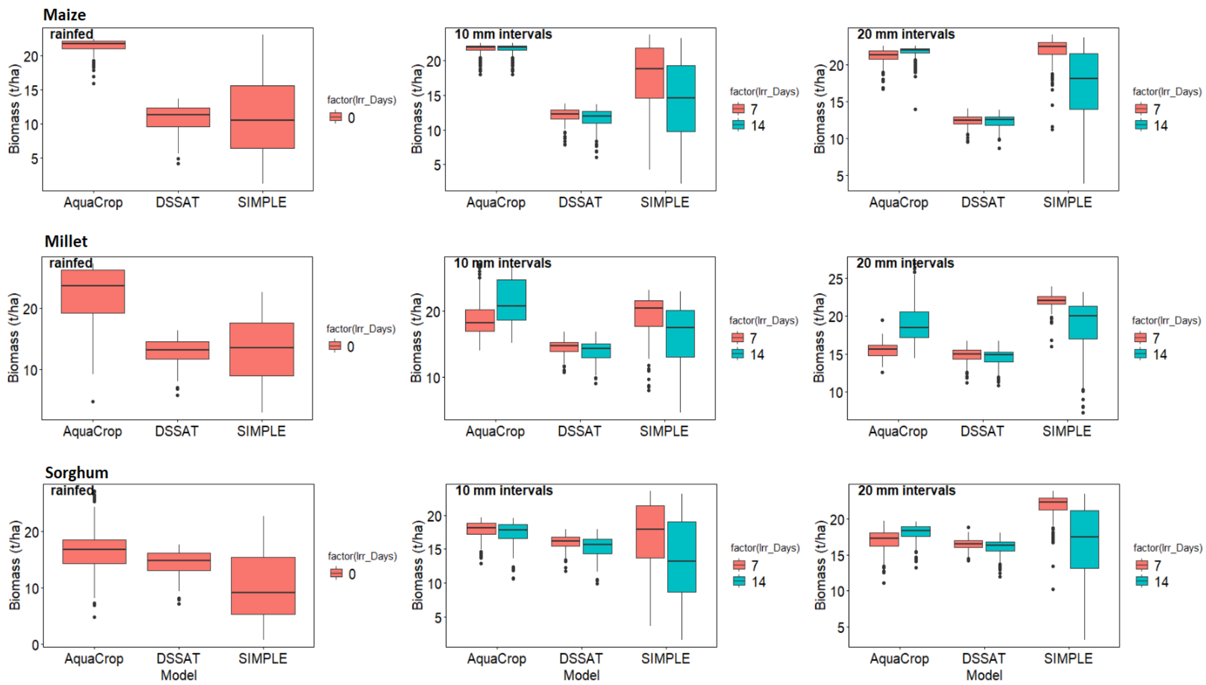
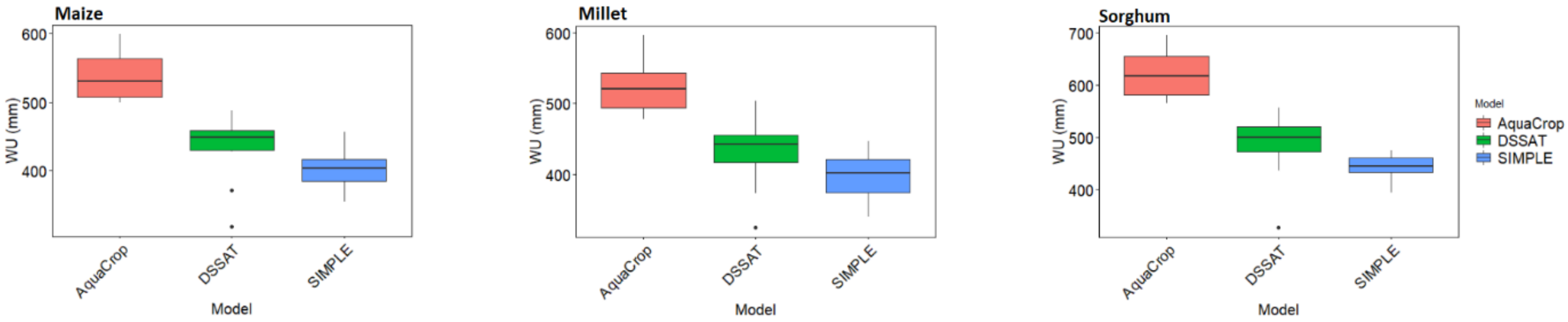


Figure 6.12: Biomass for maize, millet and sorghum simulated by AquaCrop, DSSAT and the SIMPLE model under rainfed and irrigation (10 and 20 mm)

6.3.4 Water productivity

The calculated mean for WPWP showed that SIMPLE simulations attained the highest value for maize (13.77 t/ha) and sorghum (12.89 t/ha) and DSSAT for millet (14.78 t/ha) (**Figure 6.13**). This observation was not consistent to the yield trends where the AquaCrop model simulated higher yield for maize and millet while, for sorghum, SIMPLE simulated the highest mean yield. The wider box plots shown by the AquaCrop model across maize and sorghum suggested that there was more variability in WPWP. Whereas for millet, more variability in WPWP was observed under DSSAT. Compared to other models, DSSAT depicted thinner box plots suggesting less variability in WP for maize and sorghum. This is consistent with the observed low variability in yield (**Figure 6.13**). The standard deviation calculated for WP infers that there was a high degree of standard deviation for millet (3.21) and sorghum (2.65) under the SIMPLE model, and for maize (3.16) under AquaCrop. The WP trend across all three models was consistent for maize from 2004-2018. The Mann-Kendall trend analysis showed a significant ($P<0.05$) and negative trend in WP of $\tau=-0.45$ for millet and a positive trend in WP of $\tau=0.42$ for sorghum.



WU for maize, millet and sorghum simulated by AquaCrop, DSSAT and SIMPLE

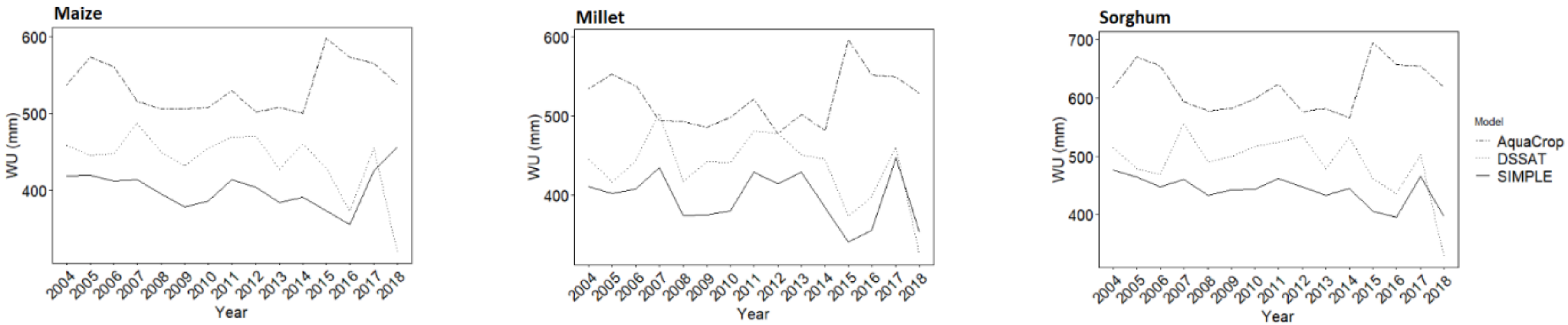


Figure 6.13: WU for maize, millet and sorghum simulated by AquaCrop, DSSAT and SIMPLE from 2004-2018

GFD simulated by AquaCrop showed a wider box plot in the late century for sorghum. The wider box plots shown by the SIMPLE model across maize, millet and sorghum suggested more variability in WP. Compared to other models, DSSAT depicted thinner box plots suggesting less variability in WP for millet and sorghum. While in WP for maize, less variations were observed in AquaCrop (**Figure 6.15**). Inconsistent results were observed in WP and WU for maize, millet, and sorghum across GCMs and models. It was depicted that the highest WP was observed under DSSAT for maize (24 kg/ha/mm) and the lowest under DSSAT for millet (5.89 kg/ha/mm). It was observed that the highest WP for GCMs was under NOR (18.04 kg/ha/mm) for maize and the lowest under CNR (8.49 kg/ha/mm) for millet. ACC predicted the highest water use (440.88 and 499.30 mm) for maize and sorghum, respectively, and CNR predicted the highest water use (445.78 mm) for millet. Meanwhile, the lowest water use predicted was under GFD (403.59 and 459.71 mm) for millet and sorghum, respectively, and NOR (354.53 mm) for maize.

There were no significant ($P>0.05$) differences in WU for maize and sorghum, while significant ($P<0.05$) differences were observed for millet across the time scale. Contrary to WU, it was observed that there were no significant ($P>0.05$) differences in WP for millet and maize, while sorghum was significantly ($P<0.05$) different. The Mann-Kendall trend analysis showed a significant ($P<0.05$) and positive ($\tau = 0.03$) trend in WU of 0.03 for sorghum. Meanwhile, in WP a significant ($P<0.05$) and positive ($\tau = 0.03$) trend was observed for maize. Additionally, the trend analysis did not detect a trend in WU for maize and millet, in WP for millet and sorghum.

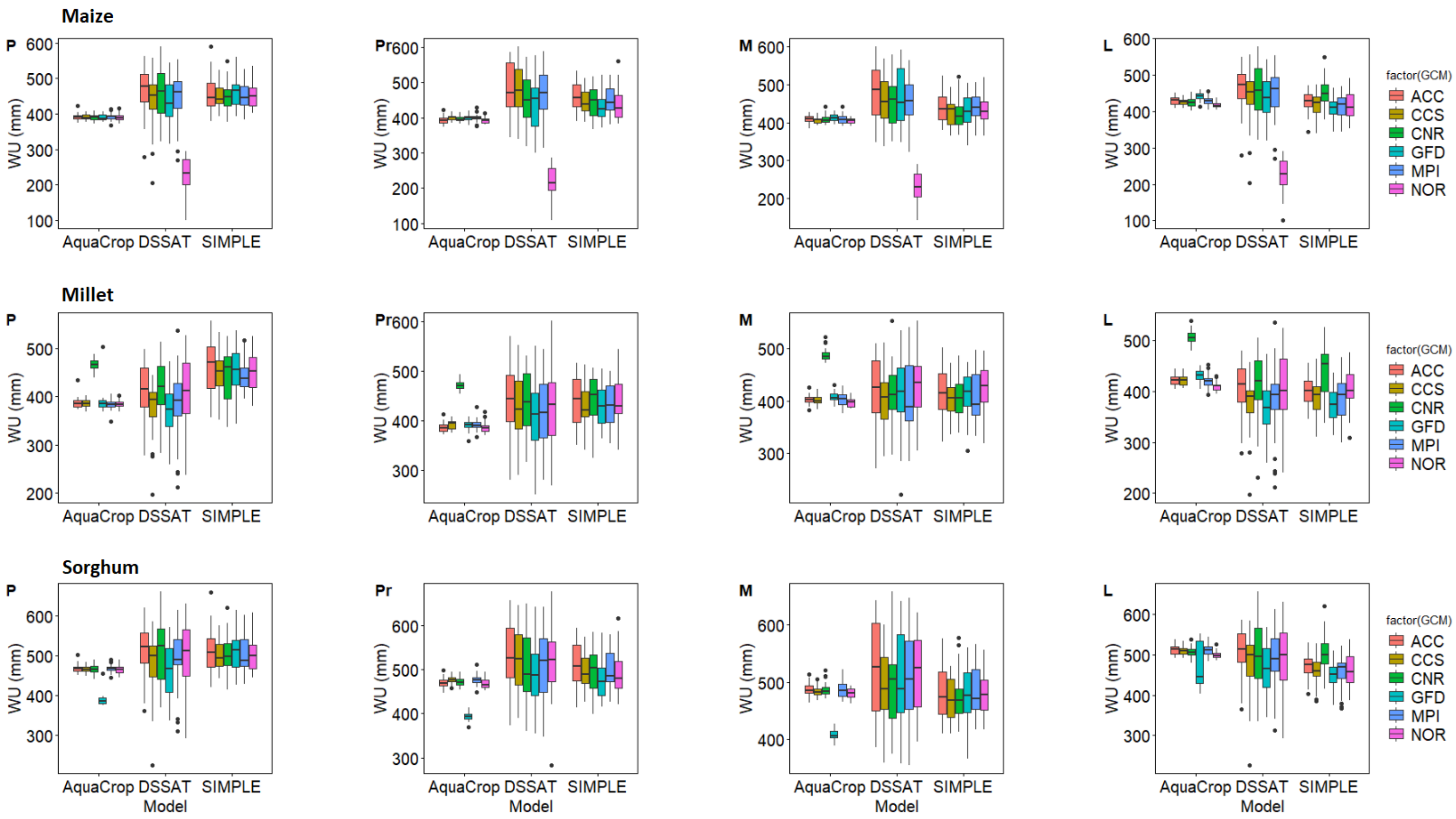


Figure 6.14: Simulated water use (mm) by AquaCrop, DSSAT and SIMPLE for maize, millet, and sorghum during four different time scales (past (P), present (Pr), mid-century (M) and late-century (L)) obtained from the six GCMs (ACC, CSS, CNR, GFD, NOR and MPI)

The Mann-Kendall trend analysis did not detect a trend in WU for maize and in WP for maize and millet. A significant ($P<0.05$) and a positive trend was observed in WU for millet (τ = 0.04) and sorghum (τ = 0.05). In WP, a significant ($P<0.05$) and positive (τ = 0.04) trend was also observed but only for sorghum. The wider box plots shown by the SIMPLE model across maize, millet and sorghum suggested more variability in WP. Compared to other models, DSSAT depicted thinner box plots suggesting less variability in WP for millet and sorghum. While in WP for maize, less variations were observed in AquaCrop (**Figure 6.15**).

ACC predicted the highest water use (475.67 and 536.53 mm) for maize and sorghum, respectively, and CNR predicted the highest water use (453.79 mm) for millet. Meanwhile, the lowest water use predicted was under GFD (442.47 and 523.66 mm) for millet and sorghum, respectively, and NOR (458.13 mm) for maize. The highest WP for GCMs was observed under ACC (15.90 kg/ha/mm) for maize and the lowest under CNR (10.43 kg/ha/mm) for sorghum. Inconsistencies of WU and WP were observed for maize, millet, and sorghum across GCMs and models. It was observed that the highest WU was observed under DSSAT for maize (530.73 mm), millet (487.90 mm) and sorghum (586.36 mm) (Figure 5.3). It was also observed that WU generated by AquaCrop remained constant for different irrigation amounts and days. It was depicted that the highest WP was observed under AquaCrop for maize (21 kg/ha/mm) and millet (15.10 kg/ha/mm), the SIMPLE model for sorghum (13.37 kg/ha/mm).

WP increased due to irrigation and an increase in irrigation amount, consistent with yield and WU. The results showed an increase in WP for maize and sorghum due to an increase in irrigation amount of 10 to 20 mm (**Figure 6.16**). Contrarily, there was a reduction in WP for millet due to an increase in irrigation amount. There was a reduction in WP for maize and sorghum, resulting from an increase in irrigation frequency of 7 to 14 days. Contrary, there was an increase in WP for millet resulting from an increase in irrigation frequency. Figure 5.4 depicts that the highest WP for maize (21.26 kg/ha/mm) was observed for AquaCrop than other models, irrigating with 10 mm every after seven days. Then, the highest WP for millet (16.85 kg/ha/mm) was observed for AquaCrop irrigating with 10 mm every after 14 days. However, compared to irrigation, rainfed millet showed the highest WP of 17.13 kg/ha/mm simulated by

AquaCrop. Lastly, the SIMPLE model output showed the highest sorghum (17.24 kg/ha/mm) WP for the irrigation amount of 20 mm frequented every after 7 days (**Figure 6.16**).

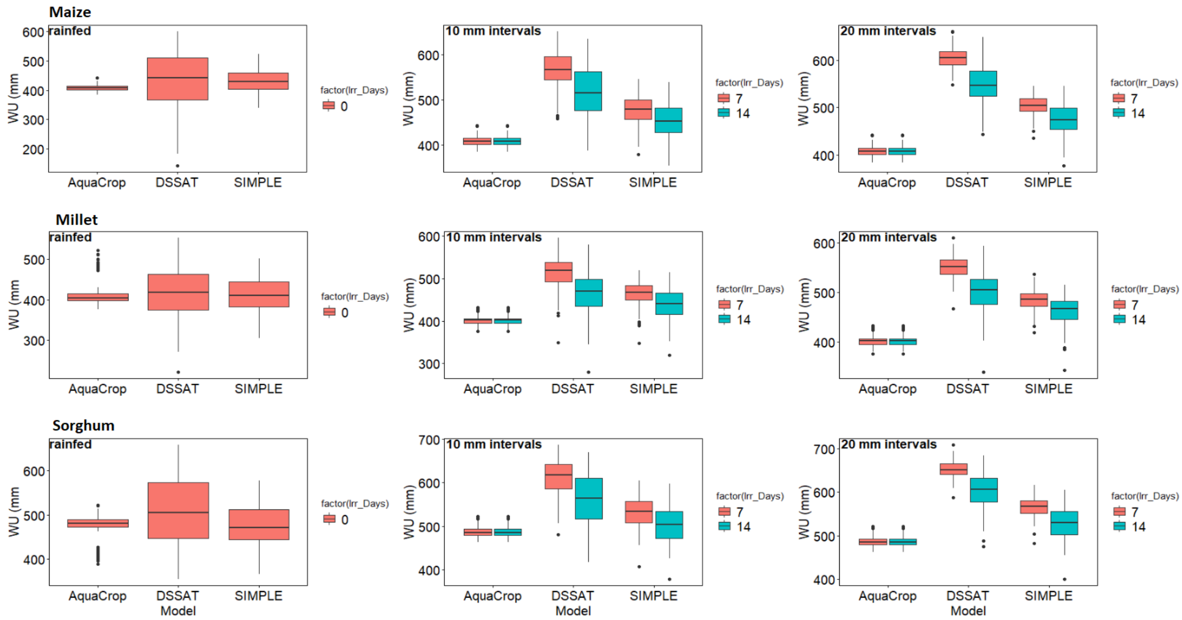


Figure 6.15: WU for maize, millet and sorghum simulated by AquaCrop, DSSAT and the SIMPLE model under no irrigation (0 mm) and irrigation (10 and 20 mm)

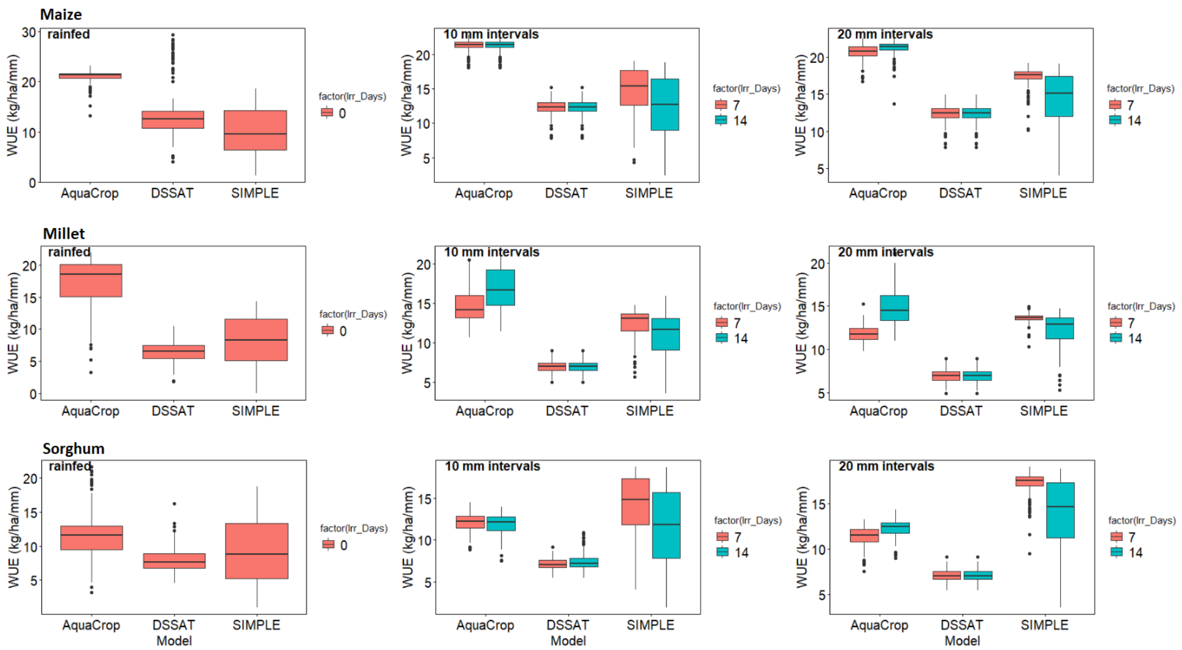


Figure 6.16: WP for maize, millet and sorghum simulated by AquaCrop, DSSAT and the SIMPLE model under rainfed and irrigation (10 and 20 mm)

6.4 Discussion

AquaCrop, DSSAT and SIMPLE were able to simulate yield, biomass and water use for selected NUS. However, the performance of the three models was observed to be statistically different across the simulated years and for the different crop species. The statistical indicators (R2 and MBE) for observed yield compared with simulated yield suggest that yield, biomass, and WU simulated by AquaCrop across the selected NUS was more satisfactory than when DSSAT and the SIMPLE model did simulations. High yield and biomass variability simulated for maize and sorghum under AquaCrop and millet under DSSAT could suggest that both these models were more sensitive to input parameters, and this sensitivity was crop-specific. Moreover, in line with statement by Manschadi et al. (2021), different simulated results in this study could be attributed to secondary data, different types of parameters, number of parameters, model types and algorithms. Similar to a study conducted by Timsina et al. (2008), the crop, soil, and climate inputs in this study have a degree of uncertainty associated with them due to random errors, bias in their measurement and calibration. Also, the three models used in the study were calibrated using secondary data that came from different sources; hence the simulated and observed results are different. The disadvantage of using secondary data is that there is a high likelihood that not all parameters were captured that were used in calibrating the models. Hence, when interpreting and extrapolating the model results, due consideration should be given to uncertainties arising from model structure, model parameters and inputs, and the experimental data used for model calibration, validation, and application (Timsina et al., 2008).

On the other hand, AquaCrop and the SIMPLE model was calibrated, and this means that the confidence in results for these models was improved, as the need to use default input values was minimised. The SIMPLE model used maize values embedded in the model for species parameters (CO2_RUE and S_Water) of the three crops; DSSAT used default files for the soil and crop data, suggesting that the confidence in results was low compared to AquaCrop and the SIMPLE model. Nevertheless, scientific processes and coefficients in AquaCrop, DSSAT and the SIMPLE model can never be complete, leading to uncertainties in model predictions (Timsina et al., 2008).

This is the case as perfect modelling can never be attained for real systems because models abstract reality.

The results indicate that AquaCrop, with a water-driven growth engine, is better than DSSAT and the SIMPLE model, with a solar energy-driven growth engine for biomass and yield simulation. DSSAT and the SIMPLE model differs from AquaCrop by calculating biomass accumulation based on RUE rather than normalized water productivity (WP*). (Albrizio & Steduto, 2005) showed high variability in RUE values but failed to normalize RUE by vapour pressure deficit to reduce climate variability. The conclusion made was that the robustness of RUE to simulate biomass in crop models was constrained. The follow-up studies also indicated that calculating biomass through WP* was more robust than RUE (Albrizio & Steduto, 2005; Steduto et al., 2009; Steduto et al., 2007) which agrees with the findings of this study.

In this study, AquaCrop was the only model previously calibrated for sorghum using soil and climate data for Ukulinga Research Farm. For DSSAT and the SIMPLE model, current simulations are done for climatic and soil conditions that might have been similar in agro-ecological classification but differed based on the year that the studies were performed. According to Asseng et al. (2013), conducting both model calibration and validation before their comparison provides more robust and reliable results. Furthermore, it is essential that there are good quality data sets to which researchers have full confidence for calibration and validation. Furthermore, previous model comparisons have shown that minimal calibration of crop models can lead to a high degree of uncertainty of yield estimates (Asseng et al., 2013; Palosuo et al., 2011; Rötter et al., 2012). Also, providing more detailed data for model calibration did not necessarily result in high model performance when applied to new situations.

Large number of input parameters resulted in large and confounding impacts on overall outputs. According to Babel et al. (2019), the performance of a model in any specific site depends on the fine-tuning of the parameters and sound validation under a range of conditions. This study confirms that DSSAT requires relatively more site-specific and crop variety-associated data, in which default files were used to accommodate for the unavailability of data. In contrast, AquaCrop is a simpler model with lesser soil and crop management data required as an input. Meanwhile, SIMPLE is a model which requires fewer input requirements in comparison to AquaCrop and DSSAT. There is limited data availability for NUS to parameterize complex models fully. The similarity in the performance of simpler models (i.e. SIMPLE and AquaCrop) and complex models (DSSAT) suggests that going forward, less complex models can be adopted to advance modelling of neglected and underutilized cereal crop productivity. Nonetheless, even with the use of simpler models, there is still a need for some input parameters to use in modelling NUS. Thus, standards and protocols for data collection must be formulated to attain the required quantity and quality of data.

Observing the past to late century, the median value of climate change projections for minimum and maximum temperatures for Ukulinga showed a consistent warming trend across all months. This suggests an increased probability of hot nights and longer and more frequent heatwaves, especially for maize. Furthermore, this may result in a faster accumulation of heat units and a reduction in growth duration and accumulation of photosynthesis and increased night-time respiration, resulting in reduced crop yield (Schlenker & Roberts, 2009). The warming trend across the selected timescales is consistent with projected trends for South Africa (Mangani et al., 2018).

AquaCrop, DSSAT and the SIMPLE model with varying complexity simulated yield, biomass and WU for maize, millet, and sorghum under changes in climate overtime. There is limited data availability for selected NUS to fully parameterize complex models. Thus, simpler models can be adopted to advance modelling on NUS as a similar performance is observed between simpler and complex models, Millet is generally sensitive to low temperatures at the seedling stage and flowering. High daytime temperatures are needed for the grain to mature. It germinates well at soil temperatures of 23 to 30 °C (DAFF, 2011). Maize is a warm-weather crop and is not grown in areas where the mean daily temperature is less than 19 ºC or where the mean of the summer months is less than 23 ºC. The critical temperature detrimentally affecting yield for maize is approximately 32 ºC (du Plessis, 2003). Sorghum is a warm-weather crop requiring a temperature of 27 to 30 ºC for optimum growth and development. However, the temperature can be as low as 21 ºC, without a dramatic effect on growth and yield (DAFF, 2010). Compared to maize, millet and sorghum are better adapted to high temperatures (DAFF, 2011), and thus, may be more resilient to projected increases in temperature (Choudhary et al., 2019).

The increase and reduction in MAP observed suggests an increase in the probability of extreme weather events such as drought and floods. The trend showed a reduction in rainfall across timescales in all GCMs. This indicates a reduction in future rainfall for the site relative to the baseline. Water availability for crop production will, therefore, be negatively affected. This suggests that it is imperative to identify crops with low levels of water use that could be introduced into the environment. The increase in ETo is consistent with the projected increase in minimum and maximum temperature and suggests increased crop water stress (Zhao et al., 2017). Differences in simulated WU across the GCMs could be that each climate model has been developed based on its assumptions and unique mathematical representations of physical climate system processes, providing different climate projections (Confalonieri et al., 2016).

Similar to work done by Roberts et al. (2017), this study presented a framework for comparing crop models that can improve prediction, clarify differences between models, and ultimately improve assumptions used in crop modelling and ascertain potential impacts of climate change. AquaCrop, DSSAT and the SIMPLE model responded differently to changes in climate change. AquaCrop showed the least variation in yield and biomass for maize, millet, and sorghum; this suggests that AquaCrop was not as sensitive to pick up changes in weather variables as compared to DSSAT. The results across the time scales, GCMs and models, verify that the climate change effect is substantial and may be difficult to capture entirely using simple process-based models (Roberts et al., 2017). The assessments of possible effects of climate changes are based on estimations. This is the case since crop models are not universal; they must choose the most appropriate model according to their objectives. Additionally, crop models cannot give accurate projections because of an inadequate understanding of natural processes and computer power limitation (Rauff & Bello, 2015).

There are differences in output components reported, and this may be due to yearly differences in climatic conditions of the Ukulinga Research Farm. To improve the predictive capacity of the models under a wide range of environmental conditions, there is a need for a better understanding and description of the fundamental processes in the various crop-soil-atmosphere sub-systems (i.e. associated modules or routines). This was illustrated in the current study for modelling yield and WU under different temperatures and rainfalls. The results simulated by AquaCrop, DSSAT and the SIMPLE model showed high yield for maize and sorghum under the mid-century period and millet under the late-century period. This suggests that under the continuous variability in climate, these crops will be better suited for production in periods in which the greatest improvement in yield is attained. Although the yield for sorghum was greater in the present century than in the late century, it was still evident that the trend results for maize, millet and sorghum were consistent with the increased probability of extreme weather events as drought and floods (Schulze, 2011). High yield and biomass variability were observed under the SIMPLE model, suggesting that it is more sensitive to climate variability.

AquaCrop, DSSAT and the SIMPLE model produced different crop performance predictions under a future climate, reflecting different biological or physical mechanisms at work within the model structures. These models cannot be correct and taking the mean of an ensemble of models may or may not improve the accuracy of predictions. The argument for ensemble modelling approaches has more traction in modelling global and regional weather systems. There is more fundamentally chaotic nature of global circulation models (Tebaldi & Knutti, 2007) but Keating (2020) was unconvinced that the same case applied in farming systems simulation. Keating (2020), then suggested that directing energy into understanding why differences in model performance under climate change are arising and then gathering data and evolving model structures or calibration would be a more useful way forward. Modelling the impacts of climate change and adaptation and mitigation options are essential. However, there are many limitations in the models' capabilities and understanding of these impacts and options. There is a need to address these uncertainties explicitly (Keating, 2020).

Overall results show that AquaCrop, DSSAT and the SIMPLE model was sensitive enough to simulate changes in yield due to added irrigation. Results imply that these models are suited for modelling the effects of irrigation management for the selected species. Numerous studies report that models become sensitive to a certain crop more than other crops. Thus, this further suggests that the SIMPLE model, DSSAT and AquaCrop could be used to predict biomass and yield with a high degree of reliability under various irrigation management strategies and specific to selected crops. Hence, these models are valuable tools to aid in decision-making for effective irrigation management strategies. The inconsistencies in yield and biomass across the mid-century period are attributed to changes in climate over time. Applying a higher amount of irrigation resulted in higher yield, biomass, and water use simulated by the three models. Additionally, irrigating more frequently resulted in higher yield, biomass, and water use. Hence, the simulation of different water management scenarios indicated that optimal irrigation management significantly improved the irrigation water use by adjusting the irrigation water applied. Nonetheless, AquaCrop is particularly well suited to simulating yield, biomass, and water use for selected NUS in different irrigation scheduling conditions.

There were reductions in yield by reducing irrigation frequency, suggesting that there were dry periods, and this implies that a shorter irrigation interval is more appropriate than a longer irrigation interval. WP with maize and millet is inconsistent with the relationship between these crops with yield and biomass. The reduction observed in WP for maize and millet is attributed to high amounts of water lost through unproductive means; Chimonyo & Mabhaudhi (2019) also reported this matter. Improvement in yield is more related to transpiration, and more water allows for carbon dioxide to be absorbed and oxygen to be transpired; hence improved yield is associated with improved water use, which is evident in this study. Water productivity (WP), which is the net benefits accrued per unit of water consumed (D. Molden et al., 2003), offers greater spatial and temporal stability and is a true efficacy parameter of the crop production process (Halsema & Vincent, 2012). The soil factors mainly drive the irrigation module, but each model interprets these factors and how the algorithm within the soil factors influences the soil water balance. Furthermore, the soil profile differs even if it is in the same area. The crop models consider only one point measured; hence, the models need more developments to accommodate this limitation.

For irrigation conditions in this study, the accuracy of DSSAT and the SIMPLE model with the Priestley-Taylor/Ritchie method for ET simulation was acceptable and close to AquaCrop. This suggests that the absence of relative humidity and wind speed among the model inputs does not limit the performance of DSSAT and the SIMPLE model under non-water stress conditions. Precise estimation of evapotranspiration (ET) constitutes the main basis for irrigation management (Qiu et al., 2019; Ran et al., 2017). In addition, better ET algorithms should demonstrate better performance in multiple aspects of the crop model simulation, not just in the ET simulation itself (Dejonge & Thorp, 2017; Thorp et al., 2019). A study conducted by Toumi et al. (2016) to validate AquaCrop showed that the precision rate for daily ET simulation was reliable overall.

The findings of this study are not in agreement with (Rogers & Alam, 1998), who verified that sorghum needs about 450-550 mm of water per growing season. Although the presented results support the potential of the AquaCrop, DSSAT and the SIMPLE model to incentivize farmers to enhance their irrigation practices, the soil proprieties must still be considered to ensure production while improving environmental sustainability (Malik & Dechmi, 2019). Overall, the three models can be used as a tool to develop the best irrigation management options for increased yield and WP for maize, millet, and sorghum under variability in rainfall and temperatures. There is a limited data availability for NUS to fully parameterize complex models. Simpler models (i.e. requiring lesser inputs) performed equally as well as the complex models in this study, suggesting that going forward, the less complex models can be adopted to advance modelling on NUS.

6.5 Conclusion

Three crop simulation models – AquaCrop (v 6.1), DSSAT (v 4.7.1) and SIMPLE (v 1.1) – were evaluated for their comparative performance for maize, millet and sorghum at Ukulinga Research Farm in Pietermaritzburg, South Africa. AquaCrop, DSSAT and the SIMPLE model simulated yield, biomass and water use for selected NUS. The presented results are based on several assumptions, and the predictions by the three models may be affected by a degree of uncertainty. These assumptions may have affected results and bias conclusions regarding estimates for yield, biomass, water use and WP. Further, the interactions between weather, soil characteristics, plant growth dynamics, and management alternatives may have affected simulation results. Despite the potential limitations, the AquaCrop, DSSAT and SIMPLE model can be used as decision support tools to assist farmers in producing NUS. However, based on the statistical differences, AquaCrop was observed as the better suitable model for simulating yield, biomass and water use for selected NUS. Further, the model can be used, and the results of this study extrapolated to other areas with similar climatic and soil environments in South Africa where crop, soil, weather, and management data are available. Even though the AquaCrop, DSSAT and SIMPLE model simulation results for sorghum showed a higher increase in yield for the present century compared to the late century, it can still be concluded that the yield and biomass of maize, millet and sorghum will increase in response to projected climate change as yield improvements were observed to be great in the mid-century for all the species. Additionally, projected climate change is expected to increase WP for maize, millet, and sorghum across the three models. AquaCrop, DSSAT and the SIMPLE model responded differently to changes in climate change; thus, the hypothesis is accepted. However, the dissimilar responsiveness of the three models suggests that AquaCrop is the better suitable model for simulating the impacts of climate change on selected NUS.

6.6 Reference

Acevedo, E., Hsiao, T.C. and Henderson, D.W., 1971. Immediate and subsequent growth responses of maize leaves to changes in water status. Plant Physiology, 48(5), pp.631-636.

Adam, M., Corbeels, M., Leffelaar, P.A., Van Keulen, H., Wery, J. and Ewert, F., 2012. Building crop models within different crop modelling frameworks. Agricultural Systems, 113, pp.57-63. https://doi.org/10.1016/j.agsy.2012.07.010

AgriSETA., 2018. Annual Report 2018/19.

Akinseye, F.M., Adam, M., Agele, S.O., Hoffmann, M.P., Traore, P.C.S. and Whitbread, A.M., 2017. Assessing crop model improvements through comparison of sorghum (sorghum bicolor L. moench) simulation models: a case study of West African varieties. Field Crops Research, 201, pp.19-31. https://doi.org/10.1016/j.fcr.2016.10.015

Akumaga, U., Tarhule, A. and Yusuf, A.A., 2017. Validation and testing of the FAO AquaCrop model under different levels of nitrogen fertilizer on rainfed maize in Nigeria, West Africa. Agricultural and Forest Meteorology, 232, pp.225-234. https://doi.org/10.1016/j.agrformet.2016.08.011

Albrizio, R. and Steduto, P., 2005. Resource use efficiency of field-grown sunflower, sorghum, wheat and chickpea: I. Radiation use efficiency. Agricultural and Forest Meteorology, 130(3-4), pp.254-268. https://doi.org/10.1016/j.agrformet.2005.03.009

Allen, R.G., Pereira, L.S., Raes, D. and Smith, M., 1998. Guidelines for computing crop water requirements-FAO Irrigation and drainage paper 56, FAO-Food and Agriculture Organisation of the United Nations, Rome (http://www. fao. org/docrep) ARPAV (2000), La caratterizzazione climatica della Regione Veneto, Quaderni per. Geophysics, 156, p.178.

Allison, P. D. and Goldstein, H., 2014. An introduction to statistical modelling.

Anothai, J., Soler, C.M.T., Green, A., Trout, T.J. and Hoogenboom, G., 2013. Evaluation of two evapotranspiration approaches simulated with the CSM-CERES-Maize model under different irrigation strategies and the impact on maize growth, development and soil moisture content for semi-arid conditions. Agricultural and Forest Meteorology, 176, pp.64-76. https://doi.org/10.1016/j.agrformet.2013.03.00

Arathoon, J. and Mtumtum, N., 2013. Maize cultivar recommendations.

Asseng, S., Ewert, F., Rosenzweig, C., Jones, J.W., Hatfield, J.L., Ruane, A.C., Boote, K.J., Thorburn, P.J., Rötter, R.P., Cammarano, D. and Brisson, N., 2013. Uncertainty in simulating wheat yields under climate change. Nature climate change, 3(9), pp.827-832. https://doi.org/10.1038/ncliamte1916

Azam-Ali, S.N., Crout, N.M.J. and Bradley, R.G., 1994. Perspectives in modelling resource capture by crops. In Resource capture by crops (pp. 125-148). Nottingham University Press Nottingham.

Azam-Ali, S.N., Sesay, A., Karikari, S.K., Massawe, F.J., Aguilar-Manjarrez, J., Bannayan, M. and Hampson, K.J., 2001. Assessing the potential of an underutilized crop – a case study using bambara groundnut. Experimental Agriculture, 37(4), pp.433-472.

Babel, M.S., Deb, P. and Soni, P., 2019. Performance evaluation of AquaCrop and DSSAT-CERES for maize under different irrigation and manure application rates in the Himalayan region of India. Agricultural Research, 8(2), pp.207-217. https://doi.org/10.1007/s40003-018-0366-y

Badu-Apraku, B. and Fakorede, M.A.B., 2017. Maize in Sub-Saharan Africa: importance and production constraints. In Advances in genetic enhancement of early and extra-early maize for Sub-Saharan Africa (pp. 3-10). Springer, Cham. https://doi.org/10.1007/978-3-319-64852-1_

Beinart, W. and Delius, P., 2018. Smallholders and land reform: A realistic perspective.

Bello, Z.A. and Walker, S., 2016. Calibration and validation of AquaCrop for pearl millet (Pennisetum glaucum). Crop and Pasture Science, 67(9), pp.948-960. https://doi.org/10.1071/CP15226

Bellocchi, G., Rivington, M., Donatelli, M. and Matthews, K., 2011. Validation of biophysical models: Issues and methodologies. In Sustainable Agriculture Volume 2 (pp. 577-603). Springer, Dordrecht. https://doi.org/10.1051/agro/2009001

Boote, K.J., Jones, J.W. and Pickering, N.B., 1996. Potential uses and limitations of crop models. Agronomy journal, 88(5), pp.704-716.

Boote, K.J., Jones, J.W., Hoogenboom, G. and White, J.W., 2010. The role of crop systems simulation in agriculture and environment. International Journal of Agricultural and Environmental Information Systems (IJAEIS), 1(1), pp.41-54. https://doi.org/10.4018/jaeis.2010101303

Boote, K.J., Jones, J.W., White, J.W., Asseng, S. and Lizaso, J.I., 2013. Putting mechanisms into crop production models. Plant, cell & environment, 36(9), pp.1658-1672. https://doi.org/10.1111/pce.12119

Cai, X., Yang, Y.C.E., Ringler, C., Zhao, J. and You, L., 2011. Agricultural water productivity assessment for the Yellow River Basin. Agricultural water management, 98(8), pp.1297-1306.

Calera, A., Martínez, C. and Meliá, J., 2001. A procedure for obtaining green plant cover: relation to NDVI in a case study for barley. International Journal of Remote Sensing, 22(17), pp.3357-3362. https://doi.org/10.1080/01431160010020100

Cannon, A.J., Sobie, S.R. and Murdock, T.Q., 2015. Bias correction of GCM precipitation by quantile mapping: how well do methods preserve changes in quantiles and extremes?. Journal of Climate, 28(17), pp.6938-6959. https://doi.org/10.1175/JCLI-D-14-00754.1

Carlson, T.N. and Ripley, D.A., 1997. On the relation between NDVI, fractional vegetation cover, and leaf area index. Remote sensing of Environment, 62(3), pp.241-252. https://doi.org/10.1016/S0034-4257(97)00104-1

Chatfield, C., 1995. Model uncertainty, data mining and statistical inference. Journal of the Royal Statistical Society: Series A (Statistics in Society), 158(3), pp.419-444.

Chibarabada, T.P., Modi, A.T. and Mabhaudhi, T., 2020. Calibration and evaluation of aquacrop for groundnut (Arachis hypogaea) under water deficit conditions. Agricultural and Forest Meteorology, 281, p.107850. https://doi.org/10.1016/j.agrformet.2019.107850

Chimonyo, V.G.P., Modi, A.T. and Mabhaudhi, T., 2016. Simulating yield and water use of a sorghum-cowpea intercrop using APSIM. Agricultural Water Management, 177, pp.317-328. https://doi.org/10.1016/j.agwat.2016.08.021
Chimonyo, V.G.P., Modi, A.T. and Mabhaudhi, T., 2016. Simulating yield and water use of a sorghum-cowpea intercrop using APSIM. Agricultural Water Management, 177, pp.317-328. https://doi.org/10.1016/j.agwat.2016.08.021
Chimonyo, V.G.P., Modi, A.T. and Mabhaudhi, T., 2019. Applying APSIM for evaluating intercropping under rainfed conditions: a preliminary assessment. In 3rd World Irrigation Forum (WIF3).

Chimonyo, V.G., Wimalasiri, E.M., Kunz, R.P., Modi, A.T. and Mabhaudhi, T., 2020. Optimizing traditional cropping systems under climate change: A case of maize landraces and Bambara groundnut. Frontiers in Sustainable Food Systems, p.186. https://doi.org/10.3389/fsufs.2020.562568

Chisanga, C.B., Phiri, E. and Chinene, V.R., 2017. Climate change impact on maize (Zea mays L.) yield using crop simulation and statistical downscaling models: A review. Scientific Research and Essays, 12(18), pp.167-187. https://doi.org/10.5897/SRE2017.6521

Chivenge, P., Mabhaudhi, T., Modi, A.T. and Mafongoya, P., 2015. The potential role of neglected and underutilised crop species as future crops under water scarce conditions in Sub-Saharan Africa. International journal of environmental research and public health, 12(6), pp.5685-5711. https://doi.org/10.3390/ijerph120605685

Choudhary, S., Guha, A., Kholova, J., Pandravada, A., Messina, C.D., Cooper, M. and Vadez, V., 2020. Maize, sorghum, and pearl millet have highly contrasting species strategies to adapt to water stress and climate change-like conditions. Plant Science, 295, p.110297. https://doi.org/10.1016/j.plantsci.2019.11029

Confalonieri, R., Orlando, F., Paleari, L., Stella, T., Gilardelli, C., Movedi, E., Pagani, V., Cappelli, G., Vertemara, A., Alberti, L. and Alberti, P., 2016. Uncertainty in crop model predictions: what is the role of users?. Environmental Modelling & Software, 81, pp.165-173. https://doi.org/10.1016/j.envsoft.2016.04.009

Corbeels, M., Chirat, G., Messad, S. and Thierfelder, C., 2016. Performance and sensitivity of the DSSAT crop growth model in simulating maize yield under conservation agriculture. European Journal of Agronomy, 76, pp.41-53. https://doi.org/10.1016/j.eja.2016.02.001

Crétat, J., Pohl, B., Richard, Y. and Drobinski, P., 2012. Uncertainties in simulating regional climate of Southern Africa: sensitivity to physical parameterizations using WRF. Climate dynamics, 38(3), pp.613-634. https://doi.org/10.1007/s00382-011-1055-8

DAFF., 2010. Sorghum: production guideline.

DAFF., 2011. Pearl millet: production guideline.

DAFF., 2014. Pearl millet. Department of Agriculture, Forestry and fisheries.

Dai, A., 2013. Increasing drought under global warming in observations and models. Nature climate change, 3(1), pp.52-58. https://doi.org/10.1038/nclimate1633
de la Casa, A., Ovando, G., Bressanini, L. and Martínez, J., 2013. Aquacrop model calibration in potato and its use to estimate yield variability under field conditions. https://doi.org/10.4236/acs.2013.33041
De Wit, C.T. and Penning de Vries, F.W.T., 1985. Predictive models in agricultural production. Philosophical Transactions of the Royal Society of London. B, Biological Sciences, 310(1144), pp.309-315.
DEA., 2016. South Africa's First Climate Change Annual Report – 2015.
DeJonge, K.C. and Thorp, K.R., 2017. Implementing standardized reference evapotranspiration and dual crop coefficient approach in the DSSAT cropping system model. Transactions of the ASABE, 60(6), pp.1965-1981.
Dias, M.P.N.M., Navaratne, C.M., Weerasinghe, K.D.N. and Hettiarachchi, R.H.A.N., 2016. Application of DSSAT crop simulation model to identify the changes of rice growth and yield in Nilwala river basin for mid-centuries under changing climatic conditions. Procedia Food Science, 6, pp.159-163. https://doi.org/10.1016/j.profoo.2016.02.039
Diepen, C.V., Wolf, J.V., Van Keulen, H. and Rappoldt, C., 1989. WOFOST: a simulation model of crop production. Soil use and management, 5(1), pp.16-24.
Doorenbos, J. and Kassam, A.H., 1979. Yield response to water. Irrigation and drainage paper, 33, p.257.
Dourado-Neto, D., Teruel, D.A., Reichardt, K., Nielsen, D.R., Frizzone, J.A. and Bacchi, O.O.S., 1998. Princípios de modelagem e simulação: I. uso de modelos matemáticos em agricultura. Scientia Agricola, 55(spe), pp.46-50. https://doi.org/10.1590/S0103-90161998000500008
DSSAT., 2021. DSSAT overview. Https://dssat.net/
Du Plessis, J., 2003. Maize production (pp. 1-38). Pretoria, South Africa: Department of Agriculture.
Engelbrecht, F.A., McGregor, J.L. and Engelbrecht, C.J., 2009. Dynamics of the Conformal-Cubic Atmospheric Model projected climate-change signal over southern Africa. International Journal of Climatology: A Journal of the Royal Meteorological Society, 29(7), pp.1013-1033. https://doi.org/10.1002/joc
Evers, J.B., Letort, V., Renton, M. and Kang, M., 2018. Computational botany: advancing plant science through functional-structural plant modelling. Annals of Botany, 121(5), pp.767-772. https://doi.org/10.1093/aob/mcy050
Ewert, F., Van Ittersum, M.K., Heckelei, T., Therond, O., Bezlepkina, I. and Andersen, E., 2011. Scale changes and model linking methods for integrated assessment of agri-environmental systems. Agriculture, Ecosystems & Environment, 142(1-2), pp.6-17. https://doi.org/10.1016/j.agee.2011.05.016
FAO., 2017. AquaCrop training handbooks Book I . Understanding AquaCrop.
FAO., 2017. The state of food and agriculture.

FAO., 2018. FAO publications catalogue 2018.
FAO., 2018. FAOSTAT online database. http://www.fao.org/faostat/en/#data/QC
Farahani, H.J., Izzi, G. and Oweis, T.Y., 2009. Parameterization and evaluation of the AquaCrop model for full and deficit irrigated cotton. Agronomy journal, 101(3), pp.469-476. https://doi.org/10.2134/agronj2008.0182s
Faures, J. M., Bartley, D., Bazza, M., Burke, J., Hoogeveen, J., Soto, D. and Steduto, P., 2013. Climate smart agriculture sourcebook.
Folberth, C., Gaiser, T., Abbaspour, K.C., Schulin, R. and Yang, H., 2012. Regionalization of a large-scale crop growth model for sub-Saharan Africa: Model setup, evaluation, and estimation of maize yields. Agriculture, ecosystems & environment, 151, pp.21-33. https://doi.org/10.1016/j.agee.2012.01.026
Foster, T., Brozović, N. and Butler, A.P., 2014. Modeling irrigation behavior in groundwater systems. Water resources research, 50(8), pp.6370-6389. https://doi.org/10.1002/2014WR015620.
Foster, T., Brozović, N., Butler, A.P., Neale, C.M.U., Raes, D., Steduto, P., Fereres, E. and Hsiao, T.C., 2017. AquaCrop-OS: An open source version of FAO's crop water productivity model. Agricultural Water Management, 181, pp.18-22. https://doi.org/10.1016/j.agwat.2016.11.015
France, J., 1984. Mathematical models in agriculture; a quantitative approach to problems in agriculture and related sciences (No. 04; S494. 5. M3, F7.).
Fraser, E.D., Simelton, E., Termansen, M., Gosling, S.N. and South, A., 2013. “Vulnerability hotspots”: Integrating socio-economic and hydrological models to identify where cereal production may decline in the future due to climate change induced drought. Agricultural and Forest Meteorology, 170, pp.195-205. https://doi.org/10.1016/j.agrformet.2012.04.008
Gain, R., 2019. The South African sorghum market.
García-Vila, M. and Fereres, E., 2012. Combining the simulation crop model AquaCrop with an economic model for the optimization of irrigation management at farm level. European Journal of Agronomy, 36(1), pp.21-31.
García-Vila, M. and Fereres, E., 2012. Combining the simulation crop model AquaCrop with an economic model for the optimization of irrigation management at farm level. European Journal of Agronomy, 36(1), pp.21-31. https://doi.org/10.1016/j.eja.2011.08.003
Geerts, S., Raes, D., Garcia, M., Miranda, R., Cusicanqui, J.A., Taboada, C., Mendoza, J., Huanca, R., Mamani, A., Condori, O. and Mamani, J., 2009. Simulating yield response of quinoa to water availability with AquaCrop. Agronomy Journal, 101(3), pp.499-508. https://doi.org/10.2134/agronj2008.0137s
Geng, S., Auburn, J., Brandstetter, E. and Li, B., 1988. A program to simulate meteorological variables: documentation for SIMMETEO. Agronomy Progress Rep, 204

Geng, S., De Vries, F.W.P. and Supit, I., 1986. A simple method for generating daily rainfall data. Agricultural and Forest meteorology, 36(4), pp.363-376. https://doi.org/10.1016/0168-1923(86)90014-6

GRAINSA., 2021. Integrated crop and pasture-based livestock production systems – Part 10: Pearl millet (Pennisetum glaucum). https://www.grainsa.co.za/integrated-crop-and-pasture-based-livestock-production-systems---part-10

Grassini, P., Thorburn, J., Burr, C. and Cassman, K.G., 2011. High-yield irrigated maize in the Western US Corn Belt: I. On-farm yield, yield potential, and impact of agronomic practices. Field crops research, 120(1), pp.142-150. https://doi.org/10.1016/j.fcr.2010.09.012

Greaves, G.E. and Wang, Y.M., 2016. Assessment of FAO AquaCrop model for simulating maize growth and productivity under deficit irrigation in a tropical environment. Water, 8(12), p.557. https://doi.org/10.3390/w8120557

Hadebe, S.T., Modi, A.T. and Mabhaudhi, T., 2017. Calibration and testing of AquaCrop for selected sorghum genotypes. Water SA, 43(2), pp.209-221. https://doi.org/10.4314/wsa.v43i2.05

Halsema, G.E. and Vincent, L., 2012. Efficiency and productivity terms for water management: A matter of contextual relativism versus general absolutism. Agricultural Water Management, 108, pp.9-15. https://doi.org/10.1016/j.agwat.2011.05.016

Hanks, R.J., 1983. Yield and water-use relationships: An overview. Limitations to efficient water use in crop production, pp.393-411.

Hardy, M., Dziba, L., Kilian, W. and Tolmay, J., 2011. Rainfed Farming Systems in South Africa. In P. Tow, I. Cooper, I. Partridge, C. Birch, & (Eds.). Rainfed Farming Systems. Springer Netherlands.

Hassan, A.A. and Hassan, S.A., 2006. Study of Chemical Treatment Effect on Chemical Composition and In Vitro Digestibility for Dried Date Palm Frond. Jordan Journal of Agricultural Sciences.

Hassan, M.J., Nawab, K. and Ali, A., 2007. Response of Specific Leaf Area (SLA), Leaf Area Index (LAI) and Leaf Area Ratio (LAR) of Maize (Zea mays L.) to plant density, rate and timing of nitrogen application.

Heng, L.K., Hsiao, T., Evett, S., Howell, T. and Steduto, P., 2009. Validating the FAO AquaCrop model for irrigated and water deficient field maize. Agronomy journal, 101(3), pp.488-498. https://doi.org/10.2134/agronj2008.0029xs

Hsiao, T.C., Heng, L., Steduto, P., Rojas-Lara, B., Raes, D. and Fereres, E., 2009. AquaCrop – the FAO crop model to simulate yield response to water: III. Parameterization and testing for maize. Agronomy Journal, 101(3), pp.448-459. https://doi.org/10.2134/agronj2008.0218s

Ince, D.C., Hatton, L. and Graham-Cumming, J., 2012. The case for open computer programs. Nature, 482(7386), pp.485-488. https://doi.org/10.1038/nature10836

Jiang, Z., Huete, A.R., Chen, J., Chen, Y., Li, J., Yan, G. and Zhang, X., 2006. Analysis of NDVI and scaled difference vegetation index retrievals of vegetation fraction. Remote sensing of environment, 101(3), pp.366-378. https://doi.org/10.1016/j.rse.2006.01.003

Johnson, L.F. and Trout, T.J., 2012. Satellite NDVI assisted monitoring of vegetable crop evapotranspiration in California's San Joaquin Valley. Remote Sensing, 4(2), pp.439-455. https://doi.org/10.3390/rs4020439

Jones, J.W., Hoogenboom, G., Porter, C.H., Boote, K.J., Batchelor, W.D., Hunt, L.A., Wilkens, P.W., Singh, U., Gijsman, A.J. and Ritchie, J.T., 2003. The DSSAT cropping system model. European journal of agronomy, 18(3-4), pp.235-265. https://doi.org/10.1016/S1161-0301(02)00107-7

Jones, J.W., Antle, J.M., Basso, B., Boote, K.J., Conant, R.T., Foster, I., Godfray, H.C.J., Herrero, M., Howitt, R.E., Janssen, S. and Keating, B.A., 2017. Brief history of agricultural systems modeling. Agricultural systems, 155, pp.240-254. https://doi.org/10.1016/j.agsy.2016.05.014

Jones, J.W., Antle, J.M., Basso, B., Boote, K.J., Conant, R.T., Foster, I., Godfray, H.C.J., Herrero, M., Howitt, R.E., Janssen, S. and Keating, B.A., 2017. Toward a new generation of agricultural system data, models, and knowledge products: State of agricultural systems science. Agricultural systems, 155, pp.269-288. https://doi.org/10.1016/j.agsy.2016.09.021

Kadiyala, M.D.M., Nedumaran, S., Singh, P., Chukka, S., Irshad, M.A. and Bantilan, M.C.S., 2015. An integrated crop model and GIS decision support system for assisting agronomic decision making under climate change. Science of the Total Environment, 521, pp.123-134. https://doi.org/10.1016/j.scitotenv.2015.03.097

Kalaba, M., Meyer, F., Kirsten, J., Matoti, B., Troskie, D., Vink, N., Boonzaaier, J., Associates, B., Louw Hettie Schönfeldt, M., Greyling, P., Mazungunye, C., Punt, J. and Van Rooyen, J., 2018. BFAP Baeline Agricultural Outlook 2018-2027..

Karunaratne, A.S., Azam-Ali, S.N., Izzi, G. and Steduto, P., 2011. Calibration and validation of FAO-AquaCrop model for irrigated and water deficient bambara groundnut. Experimental Agriculture, 47(3), pp.509-527. https://doi.org/10.1017/S001447971100011

Karunaratne, A.S., Walker, S. and Azam-Ali, S.N., 2015. Assessing the productivity and resource-use efficiency of underutilised crops: Towards an integrative system. Agricultural Water Management, 147, pp.129-134. https://doi.org/10.1016/j.agwat.2014.08.002

Keating, B.A., 2020. Crop, soil and farm systems models – science, engineering or snake oil revisited. Agricultural Systems, 184, p.102903. https://doi.org/10.1016/j.agsy.2020.102903

Keating, B.A. and Thorburn, P.J., 2018. Modelling crops and cropping systems – Evolving purpose, practice and prospects. European Journal of Agronomy, 100, pp.163-176. https://doi.org/10.1016/j.eja.2018.04.007

Kephe, P.N., Ayisi, K.K. and Petja, B.M., 2021. Challenges and opportunities in crop simulation modelling under seasonal and projected climate change scenarios for crop production in South Africa. Agriculture & Food Security, 10(1), pp.1-24. https://doi.org/10.1186/s40066-020-00283-5

Kim, D. and Kaluarachchi, J., 2015. Validating FAO AquaCrop using Landsat images and regional crop information. Agricultural Water Management, 149, pp.143-155. https://doi.org/10.1016/j.agwat.2014.10.013

Kiniry, J.R. and Bockholt, A.J., 1998. Maize and sorghum simulation in diverse Texas environments. Agronomy Journal, 90(5), pp.682-687.

Knoema., 2019. Knoema online database. https://knoema.com/FAOPRDSC2020/production-statistics-crops-crops-processed?tsId=1306980

Kobayashi, K. and Salam, M.U., 2000. Comparing simulated and measured values using mean squared deviation and its components. Agronomy Journal, 92(2), pp.345-352. https://doi.org/10.1007/s10087005004

Li, X., Yadav, R. and Siddique, K.H., 2020. Neglected and underutilized crop species: the key to improving dietary diversity and fighting hunger and malnutrition in Asia and the Pacific. Frontiers in Nutrition, p.254. https://doi.org/10.3389/fnut.2020.593711

Mabhaudhi, T., 2012. Drought tolerance and water-use of selected South African landraces of taro (Colocasia esculenta L. Schott) and bambara groundnut (Vigna subterranea L. Verdc) (Doctoral dissertation).

Mabhaudhi, T., Chibarabada, T.P., Chimonyo, V.G.P., Murugani, V.G., Pereira, L.M., Sobratee, N., Govender, L., Slotow, R. and Modi, A.T., 2018. Mainstreaming underutilized indigenous and traditional crops into food systems: A South African perspective. Sustainability, 11(1), p.172. https://doi.org/10.3390/su11010172

Mabhaudhi, T., Chibarabada, T.P., Chimonyo, V.G.P. and Modi, A.T., 2018. Modelling climate change impact: a case of bambara groundnut (Vigna subterranea). Physics and Chemistry of the Earth, Parts A/B/C, 105, pp.25-31. https://doi.org/10.1016/j.pce.2018.01.00

Mabhaudhi, T., Chimonyo, V.G., Chibarabada, T.P. and Modi, A.T., 2017. Developing a roadmap for improving neglected and underutilized crops: A case study of South Africa. Frontiers in plant science, 8, p.2143. https://doi.org/10.3389/fpls.2017.02143

Mabhaudhi, T., Modi, A.T. and Beletse, Y.G., 2014. Parameterisation and evaluation of the FAO-AquaCrop model for a South African taro (Colocasia esculenta L. Schott) landrace. Agricultural and Forest Meteorology, 192, pp.132-139. https://doi.org/10.1016/j.agrformet.2014.03.013

Mabhaudhi, T., Modi, A.T. and Beletse, Y.G., 2014. Parameterization and testing of AquaCrop for a South African bambara groundnut landrace. Agronomy journal, 106(1), pp.243-251. https://doi.org/10.2134/agronj2013.0355

Mabhaudhi, T., Mpandeli, S., Nhamo, L., Chimonyo, V.G., Nhemachena, C., Senzanje, A., Naidoo, D. and Modi, A.T., 2018. Prospects for improving irrigated agriculture in southern Africa: Linking water, energy and food. Water, 10(12), p.1881. https://doi.org/10.3390/w10121881

Magbagbeola, J.A.O., Adetoso, J.A. and Owolabi, O.A., 2010. Neglected and underutilized species (NUS): a panacea for community focused development to poverty alleviation/poverty reduction in Nigeria. Journal of Economics and International Finance, 2(10), pp.208-211

Mal, B., 2007. Neglected and underutilized crop genetic resources for sustainable agriculture. Indian Journal of Plant Genetic Resources, 20(1), pp.1-14.

Malik, W. and Dechmi, F., 2019. DSSAT modelling for best irrigation management practices assessment under Mediterranean conditions. Agricultural water management, 216, pp.27-43. https://doi.org/10.1016/j.agwat.2019.01.017

Mangani, R., Tesfamariam, E., Bellocchi, G. and Hassen, A., 2018. Modelled impacts of extreme heat and drought on maize yield in South Africa. Crop and Pasture Science, 69(7), pp.703-716. https://doi.org/10.1071/CP18117

Manschadi, A.M., Eitzinger, J., Breisch, M., Fuchs, W., Neubauer, T. and Soltani, A., 2021. Full parameterisation matters for the best performance of crop models: inter-comparison of a simple and a detailed maize model. International Journal of Plant Production, 15(1), pp.61-78. https://doi.org/10.1007/s42106-020-00116-2

Maseko, I., Nogemane, N., Beletse, Y.G. and Du Plooy, C.P., 2015. Growth, physiology and yield responses of Amaranthus cruentus, Corchorus olitorius and Vigna unguiculata to plant density under drip-irrigated commercial production. South African Journal of Plant and Soil, 32(2), pp.87-94. https://doi.org/10.1080/02571862.2014.994142

Mayes, S., Massawe, P.G., Alderson, J.A. and Roberts, S.N., Azam-Ali and Hermann, M. 2011. The potential for underutilized crops to improve security of food production. Journal of Experimental Botany,pp.1-5. https://doi.org/10.1093/jxb/err396

McGregor, J.L., 2005. C-CAM: Geometric aspects and dynamical formulation (No. 70). Dickson ACT: CSIRO Atmospheric Research.

McGregor, J.L. and Dix, M.R., 2001. IUTAM Symposium on Advances in Mathematical Modelling of Atmosphere and Ocean Dynamics. https://doi.org/10.1007/978-94-010-0792-4_25

McGregor, J.L. and Dix, M.R., 2008. An updated description of the conformal-cubic atmospheric model. In High resolution numerical modelling of the atmosphere and ocean (pp. 51-75). Springer, New York, NY. https://doi.org/10.1007/978-0-387-49791-4_4

Modi, A.T. and Mabhaudhi, T., 2013. Water use and drought tolerance of selected traditional crops. Water Research Commission (WRC). Crop Science, School of Agricultural, Earth and Environmental Sciences, pp.140-168.

Molden, D., 1997. Accounting for water use and productivity-SWIM Paper 1.

Molden, D., Murray-Rust, H., Sakthivadivel, R. and Makin, I., 2003. A water-productivity framework for understanding and action. Water productivity in agriculture: Limits and opportunities for improvement, 1.

Monteith, J.L., 1965. Light distribution and photosynthesis in field crops. Annals of Botany, 29(1), pp.17-37.

Morillo, J.G., Díaz, J.A.R., Camacho, E. and Montesinos, P., 2015. Linking water footprint accounting with irrigation management in high value crops. Journal of cleaner production, 87, pp.594-602. https://doi.org/10.1016/j.jclepro.2014.09.043

Moser, S.B., Feil, B., Jampatong, S. and Stamp, P., 2006. Effects of pre-anthesis drought, nitrogen fertilizer rate, and variety on grain yield, yield components, and harvest index of tropical maize. Agricultural Water Management, 81(1-2), pp.41-58. https://doi.org/10.1016/j.agwat.2005.04.005

Muller, B. and Martre, P., 2019. Plant and crop simulation models: powerful tools to link physiology, genetics, and phenomics. Journal of Experimental Botany, 70(9), pp.2339-2344. https://doi.org/10.1093/jxb/erz175

Muza, O., 2017. El Nino-Southern Oscillation Influences on Food Security. Journal of Sustainable Development, 10(5), pp.268-279. https://doi.org/10.5539/jsd.v10n5p26

National Planning Commission, 2010. National Planning Commission diagnostic overview. Pretoria, South Africa: National Planning Commission.

Nouri, H., Stokvis, B., Galindo, A., Blatchford, M. and Hoekstra, A.Y., 2019. Water scarcity alleviation through water footprint reduction in agriculture: the effect of soil mulching and drip irrigation. Science of the total environment, 653, pp.241-252. https://doi.org/10.1016/j.scitotenv.2018.10.311

Nyathi, M.K., Van Halsema, G.E., Annandale, J.G. and Struik, P.C., 2018. Calibration and validation of the AquaCrop model for repeatedly harvested leafy vegetables grown under different irrigation regimes. Agricultural water management, 208, pp.107-119. https://doi.org/10.1016/j.agwat.2018.06.012

O'Leary, G.J., Aggarwal, P.K., Calderini, D.F., Connor, D.J., Craufurd, P., Eigenbrode, S.D., Han, X. and Hatfield, J.L., 2018. Challenges and responses to ongoing and projected climate change for dryland cereal production systems throughout the world. Agronomy, 8(4), p.34. https://doi.org/10.3390/agronomy8040034

Orr, A., Mwema, C., Gierend, A. and Nedumaran, S., 2016. Sorghum and millets in Eastern and Southern Africa: facts, Trends and outlook.

Orrego, C.E., Salgado, N. and Botero, C.A., 2014. Developments and trends in fruit bar production and characterization. Critical reviews in food science and nutrition, 54(1), pp.84-97. https://doi.org/10.1080/10408398.2011.571798

Oteng-Darko, P., Yeboah, S., Addy, S.N.T., Amponsah, S. and Danquah, E.O., 2013. Crop modeling: A tool for agricultural research – A review.

Palosuo, T., Kersebaum, K.C., Angulo, C., Hlavinka, P., Moriondo, M., Olesen, J.E., Patil, R.H., Ruget, F., Rumbaur, C., Takáč, J. and Trnka, M., 2011. Simulation of winter wheat yield and its variability in different climates of Europe: A comparison of eight crop growth models. European Journal of Agronomy, 35(3), pp.103-114. https://doi.org/10.1016/j.eja.2011.05.001

Parent, B. and Tardieu, F., 2014. Can current crop models be used in the phenotyping era for predicting the genetic variability of yield of plants subjected to drought or high temperature?. Journal of experimental botany, 65(21), pp.6179-6189. https://doi.org/10.1093/jxb/eru223

Peng, R.D., 2011. Reproducible research in computational science. Science, 334(6060), pp.1226-1227. https://doi.org/10.1126/science.1213847

Priestley, C.H.B. and Taylor, R.J., 1972. On the assessment of surface heat flux and evaporation using large-scale parameters. Monthly weather review, 100(2), pp.81-92.

Prusinkiewicz, P. and Runions, A., 2012. Computational models of plant development and form. New Phytologist, 193(3), pp.549-569.

Qiu, R., Liu, C., Cui, N., Wu, Y., Wang, Z. and Li, G., 2019. Evapotranspiration estimation using a modified Priestley-Taylor model in a rice-wheat rotation system. Agricultural Water Management, 224, p.105755. https://doi.org/10.1016/j.agwat.2019.105755

Raes, D., Steduto, P., Hsiao, T. C. and Fereres, E., 2018. AquaCrop Version 6.0-6.1. Chapter 1 FAO crop-water productivity model to simulate yield response to water.

Raes, D., Steduto, P., Hsiao, T.C. and Fereres, E., 2009. AquaCrop – the FAO crop model to simulate yield response to water: II. Main algorithms and software description. Agronomy Journal, 101(3), pp.438-447. https://doi.org/10.2134/agronj2008.0140s

Ran, H., Kang, S., Hu, X., Li, S., Wang, W. and Liu, F., 2020. Capability of a solar energy-driven crop model for simulating water consumption and yield of maize and its comparison with a water-driven crop model. Agricultural and Forest Meteorology, 287, p.107955. https://doi.org/10.1016/j.agrformet.2020.107955

Ran, H., Kang, S., Li, F., Tong, L., Ding, R., Du, T., Li, S. and Zhang, X., 2017. Performance of AquaCrop and SIMDualKc models in evapotranspiration partitioning on full and deficit irrigated maize for seed production under plastic film-mulch in an arid region of China. Agricultural Systems, 151, pp.20-32. https://doi.org/10.1016/j.agsy.2016.11.001

Rauff, K.O. and Bello, R., 2019. Scientific research. Pesquisa Agropecuaria Tropical, 2019(13). https://doi.org/10.4236/as.2015.69105

Rezaverdinejad, V., Khorsand, A. and Shahidi, A., 2014. Evaluation and comparison of AquaCrop and FAO models for yield prediction of winter wheat under environmental stresses. J. Biodivers. Environ. Sci, 4(6), pp.438-449.

Richardson, C.W., 1981. Stochastic simulation of daily precipitation, temperature, and solar radiation. Water resources research, 17(1), pp.182-190.

Richardson, C.W., 1985. Weather simulation for crop management models. Transactions of the ASAE, 28(5), pp.1602-1606.

Rippke, U., Ramirez-Villegas, J., Jarvis, A., Vermeulen, S.J., Parker, L., Mer, F., Diekkrüger, B., Challinor, A.J. and Howden, M., 2016. Timescales of transformational climate change adaptation in sub-Saharan African agriculture. Nature Climate Change, 6(6), pp.605-609. https://doi.org/10.1038/nclimate2947

Roberts, M.J., Braun, N.O., Sinclair, T.R., Lobell, D.B. and Schlenker, W., 2017. Comparing and combining process-based crop models and statistical models with some implications for climate change. Environmental Research Letters, 12(9), p.095010. https://doi.org/10.1088/1748-9326/aa7f33

Rogers, D. H. and Alam, M., 1998. Water Management: An aid to irrigation Management. Kansas University Research and Extensin.

Rötter, R.P., Palosuo, T., Kersebaum, K.C., Angulo, C., Bindi, M., Ewert, F., Ferrise, R., Hlavinka, P., Moriondo, M., Nendel, C. and Olesen, J.E., 2012. Simulation of spring barley yield in different climatic zones of Northern and Central Europe: a comparison of nine crop models. Field Crops Research, 133, pp.23-36. https://doi.org/10.1016/j.fcr.2012.03.016

SAGIS., 2019. Maize. South African Grain Information Services. https://www.sagis.org.za/presentations.html

Salo, T.J., Palosuo, T., Kersebaum, K.C., Nendel, C., Angulo, C., Ewert, F., Bindi, M., Calanca, P., Klein, T., Moriondo, M. and Ferrise, R., 2016. Comparing the performance of 11 crop simulation models in predicting yield response to nitrogen fertilization. The Journal of Agricultural Science, 154(7), pp.1218-1240. https://doi.org/10.1017/S0021859615001124

Sarkar, R., 2009. Use of DSSAT to model cropping systems. CAB Reviews: perspectives in agriculture, veterinary science, nutrition and natural resources, 4(025), pp.1-12.

Schlenker, W. and Roberts, M.J., 2009. Nonlinear temperature effects indicate severe damages to US crop yields under climate change. Proceedings of the National Academy of sciences, 106(37), pp.15594-15598. https://doi.org/10.1073/pnas.0906865106

Schulze, R.E., 1843. A perspective on climate change and the South African water sector. Water Research Commission report, 2(11).

Schulze, R.E. and Chapman, R.D., 2007. Estimation of daily solar radiation over South Africa. South African Atlas of Climatology and Agrohydrology: WRC Report No. 1489/1/06, Section 5.2.

Schulze, R.E., Horan, M.J.C. and Freese, C.J., 2007. Hydrological modelling as a tool for ecosystem services trading: Case studies from the Drakensberg region of South Africa. Unpublished ACRUcons Report, (56).

Schulze, R.E. and Horan, M.J.C., 2010. Methods 1: delineation of South Africa, Lesotho and Swaziland into quinary catchments. Methodological approaches to assessing eco-hydrological responses to climate change in South Africa, pp.63-74.

Schulze, R.E., Horan, M.J.C., Kunz, R.P., Lumsden, T.G. and Knoesen, D.M., 2010. Methods 2: Development of the southern African quinary catchments database. Schulze RE, Hewitson BC, Barichievy KR, Tadross MA, Kunz RP Horan MJC et al. Methodological approaches to assessing eco-hydrological responses. Pretoria: Water Research Commission, pp.63-74.

Schulze, R.E., Horan, M.J.C., Kunz, R.P., Lumsden, T.G. and Knoesen, D.M., 2011. The South African quinary catchments database. Schulze, RE, pp.31-37

Zhang S., Yun, B., Zhang, J.H. and Shahzad, A.L.I., 2021. Developing a process-based and remote sensing driven crop yield model for maize (PRYM-Maize) and its validation over the Northeast China Plain. Journal of Integrative Agriculture, 20(2), pp.408-423. https://doi.org/10.1016/S2095-3119(20)63293-2

Silva, J.V. and Giller, K.E., 2020. Grand challenges for the 21st century: what crop models can and can't (yet) do. The Journal of Agricultural Science, 158(10), pp.794-805

Sinclair, T.R. and Seligman, N.A.G., 1996. Crop modeling: from infancy to maturity. Agronomy Journal, 88(5), pp.698-704

Singels, A., Annandale, J.G., De Jager, J.M., Schulze, R.E., Inman-Bamber, N.G., Durand, W., Van Rensburg, L.D., Van Heerden, P.S., Crosby, C.T., Green, G.C. and Steyn, J.M., 2010. Modelling crop growth and crop water relations in South Africa: Past achievements and lessons for the future. South African Journal of Plant and Soil, 27(1), pp.49-65. https://doi.org/10.1080/02571862.2010.10639970

Soltani, A., Alimagham, S.M., Nehbandani, A., Torabi, B., Zeinali, E., Dadrasi, A., Zand, E., Ghassemi, S., Pourshirazi, S., Alasti, O. and Hosseini, R.S., 2020. SSM-iCrop2: A simple model for diverse crop species over large areas. Agricultural Systems, 182, p.102855. https://doi.org/10.1016/j.agsy.2020.102855

Soltani, A. and Sinclair, T.R., 2015. A comparison of four wheat models with respect to robustness and transparency: Simulation in a temperate, sub-humid environment. Field Crops Research, 175, pp.37-46. https://doi.org/10.1016/j.fcr.2014.10.019

Steduto, P., Hsiao, T.C., Fereres, E. and Raes, D., 2012. Crop yield response to water (Vol. 1028). Rome: Food and Agriculture Organization of the United Nations.

Steduto, P., 2003. Biomass water-productivity. Comparing the growth-engines of crop models. FAO Expert Consultation on Crop Water Productivity Under Deficient Water Supply, 26-28 February 2003, Rome. FAO, Rome. Biomass water-productivity. Comparing the growth-engines of crop models. FAO Expert Consultation on Crop Water Productivity Under Deficient Water Supply, 26-28 February 2003, Rome. FAO, Rome.

Steduto, P., Hsiao, T.C. and Fereres, E., 2007. On the conservative behavior of biomass water productivity. Irrigation Science, 25(3), pp.189-207. https://doi.org/10.1007/s00271-007-0064-1

Steduto, P., Hsiao, T.C., Raes, D. and Fereres, E., 2009. AquaCrop the FAO crop model to predict yield response to water. I Concepts. Special issue on “Yield Response to Water: Examination of the Role of Crop Models in Predicting Water Use Efficiency”. Agronomy Journal, 101, pp.426-437. https://doi.org/10.2134/agronj2008.0139s

Steduto, P., Hsiao, T.C., Fereres, E. and Raes, D., 2012. *Crop yield response to water* (Vol. 1028). Rome: Food and Agriculture Organization of the United Nations.

Swemmer, A.M., Knapp, A.K. and Snyman, H.A., 2007. Intra-seasonal precipitation patterns and above-ground productivity in three perennial grasslands. Journal of Ecology, 95(4), pp.780-788. https://doi.org/10.1111/j.1365-2745.2007.01237.x

Tanner, C.B. and Sinclair, T.R., 1983. Efficient water use in crop production: Research or re-search?. Limitations to efficient water use in crop production, pp.1-27.

Tebaldi, C. and Knutti, R., 2007. The use of the multi-model ensemble in probabilistic climate projections. Philosophical transactions of the royal society A: mathematical, physical and engineering sciences, 365(1857), pp.2053-2075. https://doi.org/10.1098/rsta.2007.2076

Thorp, K.R., Marek, G.W., DeJonge, K.C., Evett, S.R. and Lascano, R.J., 2019. Novel methodology to evaluate and compare evapotranspiration algorithms in an agroecosystem model. Environmental Modelling & Software, 119, pp.214-227. https://doi.org/10.1016/j.envsoft.2019.06.007

Timsina, J., Godwin, D., Humphreys, E., Kukal, S.S. and Smith, D., 2008. Evaluation of options for increasing yield and water productivity of wheat in Punjab, India using the DSSAT-CSM-CERES-Wheat model. Agricultural Water Management, 95(9), pp.1099-1110. https://doi.org/10.1016/j.agwat.2008.04.009

Todorovic, M., Albrizio, R., Zivotic, L., Saab, M.T.A., Stöckle, C. and Steduto, P., 2009. Assessment of AquaCrop, CropSyst, and WOFOST models in the simulation of sunflower growth under different water regimes. Agronomy journal, 101(3), pp.509-521. https://doi.org/10.2134/agronj2008.0166s

Toumi, J., Er-Raki, S., Ezzahar, J., Khabba, S., Jarlan, L. and Chehbouni, A., 2016. Performance assessment of AquaCrop model for estimating evapotranspiration, soil water content and grain yield of winter wheat in Tensift Al Haouz (Morocco): Application to irrigation management. Agricultural Water Management, 163, pp.219-235. https://doi.org/10.1016/j.agwat.2015.09.007

Tsuji, G.Y., Hoogenboom, G. and Thornton, P.K. eds., 1998. Understanding options for agricultural production (Vol. 7). Springer Science & Business Media.

Ukeje, E., 2004. Modernizing small holder agriculture to ensure food security and gender empowerment: Issues and policy. Int Group Twenty-Four Res Pap, 23.

Ullah, A., Ahmad, I., Ahmad, A., Khaliq, T., Saeed, U., Habib-ur-Rahman, M., Hussain, J., Ullah, S. and Hoogenboom, G., 2019. Assessing climate change impacts on pearl millet under arid and semi-arid environments using CSM-CERES-Millet model. Environmental Science and Pollution Research, 26(7), pp.6745-6757. https://doi.org/10.1007/s11356-018-3925-7

Van Ittersum, M.K., Cassman, K.G., Grassini, P., Wolf, J., Tittonell, P. and Hochman, Z., 2013. Yield gap analysis with local to global relevance – a review. Field Crops Research, 143, pp.4-17. https://doi.org/10.1016/j.fcr.2012.09.009

Vanuytrecht, E., Raes, D., Steduto, P., Hsiao, T.C., Fereres, E., Heng, L.K., Vila, M.G. and Moreno, P.M., 2014. AquaCrop: FAO's crop water productivity and yield response model. Environmental Modelling & Software, 62, pp.351-360. https://doi.org/10.1016/j.envsoft.2014.08.005

Vos, J., Evers, J.B., Buck-Sorlin, G.H., Andrieu, B., Chelle, M. and De Visser, P.H., 2010. Functional-structural plant modelling: a new versatile tool in crop science. Journal of experimental Botany, 61(8), pp.2101-2115. https://doi.org/10.1093/jxb/erp345

Wallach, D., Martre, P., Liu, B., Asseng, S., Ewert, F., Thorburn, P.J., Van Ittersum, M., Aggarwal, P.K., Ahmed, M., Basso, B. and Biernath, C., 2018. Multimodel ensembles improve predictions of crop-environment-management interactions. Global change biology, 24(11), pp.5072-5083. https://doi.org/10.1111/gcb.14411

Wallach, D., Makowski, D., Jones, J.W. and Brun, F., 2018. Working with dynamic crop models

Wani, S. P., Albrizio, R. and Vajja, N. R., 2012. Sorghum. Food and Agriculture Organization of the United Nations.

Wellens, J., Raes, D., Traore, F., Denis, A., Djaby, B. and Tychon, B., 2013. Performance assessment of the FAO AquaCrop model for irrigated cabbage on farmer plots in a semi-arid environment. Agricultural water management, 127, pp.40-47. https://doi.org/10.1016/j.agwat.2013.05.012

White, J.W., Hoogenboom, G., Kimball, B.A. and Wall, G.W., 2011. Methodologies for simulating impacts of climate change on crop production. Field Crops Research, 124(3), pp.357-368. https://doi.org/10.1016/j.fcr.2011.07.001

White, J.W., Jones, J.W., Porter, C., McMaster, G.S. and Sommer, R., 2010. Issues of spatial and temporal scale in modeling the effects of field operations on soil properties. Operational Research, 10(3), pp.279-299.

Willcock, S., Hooftman, D., Sitas, N., O'Farrell, P., Hudson, M.D., Reyers, B., Eigenbrod, F. and Bullock, J.M., 2016. Do ecosystem service maps and models meet stakeholders' needs? A preliminary survey across sub-Saharan Africa. Ecosystem Services, 18, pp.110-117. https://doi.org/10.1016/j.ecoser.2016.02.038

Willmott, C.J., 1981. On the validation of models physical geography. 2: 184-194. https://doi.org/10.1080/02723646.1981.10642213

Wolf, J., Evans, L.G., Semenov, M.A., Eckersten, H. and Iglesias, A., 1996. Comparison of wheat simulation models under climate change. I. Model calibration and sensitivity analyses. Climate research, 7(3), pp.253-270.

Xiong, W., Balkovič, J., Van der Velde, M., Zhang, X., Izaurralde, R.C., Skalský, R., Lin, E., Mueller, N. and Obersteiner, M., 2014. A calibration procedure to improve global rice yield simulations with EPIC. Ecological modelling, 273, pp.128-139. https://doi.org/10.1016/j.ecolmodel.2013.10.026

Yin, X. and Struik, P.C., 2010. Modelling the crop: from system dynamics to systems biology. Journal of Experimental Botany, 61(8), pp.2171-2183. https://doi.org/10.1093/jxb/erp375

Zhao, C., Liu, B., Piao, S., Wang, X., Lobell, D.B., Huang, Y., Huang, M., Yao, Y., Bassu, S., Ciais, P. and Durand, J.L., Z, Zhu, and S. Asseng, 2017. Temperature increase reduces global yields of major crops in four independent estimates, Proceeded of the National Academy of Sciences, 114 (35): 9326-9331. https://doi.org/10.1073/pnas.1701762114

Zhao, C., Liu, B., Xiao, L., Hoogenboom, G., Boote, K.J., Kassie, B.T., Pavan, W., Shelia, V., Kim, K.S., Hernandez-Ochoa, I.M. and Wallach, D., 2019. A SIMPLE crop model. European Journal of Agronomy, 104, pp.97-106. https://doi.org/10.1016/j.eja.2019.01.009

7 OPTIMIZING TRADITIONAL CROPPING SYSTEMS UNDER CLIMATE CHANGE: A CASE OF MAIZE LANDRACES AND BAMBARA GROUNDNUT

Chimonyo V. G. P., Wimalasiri E. M., Kunz R.P., Modi A.T., and Mabhaudhi T.

Abstract

Traditional crop species are reported to be drought-tolerant and nutrient-dense with potential to contribute to sustainable food and nutrition security within marginal production systems under climate change. We hypothesized that intercropping maize landraces (*Zea mays* L.) with bambara groundnut (*Vigna subterranea* (L.) Verdc.), together with optimum management strategies, can improve productivity and water use efficiency (WUE) under climate change. Using an ex-ante approach, we assessed climate change impacts and agronomic management options, such as plant ratios, and plant sequences, on yield and WUE of intercropped maize landrace and bambara groundnut. The Agricultural Production Systems sIMulator (APSIM) model was applied over four time periods; namely past (1961-1991), present (1995-2025), mid-century (2030-2060) and late-century (2065-2095), obtained from six GCMs. Across timescales, there were no significant differences with mean annual rainfall, but late century projections of mean annual temperature and reference crop evaporation (ET_0) showed average increases of 3.5°C and 155 mm, respectively. By late century and relative to the present, the projected changes in yield and WUE were -10 and -15% and 5 and 7% for intercropped bambara groundnut and maize landrace, respectively. Regardless of timescale, increasing plant population improved yield and WUE of intercropped bambara groundnut. Asynchronous planting increased yield and WUE for both maize landrace (5 and 14%) and bambara groundnut (35 and 47%, respectively). Most significant improvements were observed when either crop was planted two to three months apart. To reduce yield gaps in intercrop systems, low-cost management options like changing plant populations and sequential cropping can increase yield and WUE under projected climate change. To further increase sustainability, there is a need to expand the research to consider other management strategies such as use of other traditional crop species, fertilization, rainwater harvesting and soil conservation techniques.

Keywords: Climate change adaptation; Food and nutrition security; Multicropping; Neglected and underutilized crops; Resilience; Water use; Climate change impacts

7.1 Introduction

Sub-Saharan Africa has a dualistic food system with the formal system taking a more national focus, and also focused on a few strategic crops while the informal system supports local food systems, which support household food and nutrition security (Mabhaudhi et al., 2019a; Tcoli, 2016). While several nations are food secure at a national level, household food insecurity remains problematic with an estimated 821 million people currently food insecure and malnourished (Abegaz, 2018; Gashu et al., 2019; Xie et al., 2019). Most of these people rely on agriculture as their mainstay; thus, the importance of agriculture within these communities provides an opportunity to improve food and nutrition security, reduce poverty, and enhance rural economic development (NEPAD, 2014). However, current crop yields are low and challenged by worsening land degradation, especially declining soil fertility (Badu-Apraku et al., 2017; Rippke et al., 2016; Ukeje, 2010), and low water use efficiency (WUE) (Mabhaudhi et al., 2018b; Nouri et al., 2019; O'Leary et al., 2018). Furthermore, climate variability and change are adversely affecting productivity through increased incidences and intensity of droughts (Mpandeli et al., 2018; Nhamo et al., 2019; O'Leary et al., 2018). There is consensus that rural agricultural systems must increase resource use efficiencies and adopt strategies to adapt to climate risk (Isaacs et al., 2016; Matthews and McCartney, 2018).

A considerable amount of literature depicts the adoption of improved technologies such as the use of high yielding, improved crop varieties (Hammer et al., 2014; Mabhaudhi et al., 2019a; Ran et al., 2017). However, marginalized farmers have experienced several challenges when trying to adopt conventional farming practices. Chief among these include inadequate access to agrochemicals, loss in agro-biodiversity and an increase in the vulnerability of the system to climate risk (Mabhaudhi et al., 2019b; Malik and Chaudhary, 2019). The low adoption and consequent challenges have partly contributed to the widening gaps in food and nutrition security (Midega et al., 2015; Mrema et al., 2018). Within the context of marginal systems, agriculture needs to sustainably contribute to food and nutrition security and rural economic development, while reducing negative impacts on the environment or improving the environment (Van Ittersum et al., 2016). Demand for more sustainable agriculture, which is less dependent on external inputs and better suited to marginal environments, has revived interest in traditional systems (Govender et al., 2016; Keatinge et al., 2015; Saharan et al., 2018). In line with this, there is a renewed focus on the inclusion of neglected and underutilised crops (NUS) as alternative crop choices in marginal cropping systems (Mabhaudhi et al., 2019a).

Neglected and underutilised crops, also referred to as underutilised indigenous and traditional crops, are defined as 'plant species that are part of more substantial biodiversity, were once popular (in and out of their centres of diversity), and are neglected by users and research but remain relevant in the regions of their diversity' (Dansi et al., 2012). They are associated with high nutritional value, adaptation to marginal soils, and tolerant of drought and heat stresses (Chibarabada et al., 2015; Chimonyo et al., 2016a; Hadebe et al., 2017; Mabhaudhi et al., 2017; Slabbert et al., 2004). They often require fewer inputs such as fertiliser and agrochemicals, as they are also tolerant of several pests and diseases (Mabhaudhi et al., 2019a). Their nutritional attributes and adaptability make them suitable crops for promotion in marginal areas where poverty and food and nutrition insecurity remain high; however, their contribution to mainstay agriculture remains low (Massawe et al., 2016). As is reflected by their name, the potential of underutilised crops has not yet been fully harnessed, but most of them contribute to diversification and resilience of agroecosystems. Therefore, they have the potential for future agriculture under adverse agro-climatic conditions (Padulosi et al., 2011). Many proponents of modern agriculture and the Green Revolution have discouraged their continued production, highlighting low productivity and resource use efficiencies (Missio et al., 2018; Tokatlidis and Vlachostergios, 2016). For example, water use efficiency of bambara groundnut was reported to be 0.45 kg ha^{-1} mm^{-1} compared to 0.89 kg ha^{-1} mm^{-1} for groundnut (Chibarabada et al., 2017), while landrace sorghum varieties had 20% less WUE relative to hybrid varieties (Hadebe et al., 2019). However, the argument is to not promote them as replacement crops for high yielding major crops, but as complementary crops (Mabhaudhi et al., 2019a), especially in marginal areas where the major crops may not perform well (Massawe et al., 2016). Within these areas, NUS have potential to contribute to improving rural livelihoods and maybe 'better bet' technologies; however, this potential remains largely untapped due to limited information detailing their genetic, eco-physiological and agronomic performance (Chivenge et al., 2015). It is against this backdrop we hypothesize that, by optimizing resource use, yields of NUS can be sustainably increased. Intercropping involves growing of two or more crops simultaneously or overlapped on the same piece of land, which can sustainably increase WUE (Martin-Guay et al., 2018).

In this study, we hypothesize that intercropping a maize landrace (*Zea mays* L.) with bambara groundnut (*Vigna subterranea* (L.) Verdc.) is beneficial because the latter's smaller canopy offers little competition to the cereal crop (Saxena et al., 2018). As a legume, bambara groundnut also fixes atmospheric nitrogen. It contributes to soil fertility (Sprent et al., 2010), and the low cost of bambara groundnut seed makes it an exemplar crop for enhancing food and nutrition security within cereal producing households (Mayes et al., 2019; Muhammad et al., 2016). While traditional cropping systems featured multicrops (Muzari et al., 2012), intercropping maize with bambara groundnut is no longer a common practice. Little information is known about crop interaction and the impacts of climate variability and change on productivity and water productivity. While intercropping, in general, could be considered positive in terms of yield (Martin-Guay et al., 2018), the performance of each crop in an intercrop system is determined by the interaction between different crops and the availability of resources. With the impacts of climate variability and change, adapting agronomic management in response to changing resources can allow for sustainable intensification of the traditional cropping systems through improved resource use efficiency. Using an ex-ante approach in APSIM, the current study assessed the productivity and water use of a maize landrace-bambara groundnut intercrop under changing climate and in response to different management options. APSIM has been used widely to study impacts of climate change on crop growth and productivity across Africa (Beveridge et al., 2018; Duku et al., 2018; Xiao et al., 2020). However, its application for studying intercrop systems remains scanty, with no known research on its application for climate change studies.

7.2 Materials and methods

7.2.1 Study area

The study area was the University of KwaZulu-Natal's Ukulinga Research Farm (29° 40'S; 30° 24'E; 809 m a.s.l.). Ukulinga Research Farm is classified as semi-arid with 77% of the mean annual rainfall of 750 mm received mostly between October and April. The summer months are warm to hot, with an average temperature of 26.5°C (Kunz et al., 2015). Soil textures are characterized as predominantly clay to clay loam and are moderately shallow, ranging from 0.6 to 0.8 m (Chimonyo et al., 2016a).

7.2.2 APSIM maize-bambara groundnut intercrop model

7.2.2.1 Brief description of the APSIM model

The APSIM version 7.10 is a daily time step, field-scale multi-year, a multi-crop model that provides an analytical tool for assessing the impacts of climate, soil factors and farming management on cropping system production (Holzworth et al. 2014). The model is driven by daily temperature, precipitation, and solar radiation and is capable of simulating soil carbon (C), soil water, phosphorus (P), and nitrogen (N) dynamics and their interaction (Keating et al., 2003). Management practices include sowing date, variety selection, irrigation water management, fertilizer application, crop residue management, crop rotations and conservation tillage; this makes the model ideal for assessing the impacts of various management options on resource use. APSIM also allows users to set up atmospheric CO_2 concentration (Jones et al., 2001), which is ideal for assessing climate change impacts. Furthermore, through the CANOPY module, the model can simulate resource use within intercrop systems. For detailed information on the technical workings of the APSIM model, refer to Dimes and Revanuru (2004), Holzworth et al. (2006; 2014), and McCown et al. (1996).

The CANOPY module determines resources intercepted by each component of the intercrop using leaf area index (LAI), extinction coefficient and height for each crop. Arbitration for water and nitrogen uptake is done based on the module changing the order each day (on a rotational basis) in which the competing species are allowed to capture soil resources. Through the CANOPY module, the model accounts for the vertical profiles of LAI in different species in a mixture (Keating and Carberry, 1993), and assumes a horizontally homogeneous canopy for each species (Gou et al., 2017a). The CANOPY module has been published and successfully applied by Smith et al. (2016) and Snapp et al. (2018) for maize and pigeon pea; Carberry et al. (1996) for maize and bean; Chimonyo et al. (2016a) for sorghum and cowpea; and Hoffmann et al. (2020) for various maize intercrop systems. Although Nelson et al. (1998a and1998b) used APSIM to simulate a maize and *Desmanthus virgatus* intercrop system, the two crops were grown as monocultures and did use the CANOPY module. It was not clear whether Amarasingha et al. (2017) used the CANOPY module when maize and mung bean intercrop systems were simulated in APSIM. In contrast, Knörzer et al. (2011) found that APSIM was unable to simulate wheat-pea and maize-pea intercropping systems in Germany because it strongly underestimates the competitive ability of the species that was planted the first relative to the one that was planted last. In this study, we used the CANOPY module to simulate the effects of climate change on a maize landrace and bambara groundnut intercrop system. The current study, therefore, adds to the existing body of knowledge on the use of ASIM in simulating intercrop systems. It goes further to simulate different management options under different climate change impacts on the intercrop system

7.2.2.2 Model calibration, testing and application

The calibration and testing of the APSIM were carried out using observed data obtained from field experiments conducted during the 2015/16 growing season for a maize landrace-bambara groundnut intercrop established at the University of KwaZulu-Natal's Ukulinga Research Farm. Sub-plots comprised intercrop combinations, that is, sole maize landrace, sole bambara groundnut and maize landrace-bambara groundnut intercrop. The irrigated treatments were used for calibration, while the rainfed treatments were used to validate the model. For a detailed description of the experiment, refer to Supplementary information 1. The simulation files were, therefore, created using observed data collected from the rainfed and irrigated treatment.

Met file

For model calibration and testing, a ten year (2009-2019) weather data file that contained daily estimates of rainfall, minimum and maximum temperatures, solar radiation and reference evapotranspiration was sourced from SASRI weather site (http://sasex.sasa.org.za/irricane/tables/Ash_tables_AR.pl) using the nearest station to the location except for Ukulinga where there is a weather station on-site. With the 5-year climate file, we were able to back-calculate and estimate the initial soil water and initial soil nitrogen at planting. APSIM require an average ambient temperature (TAV) and the annual amplitude in monthly temperature (AMP). These values are calculated using long-term daily minimum and maximum temperatures by software program named "tav_amp".

Soil file

The soil file was generated using soil details at Ukulinga research farm. Soils at the research farm have been described as being shallow clayey to clayey loam with medium fertility (Mabhaudhi et al., 2013). The soil file selected to represent this description best was Clay_Shallow_MF_101 mm. The soil module was created using information obtained from Chimonyo et al. (2016) (**Table 7.1**), and this was matched to a pre-existing soil file available in APSIM soil module – Africa (Generic).

Table 7.1: Soil water properties at different depths for soil at the experimental site.

Texture	BD[1]	HC[2]	PWP[3]	FC[4]	TAW[5]	SAT[6]	K_{SAT}[7]
	gm^{-3}	-------------------------mm m^{-1}-----------------------					$mm\ h^{-1}$
Clay	1.35	0.33	294	416	152	489	19,70

[1] Bulk density; [2] Hygroscopic moisture content; [3] Permanent wilting point; [4] Field capacity; [5] Total available water; [6] Saturation; [7] Hydraulic conductivity.

Crop files

Within maize APSIM crop file, we used the maize cultivar “mwi_local” as it best described the maize landrace used in terms of days to maturity and yield potential of

3 t ha^{-1}. However, slight iterations to genetic coefficients were done using an iterative approach until simulated values were within 9-20% of observed values (**Table 7.2**). Since APSIM does not have a bambara groundnut crop file, the groundnut cultivar “kangwana” was modified as it closely resembled bambara groundnut in terms of physiology, growth habit and phenology (**Table 7.2**). The groundnut crop module was iterated by first adjusting the reproductive parameters within the crop life cycle (phenology, e.g. time to emergence, first leaf, reproductive stages, and maturity) to resemble what was observed from the monocropped treatment during the field experiment. After that, where simulations disagreed with observations, parameters in the groundnut module were modified in a sequential approach following the order proposed by Boote et al. (2002). The steps were: (1) leaf appearance rate, canopy height, and width, (2) specific leaf area, leaf area index, and partitioning among vegetative organs, including the rate of total biomass accumulation and lastly, (3) onset, rate, and duration of pod addition and seed growth. Besides modifications based on comparisons with the observed data, some parameter modifications were made based on a literature review.

Management file

The management file considered planting date, plant densities, fertiliser rate, irrigation and harvest rules. The plant populations used to calibrate and test the model were 2 0 and 2.2 (plants m^{-2}) of the maize landrace and bambara groundnut, respectively. The plant population used represented the densities observed in the field experiment and were less than the recommended densities for dryland maize (2.6 plants m^{-2}) and bambara groundnut (4.4 plants m^{-2}) production (Jensen et al., 2003). Since the field experiment used to calibrate and test the model was conducted in one season, we used the irrigated treatments for calibration and the rainfed treatments to test model. The module "irrigate on the date" was used to apply irrigation on dates corresponding to actual irrigation dates. Observed irrigation applied per event for the field experiment was calculated to be, on average, 15 mm, which was applied thrice during the experiment. Nitrogen fertiliser was applied automatically within 50 cm depth in the soil at a rate of 50 kg ha^{-1} to avoid any nitrogen stress.

Table 7.2: Modification of groundnut crop coefficients based on experimental data and data obtained from the literature

Parameter	Description	Default Peanut crop file (*cv* kangwana)	New Bambara groundnut crop file
temp units	temperature table for thermal time	9.0 29.0 39.0	8.5 28.0 38.0
leaf_dm_init	Initial leaf dry matter	0.045	0.035[2]
ratio_root_shoot	ratio_root_shoot	0 0 1.0 1.0 0.33 0.33 0.087 0 0 0 0	0 0 1.0 0.67[1] 0.33 0.33 0.087 0 0 0 0
frac_leaf units	fraction of remaining dry matter allocated to leaves	0 0 0.58 0.58 0.58 0.45 0.45 0 0 0 0	0 0 0.60[2] 0.60[2] 0.60[2] 0.55[2] 0.55[2] 0 0 0 0
frac_pod units	fraction of dry matter allocated to pod or multiplier of grain dry matter to account for pod dry matter	0 0 0 0 0 0.18 0.25 0 0 0 0	0 0 0 0 0 0.30[2] 0.45[2] 0 0 0 0
leaf_size	leaf_size	2000 4000 4000 4000 4000	4800 4800 4800 4800 4800[2]
sla_max description	maximum specific leaf area for delta LAI	35000 30000 25000 20000 20000 20000 20000	45000 45000 40000 40000 38000 34000 30000
hi_incr	rate of HI increase	0.0056	0.0024
hi_max_pot	maximum harvest index potential	0.45	0.35[1,3]

Floral initiation (°Cd)		680	220[1]
Flowering (°Cd)	Time from flowering to start grain fill	300	340[1]
Start_grain_fill	Duration of grain filling	440	550[1]
End_grain_fill	Duration of seed maturation	10	85[1]
Height (mm)	Plant height	700	400[1]
		Default maize crop file (*cv* mwi_local)	**Iterated maize crop file**
tt_flower_to_maturity description (°Cd)	Time from flowering to maturity	780	750
potKernelWt (g 100 kernels^{-1})	Potential kernel weight	260	160

[1]Field observation; [2]model iteration; [3]Karunaratne et al. (2010)

7.2.3 Climate scenarios

Ukulinga research farm is located within quinary sub-catchment 4697 of quaternary catchment U30J (Schulze et al., 2011). In addition to historical data, the study also used downscaled future climate projections for the Ukulinga quinary. The climate projections were developed by the Council for Scientific and Industrial Research (CSIR) (**Table 7.3**) using output from six global climate models (GCMs) from the CMIP5 archive that was forced by Representative Concentration Pathway 8.5 (RCP 8.5). The climates produced under RCP 8.5 were used as they represent the most extreme scenarios. The selection of these six GCMs was based on their ability to provide a reasonable representation of the El Nino-Southern Oscillation (ENSO) phenomenon for the region.

The climate projections were dynamically downscaled to improve spatial resolution to 0.5° (~50 km) using the CCAM regional climate model developed by the Commonwealth Scientific and Industrial Research Organisation, CSIRO (McGregor, 2005; McGregor and Dix, 2001; 2008). After that, a multiple-nudging strategy was followed to obtain a downscaling to 0.1° (~10 km) resolution using CCAM in stretched-grid mode over South Africa (see Mabhaudhi et al., 2018a). Climate scenarios were then extracted for the gridded pixel that overlapped quinary sub-catchment 4697. For application in crop modelling at a local scale, it is necessary to correct for systematic and localised biases in rainfall and temperature projections produced by the climate models.

Table 7.3: Global climate models used in this study

Abbreviation	Model name	Model centre	Horizontal resolution
ACC	ACCESS1-0	Commonwealth Scientific and Industrial Research Organisation, Australia (CSIRO), and Bureau of Meteorology, Australia (BOM)	1.250 × 1.875°
CCS	CCSM4	National Center for Atmospheric Research (NCAR), USA	0.9424 × 1.250°
CNR	CNRM-CM5	Centre National de Recherches Meteorologiques, Meteo-France, France	1.4005 × 1.4065°
NOR	NorESM1-M	NorESM (Norwegian Earth System)	1.250 × 0.940°
GFD	GFDL-CM3	Geophysical Fluid Dynamics Laboratory, USA	2.000 × 2.500°
MPI	MPI-ESM-LR	Max Planck Institute for Meteorology, Hamburg Germany	1.8653 × 1.875°

When compared to observed rainfall data from the historical quinary climate database for sub-catchment 4697, the downscaled climate projections were found to have a substantially larger number of rain days, with many rain days having minimal rainfall depths (i.e. < 0.1 mm). Therefore, a quantile delta mapping method, as described and assessed by Cannon et al. (2015), was applied to bias correct the climate scenarios using a multiplicative factor for rainfall and an additive factor for temperature. The bias-corrected climate data provide daily rainfall and temperature scenarios for a continuous period from 1961 to 2100. Daily reference crop evaporation (ETo) estimates were then computed as described for the historical data set (see Schulze et al., 2011). Solar radiation for each GCM for Ukulinga was then calculated as described by Schulze and Chapman (2007). The climate database, therefore, satisfied APSIM's climate file input requirements and was used to develop projections for the past (1961-1991), present (1995-2025), mid-century (2030-2060) and late-century (2065-2095) periods. Throughout the analysis, the 'present' timescale was regarded as the baseline.

7.2.4 Management and agronomic scenarios

Two management scenarios were used to develop recommendations for best management practises. The scenarios were as follows:

Scenario 1: Planting dates

Maize production guidelines published by the Department of Agriculture, Forestry and Fisheries suggest that maize should be planted between October 1 and mid-December throughout South Africa (DAFF, 2003). As it is, South Africa exhibits a wide variation of agro-ecologies, both at the micro and macro level. Due to climate variability and change, this variation has increased, and there is an observed increase in the land area occupied by semi-arid arid agro-ecologies since 2000 (Cairns et al., 2013). Conversely, there is a continual need to redefine planting dates. In this study, we adopted five fixed dates between September 15 to January 15 as this approach is much easier for farmers to use. These dates were assumed to represent early to late planting. However, a significant weakness of this approach is the need to redefine the dates because of continuous shifting in agro-ecologies.

Scenario 2: Plant populations

Model simulations were performed using plant populations that were 50% less to 50% more than the recommended values. Simulations were carried out by maintaining the recommended plant population of one component and changing the other. The total number of simulations was a 3 by 3 factorial with maize populations of 13 000, 26 000, and 39 000 plants ha^{-1} and bambara groundnut populations of 6 500, 13 000 and 19 500 plants ha^{-1}. The lower populations would reduce resource competition and improve productivity for either component crop, while higher populations assumed that there was a need to minimize unproductive resource use from the system and improve their productive use. From this, optimum plant populations were determined for both landraces.

7.2.4.1 Model runs

For model calibration and testing, the APSIM intercrop model was ran for ten consecutive years from 2009 to 2019. The ten year ran allowed for soil conditions to stabilize around what was observed in the actual experiment. During the scenario analysis management options were run independently from each other across the six climate projections to minimize the interactive effects of the scenarios. The RCPs were ran continuously from 1961-2095 periods.

7.2.5 Data analyses

Since APSIM does not calculate WUE directly, simulated outputs of water use (WU in mm) and yield (Y in kg ha^{-1}) or biomass (B in kg ha^{-1}) were used to determine water use efficiency (WUE in kg mm^{-1} ha^{-1}) over the growing season (sowing to harvest) as follows:

$$WUE = \frac{Y/B}{WU} \qquad \textit{Equation 7. 1}$$

Within the model, WU was determined as crop water uptake from the soil profile by either maize landrace or bambara groundnut crop, i.e. maize Ep and bambara Ep and soil evaporation Es (Ep (for either maize landrace or bambara groundnut +Es).

For model calibration and validation crop simulation models was evaluated by comparing simulated versus observed values for phenology, leaf area index, WU, WUE^B, grain yield and biomass. The crop models were evaluated using correlation of determination (R^2) root mean square error (RMSE) and normalised RMSE (nRMSE). Values of R^2 range between 0 and 1 with high values indicating less error variance.

Since the interpretation of R^2 is independent, low values are only acceptable if n is huge. Then again, R^2 values are sensitive to outliers and insensitive to additive and proportional differences between S and O. The simulation was considered excellent when nRMSE < 10%, good if 10%-20%, acceptable or fair if 20%-30%, and poor if >30% of the observed mean (Granderson and Price, 2014; Jamieson et al., 1991).

Simulation outputs for yield and water use were subjected to descriptive statistics, t-test analysis and generalized linear mixed analysis (GLMM) using R statistical software (version 3.6.0). Descriptive statistics such as means, standard deviations, bubble charts and box and whisker plots were used to analyse outputs. Box and whisker plot can show stability and general distribution of the sets of data. The GLMM was used to identify significant factors influencing maize landrace and bambara groundnut yield.

7.2.6 Developing guidelines

The Food and Agriculture Organisation (FAO) suggested a list of guiding questions to review transformative elements within an intervention (Carter et al., 2018). These questions are meant to provide clarity on the adaptation planning process; but in this study, we adopted selected questions to assess the implications of the research, provide actionable recommendations and provide a way forward. Key findings were summarised in a Table 5 and implications outlined.

7.3 Results and discussion

7.3.1 Model performance

Comparisons of simulated and observed values for maize landrace and bambara groundnut phenology and LAI, and biomass, yield and water use (WU) and water use efficiency (WUE) are given in **Figure 7.1**and **Table 7.4**, respectively. For phenology, the close alignment of the points to the 1:1 line indicates that the model was able to simulate the maize landrace and bambara groundnut phenology correctly. The model could explain more than 90% of the variation of either crop in phenological stages (Figure 1). During the calibration, the nRMSE for the system LAI was less than 10%

of the observed LAI for the maize landrace and bambara groundnut intercrop system. The nRMSE for the system LAI during model validation increased slightly to 14%; this implied good simulation for the intercrop system grown under rainfed conditions. Reasonable simulations of crop water use (WU) by the model during calibration, were also observed (RMSE = 41 mm); however, during model validation, WU was over-estimated by 48%. The output suggests that the APSIM model might not be sensitive to water. A closer look at model outputs for maize landrace and bambara groundnut simulated under irrigated (used for calibration) and rainfed (used for validation) conditions showed that transpiration was mostly unaffected by the reduction in water availability. In nature, the low availability of water results in a reduction in transpiration due to the reduction in stomatal conductivity. Field results showed no significant differences between the irrigated and rainfed treatments. In this case, the model appropriately captured maize landrace and bambara groundnut physiology.

For biomass and grain yield, the model tended to overestimate the outputs for maize landrace and bambara groundnut. During model calibration, simulated yield and biomass for maize landrace as 11 and 16% higher than observed, and this implied reasonable simulation. Model simulation of maize landrace yield and biomass under rainfed conditions were satisfactory (RSME = 49 and 267 kg ha^{-1}) However, simulated yield and biomass for bambara groundnut were 32% and 55% higher than those for observed yields. The performance of APSIM would suggest that, for improved model simulations, additional parameterisation may be required to adequately simulate bambara groundnut. The WUE calculated based on model simulated biomass (WUE^{B}) of both the maize landrace and bambara groundnut showed a good fit (1 and 4 kg mm^{-1} ha^{-1}, respectively) for simulated and observed results (**Table 7.4**). Then again, the bambara cultivar used to calibrate the crop file was a landrace selection. It could be that performance under low water availability had adverse effects on its productivity, and this response was not captured by model. Considering that the model was still able to simulate low yields for the maize landrace and bambara groundnut and possible errors in the observation data (e.g. iterated cultivar parameters), the APSIM model performance was considered to be acceptable for the simulation of the intercrop system.

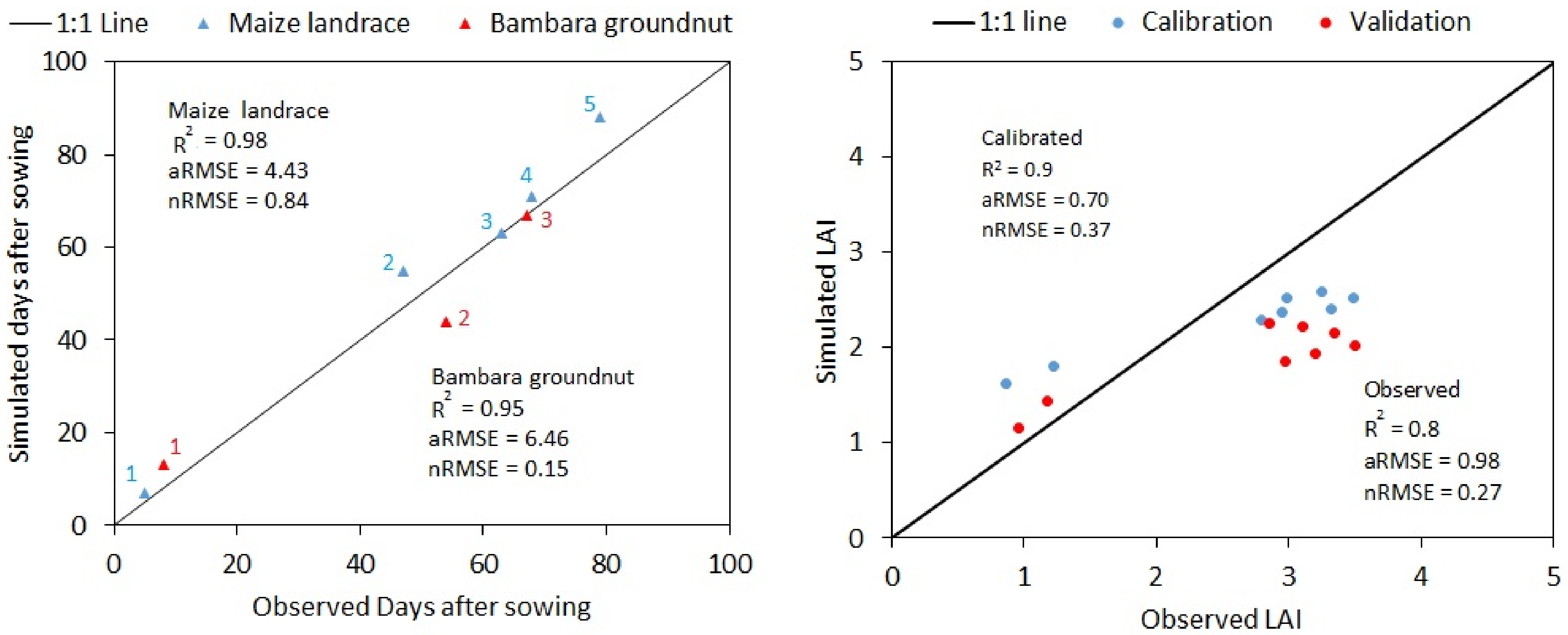


Figure 7.1 Comparison of observed and simulated values for maize landrace and bambara groundnut phenology and leaf area index (LAI) during model calibration and validation. Figure 1 a) represents maize landrace and bambara groundnut phenology and statistical output for its evaluation. Red triangles represent bambara groundnut, and associated numbers 1, 2 and 3 represent phenological stages emergence, the onset of flowering and Start of grain filling, respectively. Blue triangles represent maize landrace, and associated numbers 1, 2, 3, 4 and 5 represent phenological stages emergence, floral initiation, flag leaf formation, the onset of flowering and Start of grain filling, respectively.

Table 7.4: Calibration and validation results for observed and simulated outputs for maize landrace and bambara groundnut intercrop system for final biomass (kg ha^{-1}), yield (kg ha^{-1}) and intercrop system water use (mm).

Model calibration (Irrigated treatment)		**Observed**	**Simulated**	**RSME**
Maize landrace (kg ha^{-1})	Yield	820	918	98
	Biomass	2370	2741	371
Bambara groundnut (kg ha^{-1})	Yield	230	244	14
	Biomass	1060	1375	315
Intercrop WU (mm)		291	332	41
Intercrop WUE^{b} (kg mm^{-1} ha^{-1})		11	12	1
Model validation (Rainfed treatment)				
Maize landrace (kg ha^{-1})	Yield	870	919	49
	Biomass	2470	2737	267
Bambara groundnut (kg ha^{-1})	Yield	150	213	63
	Biomass	950	1248	398
Intercrop WU (mm)		179	266	87
Intercrop WUE^{b} (kg mm^{-1} ha^{-1})		19	15	4

7.3.2 Change in climate during the growing season

Dynamically downscaled and bias-corrected climate projections for six GCMs forced by RCP 8.5, together with an impact model APSIM 7.7, were used to simulate bambara groundnut and maize landrace yields over the past, present, mid-, and late-centuries. The primary aim was to assess how climate change may impact yield, WU and WUE of a maize landrace and bambara groundnut intercrop. Secondary to that, we assessed the impacts of various management options on mitigating the impacts of climate change. The median value of climate change projections for minimum and maximum temperatures for Ukulinga showed a consistent warming trend across all months from past to late century. **Figure 7.2** indicates a warmer future (mid- and late-century) with mean maximum temperature increasing by 4.5°C relative to the baseline maximum temperature of 24°C. This suggests an increased probability of heat stress, especially for maize landrace. This warming trend across the selected timescales is consistent with projected trends for South Africa (Mangani et al., 2018).

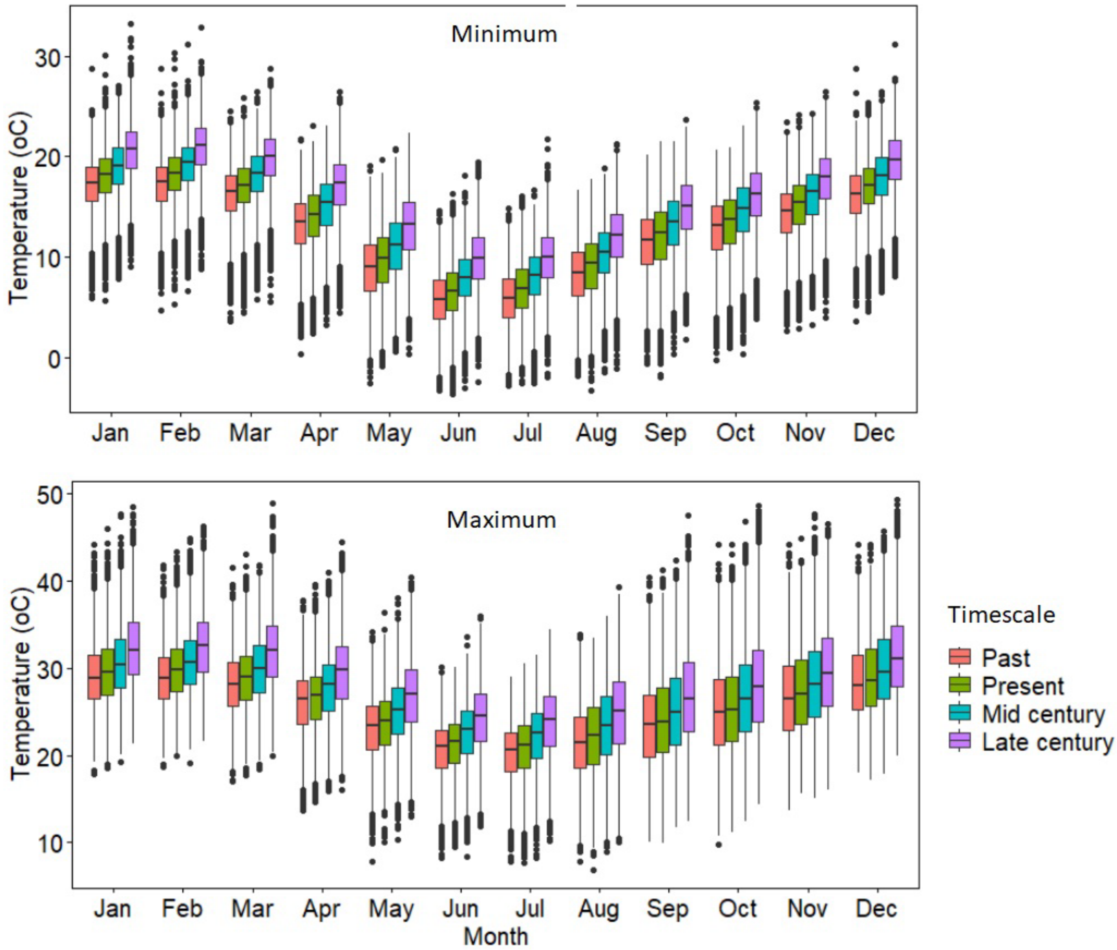


Figure 7.2 Distribution of average monthly minimum (a) and maximum (b) temperature data for the different timescales (past, present, mid- and late-century) as simulated by the six GCMs (ACC, CSS, CNR, GFD, NOR and MPI) used in this study.

The six GCMs project an increase in mean minimum temperatures in the future (mid- and late-century) that ranges from 2.0-4.8°C from a minimum baseline temperature of 13°C. The projected increases suggest an increased probability of hot nights and longer and more frequent heatwaves. The warmer temperatures may result in a faster accumulation of heat units and a reduction in growth duration and accumulation of photosynthesis and increase in night-time respiration, all resulting in reduced crop yield (Schlenker and Roberts, 2009). Unlike bambara groundnut (C3 plant), maize (C4 plant) generally originates from warmer climates (Jia et al., 2016; Leff et al., 2004) and thus, may be more resilient to projected increases of temperature (Choudhary et al., 2019). Then again, for bambara groundnut, optimum temperatures range between 28 and 35°C and the lethal temperature has been reported to be 50°C (Soni et al., 2015). The wide temperature adaptation makes the crop ideally suited for building resilience to cropping systems located in areas where temperature increases have been projected.

Results across the GCMs show that mean annual rainfall (MAP) for the future is projected to remain somewhat unchanged (**Figure 7.3**). for the late-century period, data showed that ACC and CCS predict a 10.6 and 8.3% increase in MAP respectively, while slight reductions of 3.5 and 2.5% are predicted by CNR and NOR respectively. However, the more extended box and whisper plots for ACC predict an increase in the inter-annual variability of mean rainfall (750 mm) (**Figure 7.3**). This suggests an increase in the probability of extreme weather events such as drought and floods. In all instances, projected ET_o was observed to be higher (35%) than projected rainfall and is set to increase in the future (mid and late century) (**Figure 7.3**). In this regard, the rainfall: ET_o ratio is projected to decrease in the near future. The increase in ET_o is consistent with the projected increase in minimum and maximum temperature and suggests an increase in crop water stress (Zhao et al., 2017). Then again, intercrop systems with cereals and legumes are advantageous as the cereal over-storey can lower canopy temperature and minimize evaporative losses (Biriah et al., 2018; Eskandari, 2011). The modification of microclimate within intercrop systems makes it an ideal system to mitigate against projected temperature and ET_0 increases. Our results suggest that, while the tolerances of traditional crops to high temperatures may vary, intercropping crop species with different physiological and morphological traits can be a strategy to increase the resilience of marginalized production systems to projected temperature ET_0 increases.

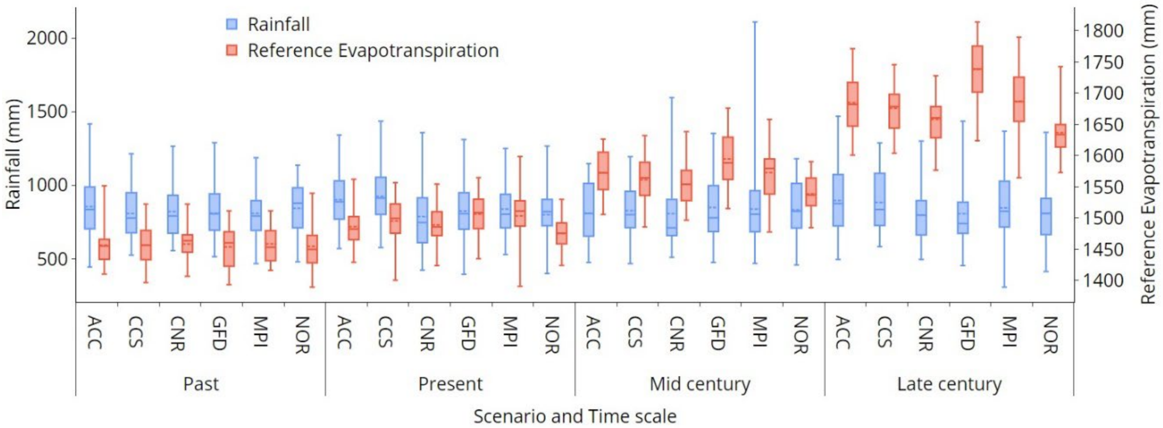


Figure 7.3 Rainfall and reference evapotranspiration data representative of four different timescales (past, present, mid- and late-century) as simulated by the six GCMs (ACC, CSS, CNR, GFD, NOR and MPI) used in the study. The mean annual rainfall represents average yearly rainfall calculated from observed rainfall data received between 2004 and 2019

7.3.3 Yield, Water Use and Water Use Efficiency

Across the GCMs, yield trends for intercropped bambara groundnut showed a gradual reduction towards the late century by 24% when compared to the baseline yield of 365 kg ha^{-1}. The observed trend for simulated bambara groundnut yield was late-century (285 ± 57) < mid-century (323 ± 62) < present (365 ± 67) < past (450 ± 65 kg ha^{-1}) (Figure 4). Across the GCMs, the magnitude of change in simulated bambara groundnut yield during the mid- and late-century periods was consistent with corresponding projected increases in ET_o and temperature. On the other hand, the mean yield trends for intercropped maize landrace across the GCMs and time scales were inconsistent with projected increases in ET_o and temperature. The observed trend for simulated maize landrace yield was past (845) < late-century (855) < present (923) < mid-century (967 kg ha^{-1}). For mid-century, although the model predicted a slight increase in maize landrace yield, results also showed larger yield variations relative to past and present. Standard deviations for the intercropped maize landrace yield were past (288) < present (363) < mid-century (351) < late-century (436 kg ha^{-1}) (**Figure 7.4**). These results are in line with the increased probability of extreme weather events such as drought and floods (Schulze, 2011). Although bambara groundnut yield decreased across the time scales, the magnitude of yield variations within each timescale and GCM was somewhat consistent with an average standard deviation of 63 kg ha^{-1}. Within each timescale, our results would suggest that yields of bambara groundnut are more stable to climate fluctuation; however, it could be more sensitive to significant climate changes.

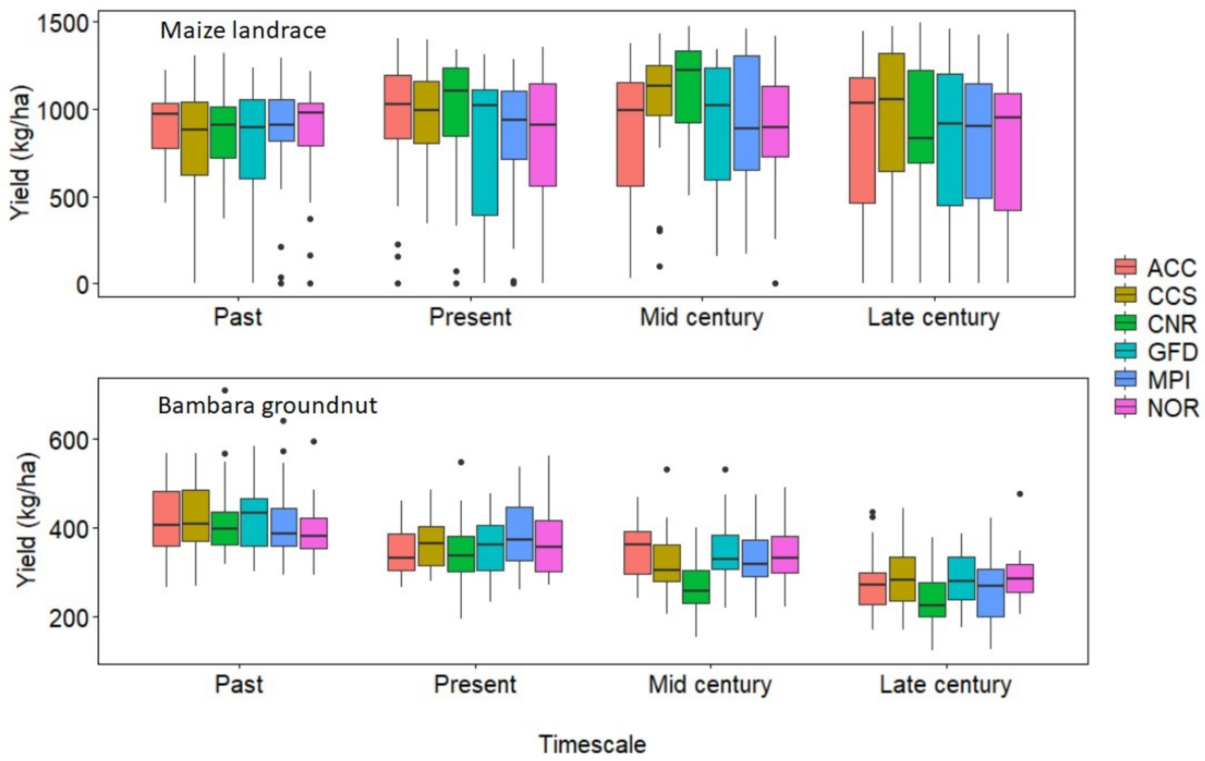


Figure 7.4 Simulated yield (kg ha^{-1}) for maize landrace and bambara groundnut during four different timescales (Past, Present, Mid-century and Late-century) under rainfed conditions obtained from the six GCMs (ACC, CSS, CNR, GFD, NOR and MPI)

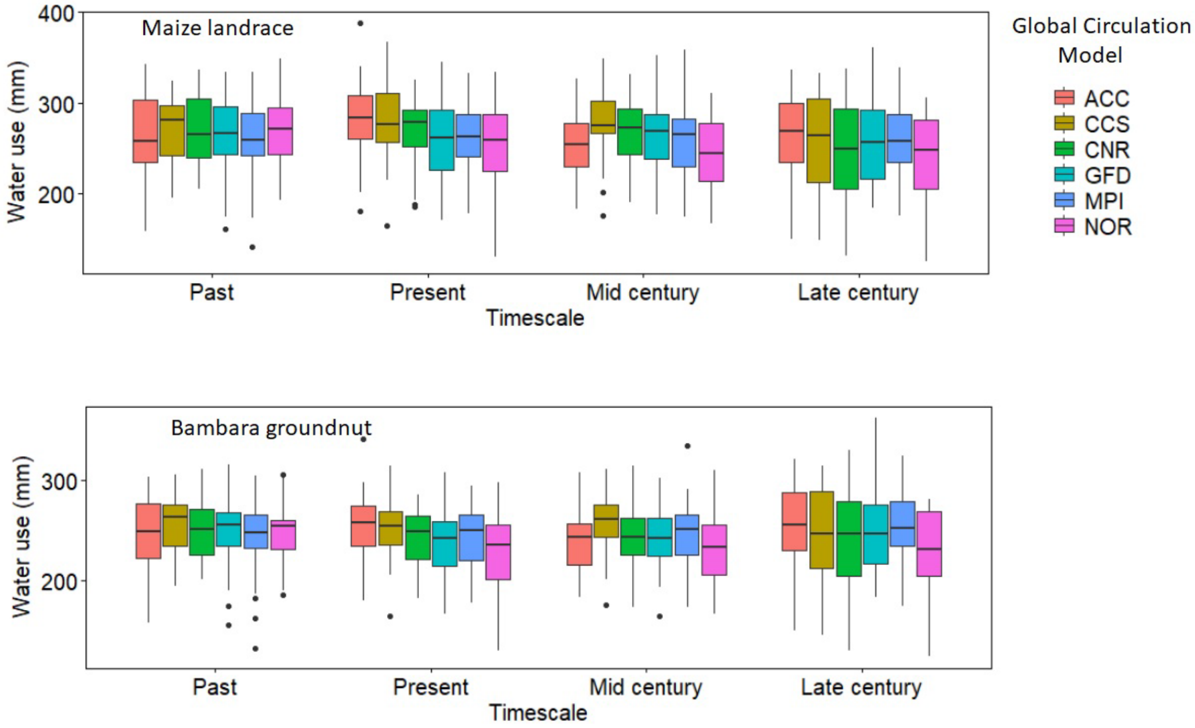


Figure 7.5 Calculated water use (mm) of maize landrace and bambara groundnuts from soil evaporation (Es), crop water use (Ep) as simulated by APSIM across the six GCMs (ACC, CSS, CNR, GFD, NOR and MPI) for each timescale (Past, Present, Mid-century and Late-century

The trend for water use in the intercropped maize landrace and bambara groundnut was inconsistent across the GCM and timescales. Overall, CCS predicted the highest water use (265 and 253 mm), while the lowest was under NOR (242 and 235 mm) for maize landrace and bambara groundnut, respectively (**Figure 7.5**). Differences in simulated WU across the GCMs could be that each climate model has been developed based on its assumptions and unique mathematical representations of physical climate system processes, providing different climate projections (Confalonieri et al., 2016). There were slight reductions in WU across the timescale; however, based on the pairwise t-test analysis, the reductions were not significant ($P > 0.05$). On the other hand, simulated results for crop water use efficiency (WUE) for intercropped bambara groundnut showed a reduction across time scales. The trend was such that past (1.78 ± 0.45) > present (1.52 ± 0.41) > mid-century (1.37 ± 0.38) > late century (1.16 ± 0.42 kg ha^{-1} mm ^{1}) (**Figure 7.6**). The observed trend was consistent with the observed reduction in future yield. Large inconsistencies were observed for maize landrace WUE across GCMs and time scales. For example, CNR predicted the highest water use (4.01 ± 1.98 kg ha^{-1} mm^{-1}), while the lowest was under NOR (3.25 ± 1.05 kg ha^{-1} mm^{-1}). The trend for maize landrace WUE across the timescale was such that present (3.58 ± 1.25) < past (3.62 ± 0.81) < late century (4.37 ± 1.38) < mid-century (4.56 ± 1.82 kg ha^{-1} mm^{-1}) (**Figure 7.6**). The observed trend was consistent with the simulated improvements of maize yield.

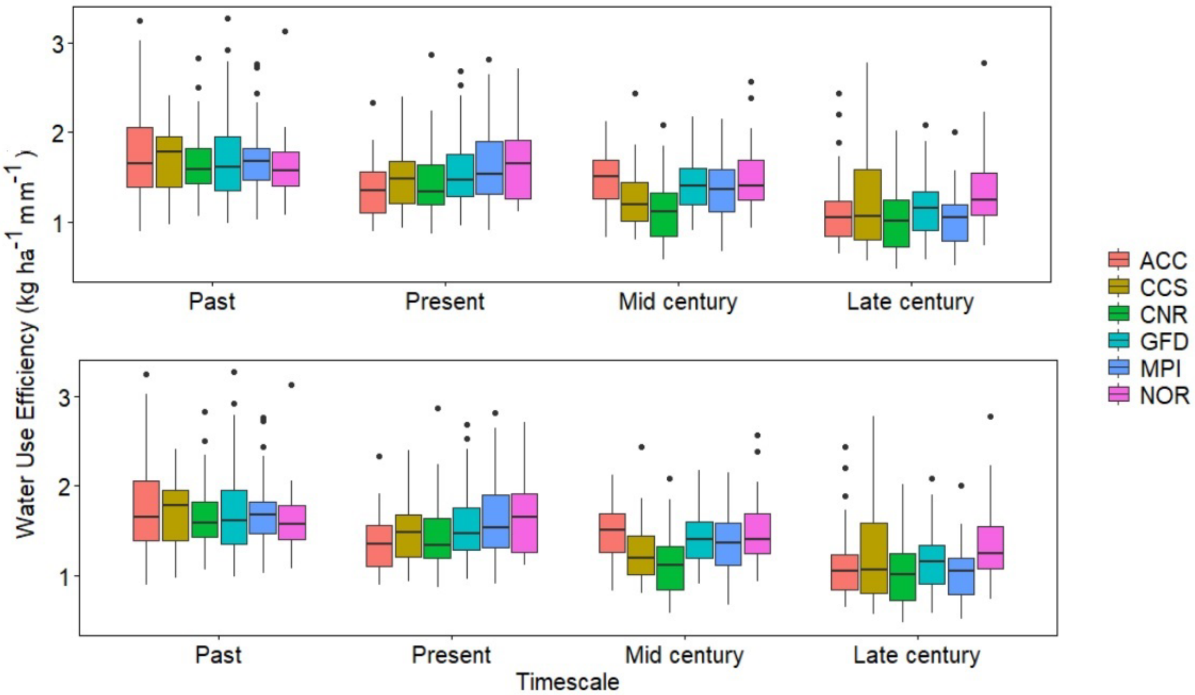


Figure 7.6: Calculated water use efficiency (kg ha^{-1} mm^{-1}) for maize landrace and bambara groundnut across the six GCMs (ACC, CSS, CNR, GFD, NOR and MPI) for each timescale (Past, Present, Mid-century and Late-century)

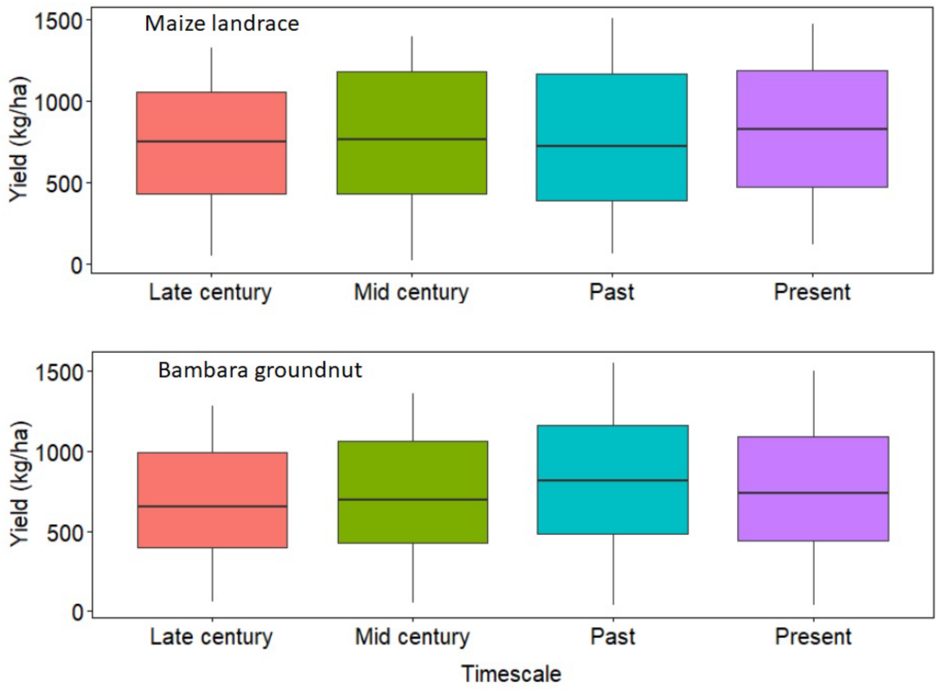


Figure 7.7: Simulated maize landrace and bambara groundnut yields (kg ha^{-1}) across different timescales from six GCM (ACC, CSS, CNR, GFD, NOR and MPI). Maize landrace F-statistic: 2.122 on 3 and 896 DF, p-value: 0.1 and bambara groundnut F-statistic: 5.031 on 3 and 896 DF, P-value: 0.001.

7.3.4 Optimizing the performance of bambara groundnut in intercrop systems

7.3.4.1 Impacts of planting density on yield and water use efficiency of a maize landrace and bambara groundnut intercrop system

Simulation results of yield and WU for intercropped maize landrace and bambara groundnut across the six GCM were not significantly ($P > 0.05$) different; therefore, the results presented in this section are average values across the six GCMs. Across timescales, the trend for maize landrace yield was past (850 ± 288) < late-century (853 ± 443) < present (893 ± 359) < mid-century (959 ± 362 kg ha^{-1}) (**Figure 7.7**). Increasing maize landrace plant population resulted in a significant increase in mean yield but did not affect WUE (**Figure 7.8**). Regardless of bambara groundnut plant population, increasing maize landrace plant population resulted in a 12% reduction in its mean yield while reducing the population resulted in an 8% improvement in its mean yield (Figure 8). On the other hand, simulated yield and WUE for intercropped bambara groundnut was significantly ($P<0.05$) affected by timescales and by the interaction between maize landrace and bambara groundnut planting date.

Across timescales, the trend for bambara groundnut yield was past (806 ± 406) > present (760 ± 404) > mid-century (717 ± 359) > late-century (674 ± 332 kg ha^{-1}) (Figure 7). Likewise, the trend for bambara groundnut WUE was past (2.54 ±1.10) > present (2.37 ± 1.23) > mid-century (2.33 ± 0.98) > late-century (2.17 ± 0.89 kg ha^{-1} mm^{-1}) (**Figure 7.8**). Although the observed WUE for bambara groundnut in the late century represented an 87% improvement relative to the baseline (1.16 ± 0.42 kg ha^{-1} mm^{-1}) for the same period, there was a 52% increase in its variability. Increasing bambara groundnut plant population increased simulated yield by 43% at the highest plant population, but also increased yield variability (standard deviation). The simulated mean yields (in kg ha^{-1}) and corresponding standard deviations were 520 ± 247 < 777 ± 353 < 921 ± 406 for intercropped bambara groundnut simulated at 2.2, 4.4 and 6.6 plants m^{-2}, respectively (**Figure 7.9**). A similar trend was observed for the calculated WUE (in kg ha^{-1} mm^{-1}), which was 1.61 ± 0.60 < 2.41 ± 0.94 < 2.98 ± 1.07 for intercropped bambara groundnut at 2.2, 4.4 and 6.6 plants m^{-2} (**Figure 7.9**). This would suggest that the currently recommended plant populations of 4.4 plants m^{2} might be low for optimum use of resources such as water.

There was a reduction in simulated mean yield for bambara groundnut with the increase in maize landrace plant population. The trend for bambara groundnut yield was 841 ± 305 > 720 ± 379 > 657 ± 422 (kg ha^{-1}) when intercropped with maize landrace at plant populations of 1.3, 2.6 and 3.9 plants m^{-2}, respectively (**Figure 7.7**). Similar to the simulated yield trend of intercropped bambara, increasing maize plant population resulted in a reduction of calculated bambara WUE and an increase in its variability (standard deviation) (**Figure 7.8**). The reduction of simulated yield and WUE maxima and minima for bambara groundnut and the increase in yield variability under high maize landrace plant populations could be attributed to increased competition for resources with the maize landrace. Peake et al. (2008) observed that increasing maize plant populations beyond a specific limit could increase the risk of crop failure due to an increase in competition for water and solar radiation. In cases were both yields of the maize landrace and bambara groundnut are desired by a farmer, it might be worthwhile to reduce maize landrace plant populations to maximize yield for bambara groundnut. Alternatively, there is a need to improve water availability through rainwater harvesting and conservation techniques to reduce competition for water within the intercrop.

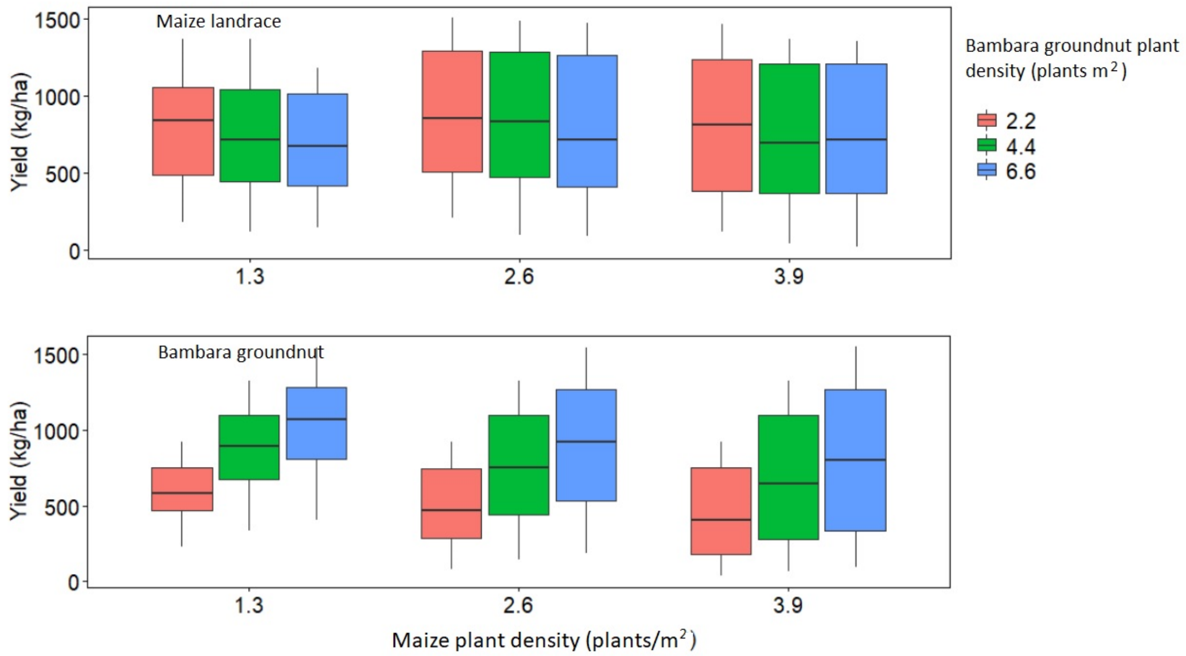


Figure 7.8: Simulated yield response of maize landrace and bambara groundnut to plant population (plant m^{-2}) for climate scenarios obtained from six GCM (ACC, CSS, CNR, GFD, NOR and MPI). The x-axis represents the maize landrace plant density (plant m^{-2}) and the coloured boxplots represent the bambara groundnut plant density (plant m^{-2}). The effect of the interaction between maize landrace plant density and bambara groundnut plant density on maize landrace grain yield – F-statistic: 62.47 on 8 and 891 DF, P-value=0.000. The effect of the interaction between maize landrace plant density and bambara groundnut plant density on bambara groundnut grain yield – F-statistic: 38.93 on 24 and 875 DF, P-value=0.000.

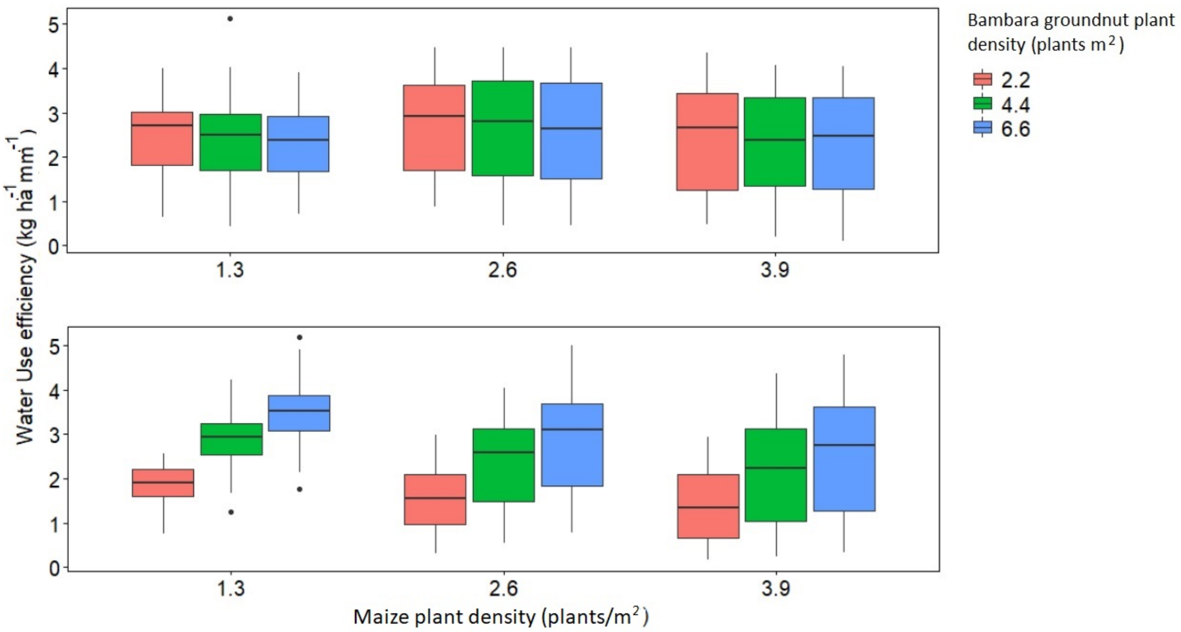


Figure 7.9: Calculated water use efficiency maize landrace and bambara groundnut to plant population (plant m^{-2}) for climate scenarios obtained from six GCM (ACC, CSS, CNR, GFD, NOR and MPI). The x-axis represents the maize landrace plant density (plant m^{-2}) and the coloured boxplots represent the bambara groundnut plant density (plant m-2). The effect of maize landrace plant density on maize landrace WUE – F-statistic: 6.78 on 2 and 891 DF, P-value=0.001. The effect of the interaction between maize landrace plant density and bambara groundnut plant density on bambara groundnut WUE – F-statistic: 38.93 on 24 and 875 DF, P-value=0.000.

7.3.4.2 Impacts of planting dates on yield and water use efficiency of maize landrace and bambara groundnut intercrop system

Simulation results for yield and WU for maize landrace and bambara groundnut across the six GCM were also not significantly different ($P > 0.05$); therefore, the results presented in this section were average values across the six GCMs. Simulated yield for maize landrace and bambara groundnut was significantly ($P < 0.05$) affected by the interaction of their planting dates (**Figure 7.10** and**Figure 7.11**). Overall, early planting (September) of maize landrace or bambara groundnut resulted in higher simulated yields relative to late planting (January). Across the planting dates, mean yield trends for intercropped bambara groundnut was September (992 ± 296) >

October (889 ± 357) > November (681 ± 383) > December (548 ± 301) >January (486 ± 283 kg ha^{-1}). On the other hand, calculated WUE trend for intercropped bambara groundnut was September (2.81 ± 0.78) > October (2.53 ± 0.96) > November (2.46 ± 1.15) > January (1.99 ± 1.12) > December (1.94 ± 1.01 kg mm^{-1}). For maize landrace, mean yield trends was September (1052 ± 116) > October (902 ± 197) > November (835 ± 213) > December (648 ± 261) >January (596 ± 283 kg ha^{-1}). On the other hand, calculated WUE trends for intercropped bambara groundnut was September (3.01 ± 0.88) > October (2.73 ± 0.76) > November (2.33 ± 0.95) > January (2.09 ± 1.00) > December (1.84 ± 0.66 kg mm^{-1}). The calculated WUE was lower (24-107%) than the calculated WUE baseline of 4.12 kg mm ^{1}. This could be attributed to a reduction in the lower quartile values (**Figure 7.10**) which would suggest an increase in maize landrace yield gap with later planting. According to several research outputs, climate change is expected to reduce the length of the growing season and increase the occurrence of dry spells (Ajetomobi, 2016; Mitchell et al., 2015; Paff and Asseng, 2018). Despite the loss of growing days, our result suggests that, when planting on the same day, early planting (September) may ensure stable yields and WUE are obtained. Rezvani Moghaddam et al. (2014) found that early planting could be used as an adaptation strategy for maize under future climate in arid regions of Iran. Hussain et al. (2018) also highlight that, regardless of planting date, yield responses are highly dependent on resource availability and distribution, in this case, rainfall.

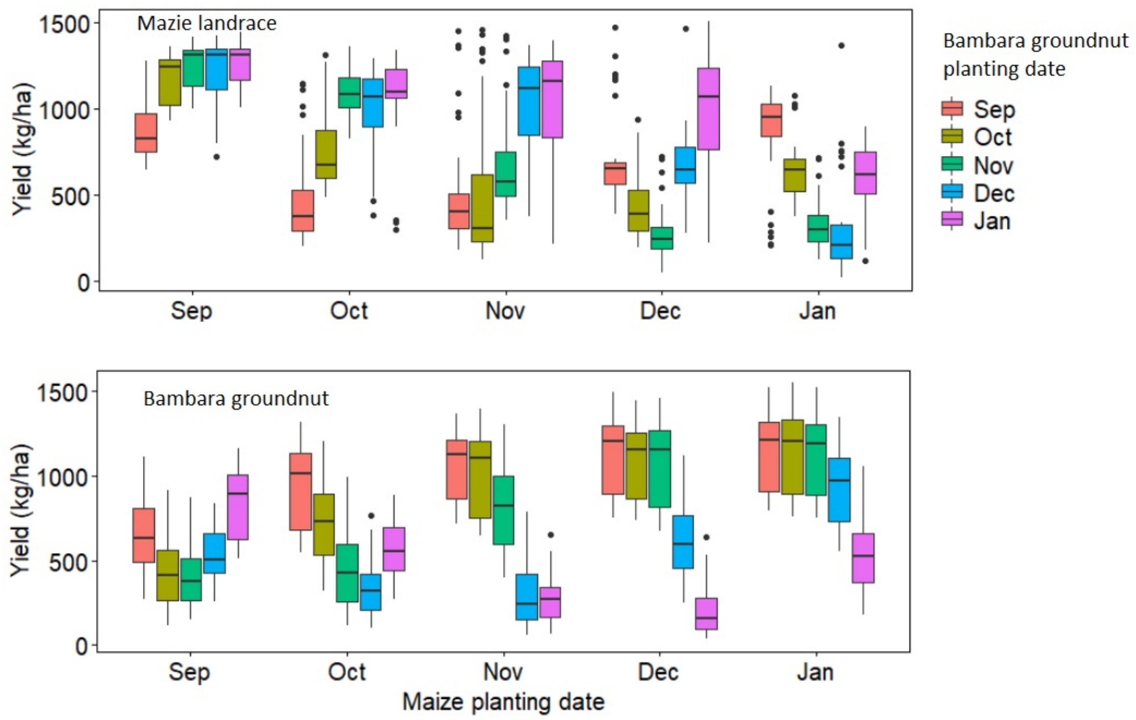


Figure 7.10: Simulated yield for maize and bambara groundnut across different planting date combinations under rainfed conditions obtained from six GCMs (ACC, CSS, CNR, GFD, NOR and MPI). The x-axis represents the maize landrace planting dates and the coloured boxplots represent the planting date for bambara groundnut. The effect of the interaction between maize landrace planting date and bambara groundnut planting date on maize landrace grain yield – F-statistic: 49.93 on 24 and 875 DF, P-value=0.000; The effect of the interaction between maize landrace planting date and bambara groundnut planting date on bambara groundnut grain yield – F-statistic: 75.37 on 24 and 875 DF, P-value=0.000

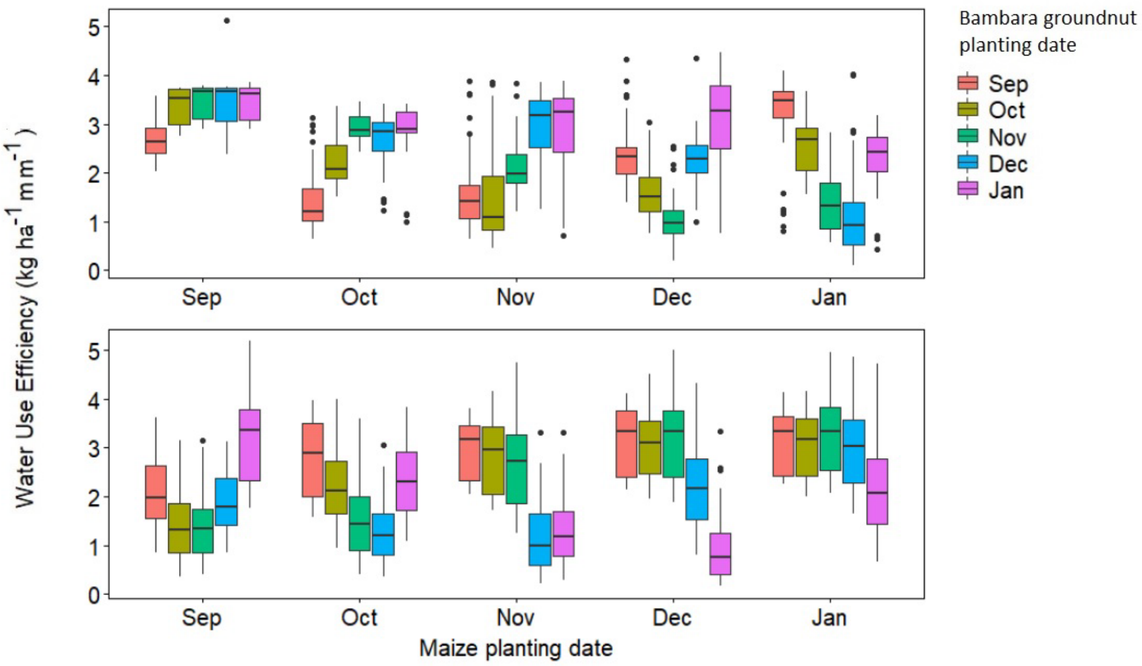


Figure 7.11: Calculated water use efficiency (kg ha^{-1} mm^{-1}) for maize and bambara groundnut across different planting date combinations under rainfed conditions obtained from six GCMs (ACC, CSS, CNR, GFD, NOR and MPI). The x-axis represents the maize landrace planting dates, and the coloured boxplots represent the planting date for bambara groundnut. The effect of the interaction between maize landrace planting date and bambara groundnut planting date on maize landrace WUE – F-statistic: 38.93 on 24 and 875 DF, P-value=0.000 and The effect of the interaction between maize landrace planting date and bambara groundnut planting date on maize landrace WUE – F-statistic: 35.16 on 24 and 875 DF, P-value=0.000

Intercropping bambara ground at different planting dates to maize landrace improved the mean yield (**Figure 7.10**), and WUE (**Figure 7.11**) provided it was done before November 15. Planting bambara groundnut a month earlier than maize landrace – for instance, planting in the former September and maize landrace in October, resulted in a 176% and 57% increase in its mean yield and WUE, respectively, relative to the baselines. Planting bambara groundnut two and three months earlier than maize landrace resulted in a 184% increase in yield (**Figure 7.10**) and improved WUE by 61% increase in WUE (**Figure 7.11**). Planting maize landrace a month earlier than bambara groundnut – for instance, planting in September and bambara groundnut in October, resulted in the most significant mean yield increase (56%) relative to the baseline (**Figure 7.11**). The asynchronous or sequential planting did not result in the overlap in critical phenological stages for both the maize landrace and bambara groundnut. This minimized the competition for water and other resources and maximized resource use through extending canopy duration, therefore improving yield and WUE for maize landrace and bambara groundnut within the intercrop. When critical periods overlap, Yu et al., (2016)suggested that the competitive balance in cereal-legume intercrops can be maintained by planting the legumes earlier than the cereals. This can be viewed as a strategy to minimize the risk of yield loss in the event of intermittent dry spells within the season. However, sequential cropping in rainfed systems is constrained by the length of growing period (Duku et al., 2018; Inthavong et al., 2011; Kotir, 2011; Minda et al., 2018; Vadez et al., 2012). In this study, we did not assess the impacts of climate change on changes in the length and shifts of the growing season, nor the probability of dry spell occurrence and duration.

7.4 Way forward and recommendations

Overall, crop simulation models (CSM) and climate scenarios provided a monitoring and surveillance system to identify climate trends and associated impacts on intercropped maize landrace and bambara groundnut yield and WUE. In this regard, the use of a CSM driven by climate projections from six GCMs provided an opportunity to assess the suitability and sustainability of intercropping traditional crops as a potential climate adaptation strategy under low input-low output production systems. Our study demonstrated that the availability of a range of GCM outputs provided useful indications of the potential magnitude of yield and WUE changes and the temporal variation that could occur for the intercrop system. This type of analysis was, therefore, helpful in improving our understanding of the type of climate risk on the maize landrace and bambara groundnut intercrop system (**Table 7.5**). We recommend that the use of a CSM with GCM output should be considered when assessing the applicability of agricultural adaptation strategy.

Our results further showed that, at present, functional crop diversity could enhance crop productivity, stability, and thus food security, through efficient water utilisation. Also, the adoption of asynchronous or sequential planting and moderating plant populations of either maize landrace or bambara groundnut can be viewed as a low-cost option to improve productivity and WUE under increasing temperature. This allows for the identification of short, medium and long-term strategies to aid in mitigating the impacts of climate change on the productivity and WUE of maize landrace and bambara groundnut intercrop system (**Table 7.5**). However, these approaches do not represent the diversity and breadth of adaptation strategies that can be adopted by marginal farmers.

To better represent adaptation, there is a need to expand the research to consider other management strategies (e.g. other traditional crop species, different cropping sequences, fertilization, rainwater harvesting and soil conservation techniques) (Seyoum et al., 2017). In addition, more system (agroecosystem) and place-based approaches that can represent local context, knowledge and aspects of food and nutrition security other than availability (e.g. nutrition, access, utilization and stability) may be required (Beveridge et al., 2018). To increase the contribution of agriculture to improving food and nutrition security, poverty reduction, and enhance rural economic development, climate impact modelling studies should be coupled with social, economic and environmental system models. This will ensure that traditional crops and associated cropping systems are assessed in a holistic manner that informs their sustainable integration into existing cropping systems. However, the adoption of traditional crops and intercropping should not be viewed as a panacea to solve all climate adaptation challenges, nor is it the only adaptation strategy. The inclusion of traditional crops into cropping systems should be considered as a complementary strategy to increasing climate resilience in marginal cropping systems.

A gap between the potential and practical realisation of adaptation exists, and the evidence from our study supports the view that adaptation strategies need to be both climate-informed and context-specific to be viable (Beveridge et al., 2018; Carter et al., 2018). The cultivation of traditional crops has been done for millennia; however, to our knowledge, no study has quantified the yield and WUE responses in an intercrop system and under the impacts of climate change. Further to this, the FAO guidelines and key questions provided a useful framework to contextualise the observed results in an informative manner (**Table 7.5**) and less prescriptive. With the impacts of climate variability and change, our results provide evidence that adapting agronomic management could allow for sustainable intensification of the traditional systems through improved resource use efficiencies. However, we acknowledge that this type of study should be repeated across other agro-ecologies different from that of Ukulinga, allowing for more robust crop management practices and adaptation strategies to be identified.

In this study, data to calibrate and validate the model was obtained from the same experimental plot and in the same growing season. Although characterised by the same probability distribution, the dataset to validate models should be independent of the calibration dataset. In the stricter sense of crop model evaluation, the data sets used for model calibration and validation were not independent. A major limitation to working with underutilised crops such as landrace varieties of maize and bambara groundnut is the unavailability of data. The calibration and validation process concerning the APSIM maize landrace and bambara groundnut intercrop study was the first attempt to evaluate the impacts of climate change on growth and water use. Furthermore, the study was designed as an *ex-ante* assessment with a secondary objective to have a better understanding of the models' capabilities of simulating underutilised crops, and pinpointing the strengths and weaknesses and showing areas for improvement. However, we acknowledge that this type of study should be repeated across other agro-ecologies and time scales different from that of the calibration data, allowing for better evaluation of model performance.

Table 7.5: FAO guidelines and key questions for assessing the impacts of adaptation strategy

FAO Guideline Question	**Key Findings**	**Comments**	**Implication**
How can CSMs and climate scenarios assist in articulating decision windows?	They provided a monitoring and surveillance system to identify short-, medium- and long-term climate trends and associated impacts on intercropped maize landrace and bambara groundnut yield and WUE Data and trends on climate indicators allowed for the identification of possible responses to increasing system resilience	By late century, there will be an increase in temperature and ET_0, while rainfall remains somewhat unchanged Maize landrace yield responses are in line with rainfall trends Bambara groundnut yield and WUE will be negatively impacted by increasing temperature Adopting "better bet" management options in bambara can mitigate the projected impacts of climate change and improve the overall performance of the intercrop system	Useful for improving understanding of climate risk and impacts Useful in building the resilience of smallholder farming systems to possible impacts of climate change For low input-low output systems, the adoption of traditional crops has the potential to support positive transformative adaptation to climate change

What are the likely short-, medium-, and long-term climate change impacts and risks for agriculture? How does risk shift further into the future?	Short-term: an increase in yield variability resulting in increases in yield gaps Medium-term: increases in climate risk will increase competition for resources within the intercrop system Long-term: reduction in water availability through increases in temperature and evaporative demand	Short-term: Use of adaptable crop species and cropping systems can reduce yield minima in marginal systems Medium-term: reducing competition of resources within intercrop through enhanced niche differentiation Long-term: There is a need to reduce the unproductive loss of water	Short-term: intercropping maize landrace and bambara groundnut under recommended guidelines will improve overall system productivity and WUE relative to corresponding monocrop systems Medium-term: adopt asynchronous or sequential planting to reduce competition within the intercrop systems Long-term: adopt rainwater harvesting and soil water conservation strategies to enhance soil water capture, storage and minimize unproductive loss of soil water
Which of these interventions are	Intercropping maize landrace at low plant population and bambara	Manipulating planting densities and dates can aid in maintaining	Sequential cropping in rainfed systems may be constrained

likely to stand the test of time rather than becoming obsolete?	groundnut at high population can sustainably improve yield and WUE of the system under projected climate change Early planting improves yield and WUE of maize landrace and bambara groundnut intercrop system under projected climate change Planting bambara groundnut two months earlier than maize landrace can minimize resource competition and enhance productivity	the competitive balance within an intercrop system	by the length of the growing period Good agronomy can result in high yield and WUE

7.5 Conclusions

There is a high probability that yield and WUE for intercropped bambara groundnut will decrease in the near to far future if current management options are maintained. Assuming future rainfall remains mostly unchanged, the primary limitations to intercropped bambara groundnut yield and WUE will be temperature and ET_o under minimal rainfall changes. However, projected changes in temperature and ET_o will increase yield and WUE variability for a maize landrace and bambara groundnut intercrop system. Improving WU, through increased plant population or asynchronous planting of maize landrace and bambara groundnut mitigated the negative impacts of changing climate on yield and WUE. In this regard, optimum plant management can optimise traditional production systems. Thus, intercrop systems of maize landrace and bambara groundnut should be promoted as a potential future system for climate change adaptations in rainfed production systems.

While the results of these simulations are limited to one agro-ecology and a single intercrop system, the findings confirm the views that traditional crops are drought tolerant and thus, are suitable for cultivation in marginal agricultural production areas. Furthermore, intercropping them can increase system resilience under changing climate. The concept of WUE, among other parameters, has been suggested in selecting management options that can sustainably increase productivity under changing climate regimes, heat and water stress, and interactions among them.

Intercropping maize landraces and bambara groundnut with the appropriate management options can be used as an adaptation strategy in environments that are projected to face increasing water scarcity. Reduced land and water demand from intercropping maize landraces and bambara groundnut and improved water use efficiencies mitigate the risks associated with increasing climate variability and extreme events such as drought. For resource-poor farmers that are inherently risk-averse, the production of traditional crops such as maize landraces and bambara groundnut, and their optimisation through inexpensive management strategies present an opportunity to build resilience in their cropping systems. Our results have important implications on how traditional crops and cropping systems should be viewed, in that their incorporation into marginal production systems can be an alternative adaptation strategy that may lead to sustainable intensification outcomes under increasing climate risk.

7.6 References

Abegaz, K.H., 2018. Prevalence of undernourishment: trend and contribution of East African countries to sub-Saharan Africa from 1991 to 2015. Agriculture & Food Security, 7(1), pp.1-6. doi:10.1186/s40066-018-0198-9.

Ajetomobi, J.O., 2016. Effects of weather extremes on crop yields in Nigeria. African journal of food, agriculture, nutrition and development, 16(4), pp.11168-11184. doi:10.18697/ajfand.76.15685.

Amarasingha, R.P.R.K., Suriyagoda, L.D.B., Marambe, B., Rathnayake, W.M.U.K., Gaydon, D.S., Galagedara, L.W., Punyawardena, R., Silva, G.L.L.P., Nidumolu, U. and Howden, M., 2017. Improving water productivity in moisture-limited rice-based cropping systems through incorporation of maize and mungbean: A modelling approach. Agricultural water management, 189, pp.111-122. doi:10.1016/j.agwat.2017.05.002.

Badu-Apraku, B. and Fakorede, M.A.B., 2017. Maize in Sub-Saharan Africa: importance and production constraints. In Advances in genetic enhancement of early and extra-early maize for Sub-Saharan Africa (pp. 3-10). Springer, Cham. doi:10.1007/978-3-319-64852-1_1.

Beveridge, L., Whitfield, S. and Challinor, A., 2018. Crop modelling: towards locally relevant and climate-informed adaptation. Climatic change, 147(3), pp.475-489. doi:10.1007/s10584-018-2160-z.

Boote, K.J., Mínguez, M.I. and Sau, F., 2002. Adapting the CROPGRO legume model to simulate growth of faba bean. Agronomy Journal, 94(4), pp.743-756. doi:10.2134/agronj2002.7430

Cairns, J.E., Hellin, J., Sonder, K., Araus, J.L., MacRobert, J.F., Thierfelder, C. and Prasanna, B.M., 2013. Adapting maize production to climate change in sub-Saharan Africa. Food Security, 5(3), pp.345-360.doi:10.1007/s12571-013-0256-x.

Cannon, A.J., Sobie, S.R. and Murdock, T.Q., 2015. Bias correction of GCM precipitation by quantile mapping: how well do methods preserve changes in quantiles and extremes?. Journal of Climate, 28(17), pp.6938-6959. doi:10.1175/JCLI-D-14-00754.1.

Carberry, P.S., Adiku, S.G.K., McCown, R.L. and Keating, B.A., 1996. Application of the APSIM cropping systems model to intercropping systems

Carter, R., Ferdinand, T. and Chan, C., 2018. Transforming agriculture for climate resilience: A framework for systemic change.

Chibarabada, T.P., Modi, A.T. and Mabhaudhi, T., 2015. Bambara groundnut (Vigna subterranea) seed quality in response to water stress on maternal plants. Acta Agriculturae Scandinavica, Section B – Soil & Plant Science, 65(4), pp.364-373. doi:10.1080/09064710.2015.1013979.

Chibarabada, T.P., Modi, A.T. and Mabhaudhi, T., 2017. Nutrient content and nutritional water productivity of selected grain legumes in response to production environment. International Journal of Environmental Research and Public Health, 14(11), p.1300. doi:10.3390/ijerph14111300.

Chimonyo, V.G.P., Modi, A.T. and Mabhaudhi, T., 2016. Simulating yield and water use of a sorghum-cowpea intercrop using APSIM. Agricultural Water Management, 177, pp.317-328. doi:10.1016/j.agwat.2016.08.021.

Chimonyo, V.G.P., Modi, A.T. and Mabhaudhi, T., 2016. Water use and productivity of a sorghum-cowpea-bottle gourd intercrop system. Agricultural Water Management, 165, pp.82-96. doi:10.1016/j.agwat.2015.11.014.

Chivenge, P., Mabhaudhi, T., Modi, A.T. and Mafongoya, P., 2015. The potential role of neglected and underutilised crop species as future crops under water scarce conditions in Sub-Saharan Africa. International journal of environmental research and public health, 12(6), pp.5685-5711. doi:10.3390/ijerph120605685.

Choudhary, S., Guha, A., Kholova, J., Pandravada, A., Messina, C.D., Cooper, M. and Vadez, V., 2020. Maize, sorghum, and pearl millet have highly contrasting species strategies to adapt to water stress and climate change-like conditions. Plant Science, 295, p.110297. doi:10.1016/j.plantsci.2019.110297.

Confalonieri, R., Orlando, F., Paleari, L., Stella, T., Gilardelli, C., Movedi, E., Pagani, V., Cappelli, G., Vertemara, A., Alberti, L. and Alberti, P., 2016. Uncertainty in crop model predictions: what is the role of users?. Environmental Modelling &

Software, 81, pp.165-173. doi:10.1016/j.envsoft.2016.04.009.

Dansi, A., Vodouhè, R., Azokpota, P., Yedomonhan, H., Assogba, P., Adjatin, A., Loko, Y.L., Dossou-Aminon, I. and Akpagana, K.J.T.S.W.J., 2012. Diversity of the neglected and underutilized crop species of importance in Benin. The scientific world journal, 2012. doi:10.1100/2012/932947.

Department of Agriculture Forestry & Fisheries (DAFF)., 2003. Maize production. Pretoria, South Africa Available at: www.nda.agric.za/publications.

Dimes, J.P. and Revanuru, S., 2004. Evaluation of APSIM to simulate plant growth response to applications of organic and inorganic N and P on an Alfisol and Vertisol in India. In Aciar Proceedings (pp. 118-125). ACIAR; 1998

Duku, C., Zwart, S.J. and Hein, L., 2018. Impacts of climate change on cropping patterns in a tropical, sub-humid watershed. PloS one, 13(3), p.e0192642. doi:10.1371/journal.pone.0192642.

Eskandari, H., 2011. Intercropping of wheat (Triticum aestivum) and bean (Vicia faba): Effects of complementarity and competition of intercrop components in resource consumption on dry matter production and weed growth. African Journal of Biotechnology, 10(77), pp.17755-17762. doi:10.5897/AJB11.2250.

Gashu, D., Demment, M.W. and Stoecker, B.J., 2019. Challenges and opportunities to the African agriculture and food systems. African Journal of Food, Agriculture, Nutrition and Development, 19(1), pp.14190-14217. doi:10.18697/AJFAND.84.BLFB2000.

Govender, L., Pillay, K., Siwela, M., Modi, A. and Mabhaudhi, T., 2017. Food and nutrition insecurity in selected rural communities of KwaZulu-Natal, South Africa – Linking human nutrition and agriculture. International Journal of Environmental Research and Public Health, 14(1), p.17. doi:10.3390/ijerph14010017

Granderson, J. and Price, P.N., 2014. Development and application of a statistical methodology to evaluate the predictive accuracy of building energy baseline models. Energy, 66, pp.981-990.

Hadebe, S.T., Mabhaudhi, T. and Modi, A.T., 2020. Water productivity of selected sorghum genotypes under rainfed conditions. International Journal of Plant Production, 14(2), pp.259-272.

Hadebe, S.T., Modi, A.T. and Mabhaudhi, T., 2017. Drought tolerance and water use of cereal crops: A focus on sorghum as a food security crop in sub-Saharan Africa. Journal of Agronomy and Crop Science, 203(3), pp.177-191. doi:10.1111/jac.12191.

Hammer, G.L., McLean, G., Chapman, S., Zheng, B., Doherty, A., Harrison, M.T., Van Oosterom, E. and Jordan, D., 2014. Crop design for specific adaptation in variable dryland production environments. Crop and Pasture Science, 65(7), pp.614-626. doi:10.1071/CP14088.

Hoffmann, M.P., Swanepoel, C.M., Nelson, W.C.D., Beukes, D.J., Van der Laan, M., Hargreaves, J.N.G. and Rötter, R.P., 2020. Simulating medium-term effects of cropping system diversification on soil fertility and crop productivity in southern Africa. European Journal of Agronomy, 119, p.126089. doi:10.1016/j.eja.2020.126089.

Holzworth, D., Meinke, H., DeVoil, P., Wegener, M., Huth, N., Hammer, G., Howden, M., Robertson, M., Carberry, P., Freebairn, D. and Murphy, C., 2006. The development of a farming systems model (APSIM) a disciplined approach.

Holzworth, D.P., Huth, N.I., deVoil, P.G., Zurcher, E.J., Herrmann, N.I., McLean, G., Chenu, K., Van Oosterom, E.J., Snow, V., Murphy, C. and Moore, A.D., 2014. APSIM-evolution towards a new generation of agricultural systems simulation. Environmental Modelling & Software, 62, pp.327-350. doi:10.1016/j.envsoft.2014.07.009.

Hussain, J., Khaliq, T., Ahmad, A. and Akhtar, J., 2018. Performance of four crop model for simulations of wheat phenology, leaf growth, biomass and yield across planting dates. PloS one, 13(6), p.e0197546. doi:10.1371/journal.pone.0197546.

Inthavong, T., Tsubo, M. and Fukai, D.S., 2011. A water balance model for characterization of length of growing period and water stress development for rainfed lowland rice. Field Crops Research, 121(2), pp.291-301. doi:10.1016/j.fcr.2010.12.019.

Isaacs, K.B., Snapp, S.S., Chung, K. and Waldman, K.B., 2016. Assessing the value of diverse cropping systems under a new agricultural policy environment in Rwanda. Food Security, 8(3), pp.491-506. doi:10.1007/s12571-016-0582-x.

Jamieson, P.D., Porter, J.R. and Wilson, D.R., 1991. A test of the computer simulation model ARCWHEAT1 on wheat crops grown in New Zealand. Field Crops

Research, 27: 337-350. doi:10.1016/0378-4290(91)90040-3.

Jia, J., Dai, Z., Li, F. and Liu, Y., 2016. How will global environmental changes affect the growth of alien plants?. Frontiers in plant science, 7, p.1623. doi:10.3389/fpls.2016.01623

Jones, J.W., Keating, B.A. and Porter, C.H., 2001. Approaches to modular model development. Agricultural Systems, 70(2-3), pp.421-443. doi:10.1016/S0308-521X(01)00054-3.

Karunaratne, A.S., Azam-Ali, S.N., Al-Shareef, I., Sesay, A., Jørgensen, S.T. and Crout, N.M.J., 2010. Modelling the canopy development of bambara groundnut. Agricultural and Forest Meteorology, 150(7-8), pp.1007-1015. doi:10.1016/j.agrformet.2010.03.006.

Keating, B.A., Carberry, P.S., Hammer, G.L., Probert, M.E., Robertson, M.J., Holzworth, D., Huth, N.I., Hargreaves, J.N., Meinke, H., Hochman, Z. and McLean, G., 2003. An overview of APSIM, a model designed for farming systems simulation. European journal of agronomy, 18(3-4), pp.267-288.

doi:10.1016/S1161-0301(02)00108-9.

Kotir, J.H., 2011. Climate change and variability in Sub-Saharan Africa: a review of current and future trends and impacts on agriculture and food security. Environment, Development and Sustainability, 13(3), pp.587-605.

Kunz, R.P., Davis, N.S., Thornton-Dibb, S.L.C., Steyn, J.M., Du Toit, E.S. and Jewitt, G.P.W., 2015. Assessment of biofuel feedstock production in South Africa: atlas of water use and yield of biofuel crops in suitable growing areas: volume 3: report to the Water Research Commission. Water Research Commission.

Leff, B., RamankuttyN., and FoleyJ. A., 2004: Geographic distribution of major crops across the world. Global Biogeochem. Cycles, 18. doi:10.1029/2003GB002108.

Mabhaudhi, T., Chibarabada, T.P., Chimonyo, V.G.P. and Modi, A.T., 2018. Modelling climate change impact: a case of bambara groundnut (Vigna subterranea). Physics and Chemistry of the Earth, Parts A/B/C, 105, pp.25-31. doi:10.1016/j.pce.2018.01.003.

Mabhaudhi, T., Chibarabada, T.P., Chimonyo, V.G.P., Murugani, V.G., Pereira, L.M., Sobratee, N., Govender, L., Slotow, R. and Modi, A.T., 2018. Mainstreaming underutilized indigenous and traditional crops into food systems: A South African perspective. Sustainability, 11(1), p.172. doi:10.3390/su11010172.

Mabhaudhi, T., Chimonyo, V.G.P., Hlahla, S., Massawe, F., Mayes, S., Nhamo, L. and Modi, A.T., 2019. Prospects of orphan crops in climate change. Planta, 250(3), pp.695-708. doi:10.1007/s00425-019-03129-y.

Mabhaudhi, T., Chimonyo, V.G. and Modi, A.T., 2017. Status of underutilised crops in South Africa: Opportunities for developing research capacity. Sustainability, 9(9), p.1569. doi:10.3390/su9091569.

Mabhaudhi, T., Modi, A.T. and Beletse, Y.G., 2013. Growth, phenological and yield responses of a bambara groundnut (Vigna subterranea L. Verdc) landrace to imposed water stress: II. Rain shelter conditions. Water Sa, 39(2), pp.191-198. doi:10.4314/wsa.v39i2.2

Mabhaudhi, T., Mpandeli, S., Nhamo, L., Chimonyo, V.G., Nhemachena, C., Senzanje, A., Naidoo, D. and Modi, A.T., 2018. Prospects for improving irrigated agriculture in southern Africa: Linking water, energy and food. Water, 10(12), p.1881. doi:10.3390/w10121881.

Malik, A.A. and Chaudhary, G., 2019. Global food security: a truncated yield of underutilized and orphan crops. In Biotechnology Products in Everyday Life (pp. 161-171). Springer, Cham. doi:10.1007/978-3-319-92399-4_11.

Mangani, R., Tesfamariam, E., Bellocchi, G. and Hassen, A., 2018. Modelled impacts of extreme heat and drought on maize yield in South Africa. Crop and Pasture Science, 69(7), pp.703-716. doi:10.1071/CP18117.

Martin-Guay, M.O., Paquette, A., Dupras, J. and Rivest, D., 2018. The new green revolution: sustainable intensification of agriculture by intercropping. Science of the Total Environment, 615, pp.767-772. doi:10.1016/j.scitotenv.2017.10.024.

Massawe, F., Mayes, S. and Cheng, A., 2016. Crop diversity: an unexploited treasure trove for food security. Trends in plant science, 21(5), pp.365-368. doi:10.1016/j.tplants.2016.02.006.

Matthews, N. and McCartney, M., 2018. Opportunities for building resilience and lessons for navigating risks: Dams and the water energy food nexus. Environmental Progress & Sustainable Energy, 37(1), pp.56-61. doi:10.1002/ep.12568.

Mayes, S., Ho, W.K., Chai, H.H., Gao, X., Kundy, A.C., Mateva, K.I., Zahrulakmal, M., Hahiree, M.K.I.M., Kendabie, P., Licea, L. and Massawe, F., 2019. Bambara groundnut: an exemplar underutilised legume for resilience under climate change. Planta, 250(3), pp.803-820. doi:10.1007/s00425-019-03191-6.

McCown, R.L., Hammer, G.L., Hargreaves, J.N.G., Holzworth, D.P. and Freebairn, D.M., 1996. APSIM: a novel software system for model development, model testing and simulation in agricultural systems research. Agricultural systems, 50(3), pp.255-271. doi:10.1016/0308-521X(94)00055-V.

Midega, C.A., Bruce, T.J., Pickett, J.A., Pittchar, J.O., Murage, A. and Khan, Z.R., 2015. Climate-adapted companion cropping increases agricultural productivity in East Africa. Field Crops Research, 180, pp.118-125. https://doi.org/10.1016/j.fcr.2015.05.022.

Minda, T.T., Van der Molen, M.K., Struik, P.C., Combe, M., Jiménez, P.A., Khan, M.S. and de Arellano, J.V.G., 2018. The combined effect of elevation and meteorology on potato crop dynamics: a 10-year study in the Gamo Highlands, Ethiopia. Agricultural and Forest Meteorology, 262, pp.166-177. doi:10.1016/j.agrformet.2018.07.009.

Missio, J.C., Rivera, A., Figàs, M.R., Casanova, C., Camí, B., Soler, S. and Simó, J., 2018. A comparison of landraces vs. modern varieties of lettuce in organic farming during the winter in the Mediterranean area: An approach considering the viewpoints of breeders, consumers, and farmers. Frontiers in plant science, p.1491.

Mitchell, S.R., Emanuel, R.E. and McGlynn, B.L., 2015. Land-atmosphere carbon and water flux relationships to vapor pressure deficit, soil moisture, and stream flow. Agricultural and Forest Meteorology, 208, pp.108-117. doi:10.1016/j.agrformet.2015.04.003.

Moghaddam, P.R., Moradi, R. and Mansoori, H., 2014. Influence of planting date, intercropping and plant growth promoting rhizobacteria on cumin (Cuminum cyminum L.) with particular respect to disease infestation in Iran. Journal of Applied Research on Medicinal and Aromatic Plants, 1(4), pp.134-143.

Mpandeli, S., Naidoo, D., Mabhaudhi, T., Nhemachena, C., Nhamo, L., Liphadzi, S., Hlahla, S. and Modi, A.T., 2018. Climate change adaptation through the water-energy-food nexus in southern Africa. International journal of environmental research and public health, 15(10), p.2306. doi:10.3390/ijerph15102306.

Mrema, G.C., Kienzle, J. and Mpagalile, J., 2018. Current status and future prospects of agricultural mechanization in sub-saharan Africa (SSA). Agricultural Mechanization in Asia, Africa and Latin America, 49(2), pp.13-30.

Muhammad, Y.Y., Massawe, F. and Mayes, S., 2016. Effects of short-term water deficit stress on physiological characteristics of Bambara groundnut (Vigna subterranea (L.) Verdc.). South African Journal of Plant and Soil, 33(1), pp.51-58. doi:10.1080/02571862.2015.1056847.

Muzari, W.G., W. and Muvhunzi, S. 2012. The impact of technology adoption on small holder agricultural productivity in Sub-saharan African. A review. Journal of sustainable development, 5(8). doi:10.5539/jsd.v5n8p69.

New Partnership for Africa's Development (NEPAD)., 2014. Implementation strategy and roadmap to achieve the vision on CAADP: Operationalizing the 2014 Malabo Declaration on Accelerated African Agricultural Growth and Transformation for Shared Prosperity and Improved Livelihood. Addis Ababa, Ethiopia .

Ndiso, J.B., Chemining'wa, G.N., Olubayo, F.M. and Saha, H.M., 2018. Effect of N-fertilizer application on soil moisture content, canopy temperature, growth and yield maize-cowpea intercrops. Journal of Advanced Studies in Agricultural, Biological and Environmental Sciences, 5(2), pp.62-78.

Nhamo, L., Matchaya, G., Mabhaudhi, T., Nhlengethwa, S., Nhemachena, C. and Mpandeli, S., 2019. Cereal production trends under climate change: Impacts and adaptation strategies in southern Africa. Agriculture, 9(2), p.30. doi:10.3390/agriculture9020030.

Nouri, H., Stokvis, B., Galindo, A., Blatchford, M. and Hoekstra, A.Y., 2019. Water scarcity alleviation through water footprint reduction in agriculture: the effect of soil mulching and drip irrigation. Science of the total environment, 653, pp.241-252. doi:10.1016/j.scitotenv.2018.10.311.

O'Leary, G.J., Aggarwal, P.K., Calderini, D.F., Connor, D.J., Craufurd, P., Eigenbrode, S.D., Han, X. and Hatfield, J.L., 2018. Challenges and responses to ongoing and projected climate change for dryland cereal production systems throughout the world. Agronomy, 8(4), p.34. doi:10.3390/agronomy8040034.

Padulosi, S., Heywood, V., Hunter, D. and Jarvis, A., 2011. Underutilized species and climate change: current status and outlook. Crop adaptation to climate change, 26, pp.507-521. doi:10.1002/9780470960929.ch35.

Paff, K. and Asseng, S., 2018. A review of tef physiology for developing a tef crop model. European journal of agronomy, 94, pp.54-66. doi:10.1016/j.eja.2018.01.008.

Peake, A.S., Robertson, M.J. and Bidstrup, R.J., 2008. Optimising maize plant population and irrigation strategies on the Darling Downs using the APSIM crop simulation model. Australian Journal of Experimental Agriculture, 48(3), pp.313-325. https://doi.org/10.1071/EA06108.

Ran, H., Kang, S., Li, F., Du, T., Ding, R., Li, S. and Tong, L., 2017. Responses of water productivity to irrigation and N supply for hybrid maize seed production in an arid region of Northwest China. Journal of Arid Land, 9(4), pp.504-514. doi:10.1007/s40333-017-0017-3.

Rippke, U., Ramirez-Villegas, J., Jarvis, A., Vermeulen, S.J., Parker, L., Mer, F., Diekkrüger, B., Challinor, A.J. and Howden, M., 2016. Timescales of transformational climate change adaptation in sub-Saharan African agriculture. Nature Climate Change, 6(6), pp.605-609. doi:10.1038/nclimate2947.

Saharan, K., Schütz, L., Kahmen, A., Wiemken, A., Boller, T. and Mathimaran, N., 2018. Finger millet growth and nutrient uptake is improved in intercropping with pigeon pea through “biofertilization” and “bioirrigation” mediated by arbuscular mycorrhizal fungi and plant growth promoting rhizobacteria. Frontiers in Environmental Science, 6, p.46. doi:10.3389/fenvs.2018.00046.

Saxena, K.B., Choudhary, A.K., Saxena, R.K. and Varshney, R.K., 2018. Breeding pigeonpea cultivars for intercropping: synthesis and strategies. Breeding science, 68(2), pp.159-167.

Schlenker, W. and Roberts, M.J., 2009. Nonlinear temperature effects indicate severe damages to US crop yields under climate change. Proceedings of the National Academy of sciences, 106(37), pp.15594-15598. doi:10.1073/pnas.0906865106.

Schulze, R.E., 1843. A perspective on climate change and the South African water sector. Water Research Commission report, 2(11)

Schulze, R.E. and Chapman, R.D., 2007. Estimation of daily solar radiation over South Africa. South African Atlas of Climatology and Agrohydrology: WRC Report No. 1489/1/06, Section 5.2

Schulze, R.E., Horan, M.J.C., Kunz, R.P., Lumsden, T.G. and Knoesen, D.M., 2011. The South African quinary catchments database. WRC, pp.31-37.

Seyoum, S., Chauhan, Y., Rachaputi, R., Fekybelu, S. and Prasanna, B., 2017. Characterising production environments for maize in eastern and southern Africa using the APSIM Model. Agricultural and Forest Meteorology, 247, pp.445-453. doi:10.1016/j.agrformet.2017.08.023

Slabbert, R., Spreeth, M., Krüger, G.H.J. and Bornman, C.H., 2004. Drought tolerance, traditional crops and biotechnology: breeding towards sustainable development. South African Journal of Botany, 70(1), pp.116-123. doi:10.1016/S0254-6299(15)30271-4.

Smith, A., Snapp, S., Dimes, J., Gwenambira, C. and Chikowo, R., 2016. Doubled-up legume rotations improve soil fertility and maintain productivity under variable conditions in maize-based cropping systems in Malawi. Agricultural Systems, 145, pp.139-149. doi:10.1016/j.agsy.2016.03.008.

Snapp, S.S., Grabowski, P., Chikowo, R., Smith, A., Anders, E., Sirrine, D., Chimonyo, V. and Bekunda, M., 2018. Maize yield and profitability tradeoffs with social, human and environmental performance: Is sustainable intensification feasible?. Agricultural Systems, 162, pp.77-88. doi:10.1016/j.agsy.2018.01.012

Sprent, J.I., Odee, D.W. and Dakora, F.D., 2010. African legumes: a vital but under-utilized resource. Journal of Experimental Botany, 61(5), pp.1257-1265.

Tacoli, C. and Vorley, B., 2016. Informal food systems and food security in rural and urban East Africa. IIED Briefing Paper-International Institute for Environment and Development, (17336).

Tokatlidis, I. and Vlachostergios, D., 2016. Sustainable stewardship of the landrace diversity. Diversity, 8(4), p.29. doi:10.3390/d8040029.

Ukeje, E., 2004. Modernizing small holder agriculture to ensure food security and gender empowerment: Issues and policy. Int Group Twenty-Four Res Pap, 23.

Vadez, V., Berger, J.D., Warkentin, T., Asseng, S., Ratnakumar, P., Rao, K., Gaur, P.M., Munier-Jolain, N., Larmure, A., Voisin, A.S. and Sharma, H.C., 2012. Adaptation of grain legumes to climate change: a review. Agronomy for Sustainable Development, 32(1), pp.31-44. doi:10.1007/s13593-011-0020-6.

Van Ittersum, M.K., Van Bussel, L.G., Wolf, J., Grassini, P., Van Wart, J., Guilpart, N., Claessens, L., De Groot, H., Wiebe, K., Mason-D'Croz, D. and Yang, H., 2016. Can sub-Saharan Africa feed itself?. Proceedings of the National Academy of Sciences, 113(52), pp.14964-14969. doi:10.1073/pnas.1610359113

Wang, J.F., Dinssa, F.F., Ebert, A.W., Hughes, J.D., Stoilova, T., Nenguwo, N., Dhillon, N.P.S., Easdown, W.J., Mavlyanova, R., Tenkouano, A. and Keatinge, J.D.H., 2014, August. Indigenous vegetables worldwide: their importance and future development. In XXIX International Horticultural Congress on Horticulture: Sustaining Lives, Livelihoods and Landscapes (IHC2014): 1102 (pp. 1-20).

Xiao, D., Li Liu, D., Wang, B., Feng, P., Bai, H. and Tang, J., 2020. Climate change impact on yields and water use of wheat and maize in the North China Plain under future climate change scenarios. Agricultural Water Management, 238, p.106238. doi:10.1016/J.AGWAT.2020.106238.

Xie, H., Huang, Y., Chen, Q., Zhang, Y. and Wu, Q., 2019. Prospects for agricultural sustainable intensification: a review of research. Land, 8(11), p.157.
doi:10.3390/land8110157.

Yu, Y., Stomph, T.J., Makowski, D., Zhang, L. and Van Der Werf, W., 2016. A meta-analysis of relative crop yields in cereal/legume mixtures suggests options for management. Field Crops Research, 198, pp.269-279. doi:10.1016/j.fcr.2016.08.001.

Zhao, C., Liu, B., Piao, S., Wang, X., Lobell, D.B., Huang, Y., Huang, M., Yao, Y., Bassu, S., Ciais, P. and Durand, J.L., Z, Zhu, and S. Asseng, 2017. Temperature increase reduces global yields of major crops in four independent estimates, Proceeded of the National Academy of Sciences, 114 (35): 9326-9331. doi:10.1073/pnas.1701762114.

Ajetomobi, J. O. (2016). Effects of weather extremes on crop yields in Nigeria. *African J. Food, Agric. Nutr. Dev.* 16, 11168-11184. doi:10.18697/ajfand.76.15685.

Amarasingha, R. P. R. K., Suriyagoda, L. D. B., Marambe, B., Rathnayake, W. M. U. K., Gaydon, D. S., Galagedara, L. W. et al. (2017). Improving water productivity in moisture-limited rice-based cropping systems through incorporation of maize and mungbean: A modelling approach. *Agric. Water Manag.* 189, 111-122. doi:10.1016/j.agwat.2017.05.002.

Badu-Apraku, B., Fakorede, M. A. B. A. B., (2017). “Maize in Sub-Saharan Africa: Importance and Production Constraints,” in *Advances in Genetic Enhancement of Early and Extra-Early Maize for Sub-Saharan Africa* (Cham: Springer International Publishing), 3-10. doi:10.1007/978-3-319-64852-1_1.

Beveridge, L., Whitfield, S., and Challinor, A. (2018). Crop modelling: towards locally relevant and climate-informed adaptation. *Clim. Change* 147, 475-489. doi:10.1007/s10584-018-2160-z.

Biriah, N. J., Ndiema, G., Olubayo, F., and Saha, H. M. (2018). Effect of N-fertilizer application on soil moisture content, canopy temperature, growth and yield maize-cowpea intercrops. *J. Adv. Stidied Agric. Biol. Environ. Sci.* 5, 62-78.

Boote, K. J., Mínguez, M. I., and Sau, F. (2002). Adapting the CROPGRO Legume Model to Simulate Growth of Faba Bean. *Agron. J.* 94, 743-756. doi:10.2134/agronj2002.7430.

Cairns, J. E., Hellin, J., Sonder, K., Araus, J. L., MacRobert, J. F., Thierfelder, C. et al. (2013). Adapting maize production to climate change in sub-Saharan Africa. *Food Secur.* 5, 345-360. doi:10.1007/s12571-013-0256-x.

Cannon, A. J., Sobie, S. R., and Murdock, T. Q. (2015). Bias Correction of GCM Precipitation by Quantile Mapping: How Well Do Methods Preserve Changes in Quantiles and Extremes? *J. Clim.* 28, 6938-6959. doi:10.1175/JCLI-D-14-00754.1.

Carberry, P. S., Adiku, S. G. K., McCown, R. L., and Keating, B. A. (1996). “Application of the APSIM cropping systems model to intercropping systems,” in *Dynamics of roots and nitrogen in cropping systems of the semi-arid tropics.* (Tsukuba, Japan: Japan International Research Center for Agricultural Sciences), 637-648.

Carter, R., Ferdinand, T., and Chan, C. (2018). Transforming Agriculture for Climate Resilience: A Framework for Systemic Change. ashington, DC Available at: https://www.wri.org/publication/transforming-agriculture-climate-resilience-framework-systemic-change.

Chibarabada, T. P., Modi, A. T., and Mabhaudhi, T. (2015). Bambara groundnut (

Vigna subterranea) seed quality in response to water stress on maternal plants. *Acta Agric. Scand. Sect. B – Soil Plant Sci.* 65, 364-373. doi:10.1080/09064710.2015.1013979.

Chibarabada, T. P., Modi, A. T., and Mabhaudhi, T. (2017). Nutrient content and nutritional water productivity of selected grain legumes in response to production environment. *Int. J. Environ. Res. Public Health* 14, 1300. doi:10.3390/ijerph14111300.

Chimonyo, V. G. P., Modi, A. T., and Mabhaudhi, T. (2016a). Simulating yield and water use of a sorghum-cowpea intercrop using APSIM. *Agric. Water Manag.* 177, 317-328. doi:10.1016/j.agwat.2016.08.021.

Chimonyo, V. G. P., Modi, A. T., and Mabhaudhi, T. (2016b). Water use and productivity of a sorghum-cowpea-bottle gourd intercrop system. *Agric. Water Manag.* 165, 82-96. doi:10.1016/j.agwat.2015.11.014.

Chivenge, P., Mabhaudhi, T., Modi, A. T. A., and Mafongoya, P. (2015). The Potential Role of Neglected and Underutilised Crop Species as Future Crops under Water Scarce Conditions in Sub-Saharan Africa. *Int. J. Environ. Res. Public Health* 12, 5685-5711. doi:10.3390/ijerph120605685.

Choudhary, S., Guha, A., Kholova, J., Pandravada, A., Messina, C. D., Cooper, M. et al. (2019). Maize, sorghum, and pearl millet have highly contrasting species strategies to adapt to water stress and climate change-like conditions. *Plant Sci.* doi:10.1016/j.plantsci.2019.110297.

Confalonieri, R., Orlando, F., Paleari, L., Stella, T., Gilardelli, C., Movedi, E. et al. (2016). Uncertainty in crop model predictions: What is the role of users? *Environ. Model. Softw.* 81, 165-173. doi:10.1016/j.envsoft.2016.04.009.

Dansi, a., Vodouhè, R., Azokpota, P., Yedomonhan, H., Assogba, P., Adjatin, A. et al. (2012). Diversity of the Neglected and Underutilized Crop Species of Importance in Benin. *Sci. World J.* 2012, 1-19. doi:10.1100/2012/932947.

Department of Agriculture Forestry & Fisheries (DAFF) (2003). Maize production. Pretoria, South Africa Available at: www.nda.agric.za/publications.

Dimes, J., and Revanuru, S. (2004). Evaluation of APSIM to Simulate Plant Growth Response to Applications of Organic and Inorganic N and P on an Alfisol and Vertisol in India. in *ACIAR PROCEEDINGS*, eds. R. Delve and M. . Probert

(Canberra: Australian Centre for International Agricultural Research), 118-125. Available at: http://www.ctu.edu.vn/~dvxe/doc/Modelling_Nutrient.pdf#page=117 [Accessed July 24, 2015].

Duku, C., Zwart, S. J., and Hein, L. (2018). Impacts of climate change on cropping patterns in a tropical, sub-humid watershed. *PLoS One* 13, e0192642. doi:10.1371/journal.pone.0192642.

Eskandari, H. (2011). Intercropping of wheat (Triticum aestivum) and bean (Vicia faba): Effects of complementarity and competition of intercrop components in resource consumption on dry matter production and weed growth. *African J. Biotechnol.* 10, 17755-17762. doi:10.5897/AJB11.2250.

Gashu, D., Demment, M. W., and Stoecker, B. J. (2019). Challenges and opportunities to the African agriculture and food systems. *African J. Food, Agric. Nutr. Dev.* 19, 14190-14217. doi:10.18697/AJFAND.84.BLFB2000.

Govender, L., Pillay, K., Siwela, M., Modi, A., and Mabhaudhi, T. (2016). Food and Nutrition Insecurity in Selected Rural Communities of KwaZulu-Natal, South Africa – Linking Human Nutrition and Agriculture. *Int. J. Environ. Res. Public Health* 14, 17. doi:10.3390/ijerph14010017.

Granderson, J., and Price, P. N. (2014). Development and application of a statistical methodology to evaluate the predictive accuracy of building energy baseline models. *Energy* 66, 981-990.

Hadebe, S. T., Mabhaudhi, T., and Modi, A. T. (2019). Water Productivity of Selected Sorghum Genotypes Under Rainfed Conditions. *Int. J. Plant Prod.* doi:10.1007/s42106-019-00082-4.

Hadebe, S. T., Modi, A. T., and Mabhaudhi, T. (2017). Drought Tolerance and Water Use of Cereal Crops: A Focus on Sorghum as a Food Security Crop in Sub-Saharan Africa. *J. Agron. Crop Sci.* 203, 177-199. doi:10.1111/jac.12191.

Hammer, G. L., McLean, G., Chapman, S., Zheng, B., Doherty, A., Harrison, M. T. et al. (2014). Crop design for specific adaptation in variable dryland production environments. *Crop Pasture Sci.* 65, 614-626. doi:10.1071/CP14088.

Hoffmann, M. P., Swanepoel, C. M., Nelson, W. C. D., Beukes, D. J., Van der Laan, M., Hargreaves, J. N. G. et al. (2020). Simulating medium-term effects of cropping system diversification on soil fertility and crop productivity in southern Africa. *Eur.*

J. Agron. 119, 126089. doi:10.1016/j.eja.2020.126089.

Holzworth, D., Meinke, H., DeVoil, P., Wegener, M., Huth, N., Hammer, G. et al. (2006). The development of a farming systems model (APSIM) – A disciplined approach. in (CSIRO Sustainable Ecosystems, APSRU, P.O. Box 102, Toowoomba, QLD, 4350, Australia). Available at: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84858674167&partnerID=40&md5=12efdea157d1ef6fd4ee09b58cadaffe.

Holzworth, D. P., Huth, N. I., deVoil, P. G., Zurcher, E. J., Herrmann, N. I., McLean, G. et al. (2014). APSIM-Evolution towards a new generation of agricultural systems simulation. *Environ. Model. Softw.* 62, 327-350. doi:10.1016/j.envsoft.2014.07.009.

Hussain, J., Khaliq, T., Ahmad, A., and Akhtar, J. (2018). Performance of four crop model for simulations of wheat phenology, leaf growth, biomass and yield across planting dates. *PLoS One* 13. doi:10.1371/journal.pone.0197546.

Inthavong, T., Tsubo, M., and Fukai, S. (2011). A water balance model for characterization of length of growing period and water stress development for rainfed lowland rice. *F. Crop. Res.* 121, 291-301. doi:10.1016/j.fcr.2010.12.019.

Isaacs, K. B., Snapp, S. S., Chung, K., and Waldman, K. B. (2016). Assessing the value of diverse cropping systems under a new agricultural policy environment in Rwanda. *Food Secur.* 8, 491-506. doi:10.1007/s12571-016-0582-x.

Jamieson, P. D., Porter, J. R., and Wilson, D. R. (1991). A test of the computer simulation model ARCWHEAT1 on wheat crops grown in New Zealand. *F. Crop. Res.* 27, 337-350. doi:10.1016/0378-4290(91)90040-3.

Jia, J., Dai, Z., Li, F., and Liu, Y. (2016). How Will Global Environmental Changes Affect the Growth of Alien Plants? *Front. Plant Sci.* 7, 1623. doi:10.3389/fpls.2016.01623.

Jones, J. W. W., Keating, B. A. a., and Porter, C. H. H. (2001). Approaches to modular model development. *Agric. Syst.* 70, 421-443. doi:10.1016/S0308-521X(01)00054-3.

Karunaratne, A. S., Azam-Ali, S. N., Al-Shareef, I., Sesay, A., Jørgensen, S. T., and Crout, N. M. J. (2010). Modelling the canopy development of bambara groundnut. *Agric. For. Meteorol.* 150, 1007-1015. doi:10.1016/j.agrformet.2010.03.006.

Keating, B. A., Carberry, P. S., Hammer, G. L., Probert, M. E., Robertson, M. J., Holzworth, D. et al. (2003). An overview of APSIM, a model designed for farming systems simulation. *Eur. J. Agron.* 18, 267-288. doi:10.1016/S1161-0301(02)00108-9.

Keatinge, J. D. H., Wang, J.-F., Dinssa, F. F., Ebert, A. W., Hughes, J. D. A., Stoilova, T. et al. (2015). *Indigenous vegetables worldwide: Their importance and future development*. doi:10.17660/ActaHortic.2015.1102.1.

Kotir, J. H. (2011). Climate change and variability in Sub-Saharan Africa: A review of current and future trends and impacts on agriculture and food security. *Environ. Dev. Sustain.* 13, 587-605.

Kunz, R. P., Davis, N. S., Thornton-Dibb, S., Steyn, J. M., and Jewitt, G. (2015). *Assessment of biofuel feedstock production in South Africa: Atlas of water use and yield of biofuel crops in suitable growing areas (Volume 3) Report to the WATER RESEARCH COMMISSION*.

Leff, B., Ramankutty, N., and Foley, J. A. (2004). Geographic distribution of major crops across the world. *Global Biogeochem. Cycles* 18, n/a-n/a. doi:10.1029/2003GB002108.

Mabhaudhi, T., Chibarabada, T. P., Chimonyo, V. G. P., and Modi, A. T. (2018a). Modelling climate change impact: A case of bambara groundnut (Vigna subterranea). *Phys. Chem. Earth, Parts A/B/C* 105, 25-31. doi:10.1016/j.pce.2018.01.003.

Mabhaudhi, T., Chibarabada, T. P., Chimonyo, V., Murugani, V., Pereira, L., Sobratee, N. et al. (2019a). Mainstreaming Underutilized Indigenous and Traditional Crops into Food Systems: A South African Perspective. *Sustainability* 11, 172. doi:10.3390/su11010172.

Mabhaudhi, T., Chimonyo, V. G. P., Hlahla, S., Massawe, F., Mayes, S., Nhamo, L. et al. (2019b). Prospects of orphan crops in climate change. *Planta*. doi:10.1007/s00425-019-03129-y.

Mabhaudhi, T., Chimonyo, V. G. P., and Modi, A. T. (2017). Status of Underutilised Crops in South Africa: Opportunities for Developing Research Capacity. *Sustainability* 9, 1569. doi:10.3390/su9091569.

Mabhaudhi, T., Modi, A. T., and Beletse, Y. G. (2013). Growth, phenological and yield responses of a bambara groundnut (Vigna subterranea L. Verdc) landrace to imposed water stress: II. Rain shelter conditions. *Water SA* 39, 191-198. doi:10.4314/wsa.v39i2.2.

Mabhaudhi, T., Mpandeli, S., Nhamo, L., Chimonyo, V. G. P. P., Nhemachena, C., Senzanje, A. et al. (2018b). Prospects for Improving Irrigated Agriculture in Southern Africa: Linking Water, Energy and Food. *Water* 10, 1881. doi:10.3390/w10121881.

Malik, A. A., and Chaudhary, G. (2019). "Global Food Security: A Truncated Yield of Underutilized and Orphan Crops," in, 161-171. doi:10.1007/978-3-319-92399-4_11.

Mangani, R., Tesfamariam, E., Bellocchi, G., and Hassen, A. (2018). Modelled impacts of extreme heat and drought on maize yield in South Africa. *Crop Pasture Sci.* 69, 703-716. doi:10.1071/CP18117.

Martin-Guay, M.-O., Paquette, A., Dupras, J., and Rivest, D. (2018). The new Green Revolution: Sustainable intensification of agriculture by intercropping. *Sci. Total Environ.* 615, 767-772. doi:10.1016/j.scitotenv.2017.10.024.

Massawe, F., Mayes, S., and Cheng, A. (2016). Crop Diversity: An Unexploited Treasure Trove for Food Security. *Trends Plant Sci.* 21, 365-368. doi:10.1016/j.tplants.2016.02.006.

Matthews, N., and McCartney, M. (2018). Opportunities for building resilience and lessons for navigating risks: Dams and the water energy food nexus. *Environ. Prog. Sustain. Energy* 37, 56-61. doi:10.1002/ep.12568.

Mayes, S., Ho, W. K., Chai, H. H., Gao, X., Kundy, A. C., Mateva, K. I. et al. (2019). Bambara groundnut: an exemplar underutilised legume for resilience under climate change. *Planta* 250, 803-820. doi:10.1007/s00425-019-03191-6.

McCown, R. L., Hammer, G. L., Hargreaves, J. N. G., Holzworth, D. P., and Freebairn, D. M. (1996). APSIM: a novel software system for model development, model testing and simulation in agricultural systems research. *Agric. Syst.* 50, 255-271. doi:10.1016/0308-521X(94)00055-V.

Midega, C. A. O., Bruce, T. J. A., Pickett, J. A., Pittchar, J. O., Murage, A., and Khan, Z. R. (2015). Climate-adapted companion cropping increases agricultural productivity in East Africa. *F. Crop. Res.* 180, 118-125.

doi:https://doi.org/10.1016/j.fcr.2015.05.022.

Minda, T. T., Van der Molen, M. K., Struik, P. C., Combe, M., Jiménez, P. A., Khan, M. S. et al. (2018). The combined effect of elevation and meteorology on potato crop dynamics: A 10-year study in the Gamo Highlands, Ethiopia. *Agric. For. Meteorol.* 262, 166-177. doi:10.1016/j.agrformet.2018.07.009.

Missio, J. C., Rivera, A., Figàs, M. R., Casanova, C., Camí, B., Soler, S. et al. (2018). A Comparison of Landraces vs. Modern Varieties of Lettuce in Organic Farming During the Winter in the Mediterranean Area: An Approach Considering the Viewpoints of Breeders, Consumers, and Farmers . *Front. Plant Sci.* 9, 1491. Available at: https://www.frontiersin.org/article/10.3389/fpls.2018.01491.

Mitchell, S. R., Emanuel, R. E., and McGlynn, B. L. (2015). Land-atmosphere carbon and water flux relationships to vapor pressure deficit, soil moisture, and stream flow. *Agric. For. Meteorol.* 208, 108-117. doi:10.1016/j.agrformet.2015.04.003.

Mpandeli, S., Naidoo, D., Mabhaudhi, T., Nhemachena, C., Nhamo, L., Liphadzi, S. et al. (2018). Climate change adaptation through the water-energy-food nexus in Southern Africa. *Int. J. Environ. Res. Public Health* 15. doi:10.3390/ijerph15102306.

Mrema, G. C., Kienzle, J., and Mpagalile, J. (2018). Current status and future prospects of agricultural mechanization in Sub-Saharan Africa [SSA]. *AMA, Agric. Mech. Asia, Africa Lat. Am.* 49, 13-30. Available at: https://www.researchgate.net/profile/Geoffrey_Mrema/publication/324542258_Current_Status_and_Future_Prospects_of_Agricultural_Mechanization_in_Sub-Saharan_Africa_SSA/links/5ad49764a6fdcc29358083ed/Current-Status-and-Future-Prospects-of-Agricultural-Mechan [Accessed September 18, 2019].

Muhammad, Y. Y., Mayes, S., and Massawe, F. (2016). Effects of short-Term water deficit stress on physiological characteristics of Bambara groundnut (Vigna subterranea (L.) Verdc.). *South African J. Plant Soil* 33, 51-58. doi:10.1080/02571862.2015.1056847.

Muzari, W., Gatsi, W., and Muvhunzi, S. (2012). The Impacts of Technology Adoption on Smallholder Agricultural Productivity in Sub-Saharan Africa: A Review. *J. Sustain. Dev.* 5, 69-77. doi:10.5539/jsd.v5n8p69.

NEPAD (New Partnership for Africa’s Development) (2014). Implementation strategy and roadmap to achieve the vision on CAADP: Operationalizing the 2014 Malabo Declaration on Accelerated African Agricultural Growth and Transformation for Shared Prosperity and Improved Livelihood. Addis Ababa, Ethiopia Available at: http://www.nepad-caadp.net/sites/default/files/Core-Meetings/implementation_strategy_report_english.pdf.

Nhamo, L., Mathcaya, G., Mabhaudhi, T., Nhlengethwa, S., Nhemachena, C., Mpandeli, S. et al. (2019). Cereal Production Trends under Climate Change: Impacts and Adaptation Strategies in Southern Africa. *Agriculture* 9, 30. doi:10.3390/agriculture9020030.

Nouri, H., Stokvis, B., Galindo, A., Blatchford, M., and Hoekstra, A. Y. (2019). Water scarcity alleviation through water footprint reduction in agriculture: The effect of soil mulching and drip irrigation. *Sci. Total Environ.* 653, 241-252. doi:10.1016/j.scitotenv.2018.10.311.

O'Leary, G. J., Aggarwal, P. K., Calderini, D. F., Connor, D. J., Craufurd, P., Eigenbrode, S. D. et al. (2018). Challenges and responses to ongoing and projected climate change for dryland cereal production systems throughout the world. *Agronomy* 8. doi:10.3390/agronomy8040034.

Padulosi, S., Heywood, V., Hunter, D., and Jarvis, A. (2011). "Underutilized Species and Climate Change: Current Status and Outlook," in *Crop Adaptation to Climate Change* (Oxford, UK: Wiley-Blackwell), 507-521. doi:10.1002/9780470960929.ch35.

Paff, K., and Asseng, S. (2018). A review of tef physiology for developing a tef crop model. *Eur. J. Agron.* 94, 54-66. doi:10.1016/j.eja.2018.01.008.

Peake, A. S., Robertson, M. J., and Bidstrup, R. J. (2008). Optimising maize plant population and irrigation strategies on the Darling Downs using the APSIM crop simulation model. *Aust. J. Exp. Agric.* 48, 313-325. Available at: https://doi.org/10.1071/EA06108.

Ran, H., Kang, S., Li, F., Du, T., Ding, R., Li, S. et al. (2017). Responses of water productivity to irrigation and N supply for hybrid maize seed production in an arid region of Northwest China. *J. Arid Land* 9, 504-514. doi:10.1007/s40333-017-0017-3.

Rezvani Moghaddam, P., Moradi, R., and Mansoori, H. (2014). Influence of planting date, intercropping and plant growth promoting rhizobacteria on cumin (Cuminum cyminum L.) with particular respect to disease infestation in Iran. *J. Appl. Res. Med. Aromat. Plants* 1, 134-143. doi:10.1016/j.jarmap.2014.10.003.

Rippke, U., Ramirez-Villegas, J., Jarvis, A., Vermeulen, S. J., Parker, L., Mer, F. et al. (2016). Timescales of transformational climate change adaptation in sub-Saharan African agriculture. *Nat. Clim. Chang.* 6, 605-609. doi:10.1038/nclimate2947.

Saharan, K., Schütz, L., Kahmen, A., Wiemken, A., Boller, T., and Mathimaran, N. (2018). Finger millet growth and nutrient uptake is improved in intercropping with pigeon pea through “biofertilization” and “bioirrigation” mediated by arbuscular mycorrhizal fungi and plant growth promoting rhizobacteria. *Front. Environ. Sci.* 6. doi:10.3389/fenvs.2018.00046.

Saxena, K. B., Choudhary, A. K., Saxena, R. K., and Varshney, R. K. (2018). Breeding pigeonpea cultivars for intercropping: synthesis and strategies. *Breed. Sci.* 68, 159-167.

Schlenker, W., and Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proc. Natl. Acad. Sci. U. S. A.* 106, 15594-8. doi:10.1073/pnas.0906865106.

Schulze, R. (2011). Perspective on Climate Change and the South AfricanWater Sector. Pretoria, South Africa.

Schulze, R. E., and Chapman, R. D. (2007). Estimation of daily solar radiation over South Africa. *South African Atlas Climatol. Agrohydrology. WRC Rep.*, 6.

Schulze, R., Horan, M., Kunz, R.P., Lumsden, T., and Knoesen, D. (2011). Methods 2: Development of the Southern African Quinary Catchments Database. WRC Report No. 1562/1/10. , eds. R. Schulze, B. Hewitson, K. Barichievy, M. Tadross, R. P. Kunz, M. Horan et al. Pretoria.

Seyoum, S., Chauhan, Y., Rachaputi, R., Fekybelu, S., and Prasanna, B. (2017). Characterising production environments for maize in eastern and southern Africa using the APSIM Model. *Agric. For. Meteorol.* 247, 445-453. doi:10.1016/j.agrformet.2017.08.023.

Slabbert, R., Spreeth, M., Krüger, G. H. J., and Bornman, C. H. (2004). Drought tolerance, traditional crops and biotechnology: breeding towards sustainable development. *South African J. Bot.* 70, 116-123. doi:10.1016/S0254-

6299(15)30271-4.

Smith, A., Snapp, S., Dimes, J., Gwenambira, C., and Chikowo, R. (2016). Doubled-up legume rotations improve soil fertility and maintain productivity under variable conditions in maize-based cropping systems in Malawi. *Agric. Syst.* 145, 139-149. doi:10.1016/j.agsy.2016.03.008.

Snapp, S. S. S., Grabowski, P., Chikowo, R., Smith, A., Anders, E., Sirrine, D. et al. (2018). Maize yield and profitability tradeoffs with social, human and environmental performance: Is sustainable intensification feasible? *Agric. Syst.* 162, 77-88. doi:10.1016/j.agsy.2018.01.012.

Sprent, J. I., Odee, D. W., and Dakora, F. D. (2010). African legumes: a vital but under-utilized resource. *J. Exp. Bot.* 61, 1257-1265.

Tcoli, C. (2016). Informal food systems and food security in rural and urban East Africa. *Ifad*, 1-4. Available at: http://pubs.iied.org/pdfs/17336IIED.pdf.

Tokatlidis, I., and Vlachostergios, D. (2016). Sustainable Stewardship of the Landrace Diversity. *Diversity* 8, 29. doi:10.3390/d8040029.

Ukeje, E. (2010). Modernizing small holder agriculture to ensure food security and gender empowerment: issues and policy. 1-23. Available at: http://www.africaportal.org/articles/2010/09/29/modernizing-smallholder-agriculture-ensure-food-security-and-gender-empowerment-.

Vadez, V., Berger, J. D., Warkentin, T., Asseng, S., Ratnakumar, P., Rao, K. P. C. et al. (2012). Adaptation of grain legumes to climate change: A review. *Agron. Sustain. Dev.* 32, 31-44. doi:10.1007/s13593-011-0020-6.

Van Ittersum, M. K., Van Bussel, L. G. J., Wolf, J., Grassini, P., Van Wart, J., Guilpart, N. et al. (2016). Can sub-Saharan Africa feed itself? *Proc. Natl. Acad. Sci.* 113, 14964-14969. doi:10.1073/pnas.1610359113.

Xiao, D., Liu, D. L., Wang, B., Feng, P., Bai, H., and Tang, J. (2020). Climate change impact on yields and water use of wheat and maize in the North China Plain under future climate change scenarios. *Agric. Water Manag.* 238, 106238. doi:10.1016/J.AGWAT.2020.106238.

Xie, H., Huang, Y., Chen, Q., Zhang, Y., and Wu, Q. (2019). Prospects for agricultural sustainable intensification: A review of research. *Land* 8, 1-27. doi:10.3390/land8110157.

Yu, Y., Stomph, T. J., Makowski, D., Zhang, L., and Van der Werf, W. (2016). A meta-analysis of relative crop yields in cereal/legume mixtures suggests options for management. *F. Crop. Res.* 198, 269-279. doi:10.1016/j.fcr.2016.08.001.

Zhao, C., Liu, B., Piao, S., Wang, X., Lobell, D. B., Huang, Y. et al. (2017). Temperature increase reduces global yields of major crops in four independent estimates. *Proc. Natl. Acad. Sci.* 114, 9326-9331. doi:10.1073/pnas.1701762114.

8 GENERAL DISCUSSION, CONCLUSIONS AND RECOMMENDATIONS

8.1 General discussion

8.1.1 Mapping bio-climatic regions suitable for the rainfed production of selected underutilised crops in South Africa

Neglected and underutilised crop species are crops that have not been previously classified as major crops, are under-researched, occupy low utilisation levels, and are mainly confined to smallholder farming areas. They are well known for tolerating adverse conditions such as climate variability, climate change and marginal land. Despite this, the importance of NUS in rural food systems and information regarding their suitability across diverse agricultural landscapes remains mainly anecdotal, with limited information detailing "where" they can grow and "why" they grow. Such information is essential if NUS are to be incorporated into existing cropping systems, increase the productivity of marginal landscapes, and reclaim degraded agricultural land. Further improvements in NUS production can improve food security globally, especially in marginal land where most smallholder farmers reside.

The introduction of NUS into regions classified as moderately suitable (S3) to highly suitable (S1) could increase the crop choices available and also contribute to biodiversity (SDG 15) (***cf*** Chapter 3). The low environmental impacts and increased biodiversity brought about by the introduction of NUS can be viewed as a climate change adaptation strategy (SDG 13) for increasing farmer resilience. This is especially true for marginalised farming communities with limited access to improved technologies such as hybrid seed and fertiliser. In this regard, the introduction of NUS into existing cropping systems can be viewed as a sustainable intensification approach (Harvey, 2010). Also, promoting NUS in marginal lands can contribute to food and nutrition security (SDG 2), poverty alleviation (SDG 1) through creating new value chains and human health and wellbeing (SDG 3).

Promoting or introducing NUS in mapped zones can be essential for addressing food insecurity, specifically malnutrition, reducing vulnerability to climate variability and change, environmental degradation, and gender inequality. It is argued that holistic land suitability maps, which consider several socio-economic indices, could be more helpful to policymakers and enhance the participation of marginalised farmers in the food system. The exclusion of key socio-economic indicators in developing suitability maps might affect the uptake and adoption of these crop species in areas where they are biophysically suitable. Therefore, to generate information of socio-economic indicators, there is a need for future studies to identify innovative ways to derive maximum value from the possible integration of GIS with block-chain, big data, and Internet of Things (IoT) technologies to mine updated data, especially on climatic data and social-economic factors.

8.1.2 Parameterisation and validation of crop models for selected underutilised crops

Process-based crop simulation models (CSMs) are dynamic computational tools that simulate the development and growth of a crop in relation to environmental conditions (e.g. air temperature, soil water, evaporative demand, and atmospheric CO_2 concentration) and management practices (e.g. sowing date, N fertilizer application, and crop residue). Crop models can be used to quantify the relationship between crop growth and its environment by simulating physiological processes. The determination of the initial conditions, model parameters, and driving variables (meteorological data, soil properties, field management, etc.) is important to successfully simulate crop growth at various spatial scales. The usefulness of any model can only be understood by evaluating how useful it is for giving an answer to a specific practical or research problem. Moreover, proper calibration of the models will decrease the error in simulation so that the model output fits closer to observations of dependent variables. The development of parameters for new cultivars for use in crop models requires extensive information about the crop and crop processes in response to growth factors. The uncertainties in modelling underutilised crops are derived not only from the model input dataset but also from the chosen modelling approach (Mirschel et al., 2004) (***cf***. Chapter 5-7). Thus, finding the right balance between input data quality and quantity, with an ideal modelling approach to address the modelling objective is key in their applications. Hence, there is no perfect model that can be applied.

The fact that AquaCrop, DSSAT and SIMPLE are successfully used to simulate yields, biomass, and WU for a range of cereal crops under climate change and varying irrigation regimes may imply that the use of these models can be widely applicable. With relatively comparable results (i.e. yield disagreement and yield variability) to the DSSAT and SIMPLE models, AquaCrop was observed as the more suitable model for simulating yield, biomass and WU under climate change impacts and irrigation management. This may be attributed to the crop or cultivar, soil and climate inputs used in this study being previously used in AquaCrop calibration studies.

8.1.3 Crop models to develop production guidelines for selected underutilised crops

Optimization of management of NUS is extremely important for maximizing return from the declining water allocation to this sector as it competes with various other pressing needs of the burgeoning human population. With increasing complexities of modern agriculture consequent to environmental concerns and more frequent droughts, there is need for a whole system quantitative approach to optimize the use of limited water, as well as N and other inputs, for varying weather conditions. Well calibrated and validated crop models that quantify the various physical, chemical, and biological processes in the soil-plant-atmosphere system, and their dynamics and management effects that contribute to crop growth and development, are being widely recognized as promising tools for decision support in this direction. Results of the study reinforce the high potential and promise of crop simulation models for the above purpose. They also enable faster and cheaper transfer of agrotechnology developed at the experimental stations to the farmer's fields or other locations.

Smallholder farmers in SSA have limited options for investment (seed, insurance, fertilisers, pesticides, machines) and irrigation to adapt to climate-related risks. The study was the first to model a range of ALVs (amaranth, cowpea, sweet potato, and wild mustard) in APSIM (***cf.*** Chapter 5). There was a significant effect on growth and productivity observed in ALVs upon changing agronomic management practices, with irrigation as the exception. The observed model outcomes are somewhat consistent with results on suitability (***cf.*** Chapter 4). It was observed that the general wide suitability of amaranth was associated with the growth requirements of the crop that allow for its production even under extremely marginal conditions. As such, simulating the addition of any amount of water resulted in no change in terms of growth and development of this crop and other ALVs.

8.2 Conclusions

We investigated potential land suitability for sorghum, cowpea, amaranth and taro in South Africa. Rainfall was the most critical variable and criterion with the highest impact on land suitability of NUS. Nevertheless, it was observed that NUS could still be grown on marginal land, and they can complement major crops and create greater diversity in cropping systems for building resilient cropping systems. The analysis indicated that sorghum, cowpea, and amaranth could be grown in marginal areas in S3 zones where land has moderate limitations for agricultural use. Mapping NUS production potential in SA is key to promoting their production by providing evidence to assist decision- and policymakers on crop choice. Specifically, the results help inform the Climate Smart Agriculture Strategy, National Policy on Comprehensive Producer Development Support and Indigenous Food Crops Strategy currently under development in South Africa. The land suitability maps are also helpful in informing decisions on climate change adaptation (climate-smart agriculture) and sustainable agriculture practices, as well as informing decisions on creating markets for NUS.

However, more research should focus on modelling indigenous crops. To achieve this, researchers must develop a better understanding of these crops' agronomy. Simpler models (i.e. with fewer input requirements) performed equally as well as more complex models, suggesting that going forward, less complex models can be adopted to advance modelling on NUS. Following Jones et al. (2016; 2017), this study has shown that some analyses can be performed which are needed to advise a farmer, but the availability of input data for agricultural systems models remains a major limitation. It is important to formulate necessary steps in collecting data inputs for crop simulation models. Worth noting is that the ease with which such data can be obtained will depend on the user’s expertise and familiarity with the proposed data collection methods. Methods of data collection involve qualitative and quantitative approaches, using both primary and secondary data sources. The methods used as input data sources range from grey literature review, field trials, controlled environment (greenhouse) experiments, remote sensing, models, software, and geographic information systems.

ALVs are generally grown under dry environments where they experience water stress, so correct management of these crops may improve productivity. The ALVs considered in this study establish in a short period (4-5 weeks) and mostly favour by early planting. Nonetheless, this may compromise their water productivity. As noticed, plant density plays a vital role in the growth and productivity of ALVs; increasing it to a certain threshold may result in growth, yield and productivity being compromised. The unresponsiveness of fertiliser to leaf number was not expected as fertiliser application is thought to improve vegetative growth. In this study, the use of irrigation was shown to contradict findings of certain previous studies. Therefore, it might be of interest that future studies revisit these sections for validation and correction.

8.3 Recommendations

- The suitability maps generated in this study indicate where NUS can be promoted as alternative crop choices or to complement the current range of crops grown within marginalised cropping systems. As such, the maps can be used to inform site-specific crop diversification recommendations as a sustainable intensification strategy.
- When planning for future sustainable crop production, the interactions of biophysical and social-economic factors are critical for identifying areas with the potential to support NUS.
- To generate information of socio-economic indicators, there is a need for future studies to identify innovative ways to derive maximum value from the possible integration of GIS with block-chain, big data, and IoT technologies to mine updated data, especially on climatic data and social-economic factors.
- There must be convergence on how to model biophysical processes for which the basic understanding has been in place for decades.

- More research should focus on modelling indigenous crops and to achieve this, researchers must develop a better understanding of these crops' agronomy.
- While model development always demands sagacity to integrate principles and empirical knowledge, the space requiring the most work is likely the root-soil interaction to determine root exploration and water uptake as well as nutrient acquisition. Maximum rooting depth or root distributions are sometimes imposed without empirical support. Yet, being able to predict rather than impose how roots explore the soil (or how much water is accessible) is of critical importance for practical applications.
- Uncertainty in prediction is another challenge in decision-making when using crop models for determining proper management practices. Hence, there is a need to quantify such uncertainties so that the decisions and associated risk can be handled for adjusting required crop management measures.
- Models cannot become even more difficult to use and therefore, setup, calibration, and application should be seamlessly integrated, otherwise the user may have more influence on the output than the model.
- Crops require different management strategies. The study has shown that:
    - Early plantings of ALVs (September) favoured a higher number of leaves. Contrary to this, late plantings (March) resulted in a low leaf number. However, planting in March resulted in the highest LAI when compared to a November planting, which had the lowest simulated values.
    - Applying irrigation can result in higher yield, biomass, and WUE simulated for millet and sorghum, but does not always result in improved WUE of other ALVs (e.g. amaranth).
    - Since the use of irrigation was shown to contradict findings of certain previous studies, it is suggested that future studies should revisit Chapter 5 for validation and correction.
    - Intercropping maize and bambara groundnut under recommended guidelines will improve overall system productivity and WUE relative to corresponding monocrop systems. The adoption of asynchronous or

sequential planting can be used to reduce competition within the intercrop systems.

- Intercropping maize at low plant population and bambara groundnut at high population can sustainably improve yield and WUE of the system under projected climate change.

9 APPENDIX I: REPORT ON RESEARCH DISSEMINATION

A. Peer reviewed articles

- Mugiyo, H., V.G.P. Chimonyo, M. Sibanda, R.P. Kunz, L. Nhamo et al. 2021. Multi-criteria suitability analysis for neglected and underutilised crop species in South Africa (A. Chemura, editor). PLoS One 16(1): e0244734. doi: 10.1371/journal.pone.0244734.
- Mugiyo, H., V.G.P. Chimonyo, M. Sibanda, R.P. Kunz, C.R. Masemola et al. 2021. Evaluation of Land Suitability Methods with Reference to Neglected cpand Underutilised Crop Species: A Scoping Review. Land 10(2): 125. doi: 10.3390/land10020125.
- Chimonyo, V.G.P., Kunz, R.P., Modi, A., Mabhaudhi, T., Wimalasiri, E.M. (2020). Optimizing traditional cropping systems under climate change: A case of maize landraces and bambara groundnut. Frontiers in Sustainable food systems. doi: 10.3389/fsufs.2020.562568
- Mabhaudhi, T., Chibarabada, T.P., Chimonyo, V.G.P., and Modi, A.T. (2018). Modelling climate change impact: A case of bambara groundnut (Vigna subterranea). Physics and Chemistry of the Earth – Parts A/B/C. doi:10.1016/j.pce.2018.01.003.
- Edwin Kimutai Kanda, Aidan Senzanje, Tafadzwanashe Mabhaudhi, and Shadrack Chisenga Mubanga. 2020. Nutritional yield and nutritional water productivity of cowpea (Vigna unguiculata L. Walp) under varying irrigation water regimes. Water SA 46(3 July). doi: 10.17159/wsa/2020.v46.i3.8651.
- Kanda, E.K., A. Senzanje, and T. Mabhaudhi. 2020. Calibration and validation of the AquaCrop model for full and deficit irrigated cowpea (Vigna unguiculata (L.) Walp). Phys. Chem. Earth, Parts A/B/C: 102941. doi: 10.1016/j.pce.2020.102941.
- Shayanowako, A.I.T., Morrissey, O., Tanzi, A., Muchuweti, M., Mendiondo, G.M., Mayes, S., Modi, A.T. and Mabhaudhi, T., 2021. African Leafy Vegetables for Improved Human Nutrition and Food System Resilience in Southern Africa: A Scoping Review. Sustainability, 13(5), p.2896.

B. Other publications

- Mabhaudhi, T., Chimonyo, V.G. and Modi, A.T., 2021. Underutilised crop species offer options for drought mitigation in South Africa. Water Wheel, 20(1), pp.33-35.

C. Book chapter

- Chimonyo V.G.P, Chivenge P.P., Nhamo L., Mpandeli S., Modi A.T. and Mabhaudhi T. (2020). Yield and water use gaps in cereal multi-crop systems in sub-Saharan Africa under climate change. In: Sareen S, Sharma P, Singh C, Jasrotia P, Singh GP and Sarial AK. Improving Cereal Productivity through Climate Smart Practices. Elsevier, India. Woodhead Publishing, pp. 313-329. https://doi.org/10.1016/B978-0-12-821316-2.00018-2

D. Thesis

- Hillary Mugiyo (2022) Crop suitability mapping for underutilized crops in South Africa. PhD Thesis. University Of Kwazulu-Natal, Pietermaritzburg, South Africa
- Thobeka Kunene (2021) Assessing Nutritional Water Productivity of Selected African Leafy Vegetables Using The Agricultural Production Systems Simulator Model. MSc Dissertation. University Of Kwazulu-Natal, Pietermaritzburg, South Africa
- Thembelihle Nzimande (2021) Application and evaluation of AquaCrop, DSSAT and SIMPLE model in simulating NUS production. MSc Dissertation. University Of Kwazulu-Natal, Pietermaritzburg, South Africa

E. Conferences and Webinars

- **Agroecology for the 21st century Conference Cape town – South Africa, 28-30 January 2019. [https://www.agroecologyconference.co.za/elective-events/]; *Title*** Linking agroecology to resilience and sustainable food systems: translating research into policy and practice; ***Medium***: Panel discussion; ***Participants***: Prof Paramu Mafongoya (University of KwaZulu-Natal), Laura

Pereira (City, University of London/University of KwaZulu-Natal), Garikai Magaya

- **3rd World Irrigation Forum (WIF3), Bali, Indonesia, 1-7 September 2019 [http://icid-ciid.org/inner_page/89];** ***Title*** Applying APSIM for evaluating intercropping under rainfed conditions: a preliminary assessment; ***Presenters:*** Chimonyo VGP, Modi AT, Mabhaudhi T
- **3rd World Irrigation Forum (WIF3), Bali, Indonesia, 1-7 September 2019 [http://icid-ciid.org/inner_page/89];** ***Title***: Options for improving agricultural water productivity under increasing water scarcity in South Africa; ***Presenters:*** Mabhaudhi T., Mpandeli S., Nhamo L., Senzanje A, Chimonyo VGP, and Modi T
- **20th WaterNet/WARFSA/GWPSA Symposium – WaterNet, Johannesburg, South Africa, 30 October - 1 November 2019;** ***Title***: Multi-criteria land evaluation for suitability analysis of neglected and underutilized species: a case study of South Africa; ***Presenters***: Hillary Mugiyo, Richard Kunz, Vimbayi G.P. Chimonyo, Tafadzwanashe Mabhaudhi
- **21st WaterNet/WARFSA/GWPSA Symposium, On-line, 28-30 October 2020 [https://www.waternetonline.org/calendar/2020/10/28/21st-waternet-warfsa-gwpsa-symposium]** ***Title:*** Optimizing traditional cropping systems under climate change: a case of maize landraces and bambara groundnut; ***Presenters***: Chimonyo VGP, Wimalasiri EM, Kunz RP, Modi AT, Mabhaudhi T
- **ICROPM2020 Crop modelling for Agriculture and Food Security under Global Change, February 3-5, 2020; Montpellier, Le Corum conference center, France [https://www.icropm2020.org/];** ***Attendee***: Chimonyo VGP
- **Special session;** ***Title*** of the Special Session: Reinforcing the role of underutilized indigenous and traditional crops: Linking Water, Agriculture, Nutrition and Health; ***Hosts***: Water Research Commission of South Africa in partnership with the Centre for Transformative Agricultural and Food Systems of the University of KwaZulu-Natal

10 APPENDIX II: CAPACITY BUILDING

Provision was made in the budget to fund three full-time students over the project's five-year period. A summary of capacity building to date is presented in sections that follow.

10.1 Post-graduate capacity building

The project has exceeded the original capacity development targets. The contractual obligation was to train three MSc students. To date, the project has enrolled the following postgraduate students:

- 2 Honours: Ms Thembelihle Nzimande and Ms Zinhle;
- 3 MSc students: Ms Thembelihle Nzimande, Ms Thobeka Kunene and Mr Thalente Ndebele;
- 2 PhD students: Mr Hillary Mugiyo and Miss Mendy Ndlovu;
- 2 postdocs: Dr VGP Chimonyo and Dr Zolo (Serge) Kiala.

Both Honours students completed their studies. Ms T. Kunene graduated in 2021 with a distinction. Ms Nzimande graduated cum laude in November 2021. Mr Mugiyo submitted his thesis for examination and is currently doing revisions from the examination. He is expected to graduate in April 2022. Miss Ndlovu is expected to complete during 2022. An additional MSc student, Mr Thalente Ndebele was recruited in 2021 and is expected to complete in 2022.

10.1.1 Student Abstracts

Hillary Mugiyo (2022)

Title: Crop suitability mapping for underutilized crops in South Africa.

Degree: PhD (Crop science)

Abstract: Several neglected and underutilized species (NUS) provide solutions to climate change and creating a Zero Hunger world, the Sustainable Development Goal 2. However, limited information describing their agronomy, water use, and evaluation of potential growing zones to improve sustainable production has previously been

cited as the bottlenecks to their promotion in South Africa's (SA) marginal areas. Therefore, the thesis outlines a series of assessments aimed at fitting NUS into dryland farming systems of SA. Initially, the study conducted a scoping review of land suitability methods. After that, South African bioclimatic zones with high rainfall variability and water scarcity were mapped. Using the analytic hierarchy process (AHP), the suitability for selected NUS sorghum (Sorghum bicolor), cowpea (Vigna unguiculata), amaranth and taro (Colocasia esculenta) was mapped. The future growing zones for NUS was assessed using the MaxEnt model. This was only done for KwaZulu Natal. Lastly, the study assessed management strategies such as optimum planting date, plant density, row spacing, and fertilizer inputs for sorghum. The review classified LSA methods reported in articles as traditional (26.6%) and modern (63.4%). Modern approaches, including multi-criteria decision-making (MCDM) methods such as AHP (14.9%) and fuzzy methods (12.9%); crop simulation models (9.9%) and machine-learning related methods (25.7%), are gaining popularity over traditional methods. Mapping high-risk agricultural drought areas were achieved by using the Vegetation Drought Response Index (VegDRI), a hybrid drought index that integrates the Standardized Precipitation Index (SPI), Temperature Condition Index (TCI), and the Vegetation Condition Index (VCI). The VegDRI indicated that SA arable land is prone to drought, with 16% experiencing severe drought, 34% – severe drought, 38% – moderate drought, 11% slight drought, and 1% no drought conditions. In NUS production, land use and land classification address questions such as “where”, “why”, and “when” a particular crop is grown within particular agroecology. The results indicated that sorghum was highly suitable (S1) = 2%, moderately suitable (S2) = 61%, marginally suitable (S3) = 33%, and unsuitable (N1) = 4%, cowpea S1= 3%, S2 = 56%, S3 = 39%, N1 = 2%, amaranth S1 = 8%, S2 = 81%, S3 = 11%, and taro S1 = 0.4%, S2 = 28%, S3 = 64%, N1 = 7%, of calculated arable land of SA (12 655 859 ha). The future distribution of NUS were modelled based on three representative concentration pathways (RCPs 2.6, 4.5 and 8.5) for the years between 2030 to 2070 using the maximum entropy (MaxEnt) model. The study identified seasonal precipitation, length of growing period (LGP), maximum-minimum temperature and isothermality variables that made relatively higher contributions in the model. The analysis showed a 4.2-25% increase under S1-S3 for sorghum, cowpea, and amaranth growing areas from 2030 to 2070. Across all RCPs, taro is predicted to decrease by 0.3-18% under S3 from 2050 to 2070 for all three RCPs. Best sorghum management practices were identified using the Sensitivity Analysis and generalized likelihood uncertainty estimation (GLUE) tools in DSSAT. Planting criteria (25 mm in 5 days – Department of Agriculture, Forestry and Fisheries-DAFF and 40 mm in 4 days-DEPTH criterion) was calculated in R-INSTAT. The developed maps are important for designing appropriate production guidelines aligned to climate-smart technologies. The best sorghum management is identified by an optimization procedure that selects the optimum sowing time, planting density-targeting 51,100, 68,200, 102,500, 205,000 and 300 000 plants ha^{-1} and fertilizer application rate (75 and 100 kg ha^{-1}) with maximum long-term mean yield. The best combination of management was within the DAFF planting criterion; usually, the second week of November, planting density 68,200 plants ha^{-1} and 100 kg of ammonium nitrate applied under as basal 50% and then 50% on the 28th day after sowing. The NUS are suitable for drought-prone areas, making them ideal for marginalised farming systems to enhance food and nutrition security.

Thobeka Kunene (2021)

Title: Assessing Nutritional Water Productivity of Selected African Leafy Vegetables Using The Agricultural Production Systems Simulator Model.

Degree: MSc (Crop science)

Abstract: Food and nutrition insecurity are regarded as one of the main challenges in the Sub-Saharan region. While substantial progress has been made to address food and nutrition challenges, this progress has varied across the region and over time in response to climate change hazards. Agriculture has been used as the main driver to improve food and nutrition security; however, productivity in these marginalised communities remains low. African leafy vegetables (ALVs) provide an unprecedented opportunity to ensure food security, lessen poverty and diversify farming systems while improving human health and increasing income. Crop modelling can contribute to generating information or data about growth, development and, water and nutritional needs of the crop. The primary objectives of this study were (i) to assess growth and productivity of selected ALVs (amaranth (Amaranth spp), cowpea (Vigna unguiculata), sweet potato (Ipomoea batatas) and wild mustard (Sinapis arvensis)) under different management practices, and (ii) assess water productivity (WP) and nutritional water productivity (NWP) of the selected ALVs. The Agricultural Production systems SImulator (APSIM) was used to simulate growth and productivities under different management scenarios of planting date, plant density, fertiliser application and irrigation. The soil and climatic data from the University of KwaZulu-Natal's research farm (Ukulinga Research Farm) situated in Pietermaritzburg, South Africa (29°37′S; 30°16′E; 775 m a.s.l.) was used to calibrate the model. To achieve these objectives, desktop-based research was conducted. Secondary literature was used to gather the information on the agronomy of the studied crops was obtained through careful literature search and selection. This was used to determine the nutrient content of the investigated ALVs. Relevant agronomic information was then used to model growth and productivity for the quantification of nutritional water productivity at different management practices. All data analysis was done using descriptive statistical analysis (R software). All mean values were subjected to a t-test set at $p<0.05$ significance. The results showed that depending on crop species, different management practices can be relevant to achieve optimum growth and productivity for different purposes. The investigated ALVs were found to have high nutrient content. Compared to one another, amaranth was more nutrient-dense and wild mustard the least dense crop compared to the others. On the other hand, NWP was comparatively high on both amaranth and cowpea.

Thembelihle Nzimande (2021)

Title: Application and evaluation of AQUACROP, DSSAT and SIMPLE model in simulating NUS production**.**

Degree: MSc (Crop Science)

Abstract: The study compared yield, biomass, and water use (WU) for maize, sorghum, and millet simulated using three crop models of varying complexity: AquaCrop, DSSAT and the SIMPLE model. The hypothesis was that less complex models with low input requirements perform similarly with complex models with more

input requirements. A standard set of crop parameters was used to develop crop files for all the three models. Similar soil, climate and management descriptions attained from the Ukulinga Research Farm were used across the models. Six general circulation models (GCMs) were used as climate input data to model past, present, mid-, and late-century climate change impacts on cereal crops. The effect of irrigation (as a management practice) on yield and water use was assessed using the mid-century projections. The performance of the three models was observed to be statistically different. Based on the mean bias error, all models overestimated yield, but the lowest overestimation was with AquaCrop (0.22 t/ha) followed by DSSAT (0.243 t/ha) and the SIMPLE model (0.687 t/ha). Other statistical indicators, viz., RMSE and R2, illustrate that the simulation of yield and WUE in AquaCrop was more satisfactory than DSSAT and the SIMPLE model. Across all the time scales, it was observed that AquaCrop simulated the highest yield and biomass, and the SIMPLE model simulated the lowest yield across the GCMs, which were inconsistent. Applying a higher amount of irrigation at more frequent intervals resulted in higher yield, biomass and WUE. AquaCrop showed the highest simulated mean yield for maize (8.34 t/ha), millet (6.86 t/ha) and sorghum (5.28 t/ha). Highest WUE was observed under AquaCrop for maize (21 kg/ha/mm) and millet (15.10 kg/ha/mm), the SIMPLE model for sorghum (13.37 kg/ha/mm). The study confirms that DSSAT requires relatively more input data but does not always perform more satisfactorily. The SIMPLE model requires fewer input requirements than AquaCrop and DSSAT; however, it is less sensitive to management changes. AquaCrop had relatively incomparable results to DSSAT and the SIMPLE model and was observed as the most suitable model for simulating yield, biomass, and WU of the selected cereal NUS under climate change and irrigation management scenarios. It is essential to calibrate crop growth parameters for local conditions or use parameters from local field studies when applying complex crop models such as DSSAT specifically for marginal environments, such as South Africa, before their application. On the other hand, AquaCrop performed reasonably well with minimal input requirement, confirming its reliability for application in data-limited and marginal environments. However, it is recommended that there must be calibration for all the models using inputs specific to locations.

10.2 Institutional capacity building

The Project Leader, Prof Mabhaudhi, attended a training workshop on the DSSAT Model that was conducted at University of Georgia, USA from the 15-20 May 2017. Mr Hilary Mugiyo also attended a similar DSSAT training workshop at the end of September 2019 in Pretoria. Both trainings have been helpful and enabled the Project Team and Mr Mugiyo to be able to supervise and mentor postgraduate students who are using DSSAT in the current project as well as in other projects. Already, Prof Mabhaudhi has assisted Ms Zoleka Ncoyini, a developmental lecturer in Agrometeorology, on how to use DSSAT. In 2018, the Project Team successfully hosted a R statistic training workshop for 20 UKZN students, including students on the project. The DSSAT and R statistics training has contributed to institutional capacity development at UKZN.

11 APPENDIX III: PRODUCTION GUIDELINES

1.1 Sorghum

1.1.1 Crop morphology and physiology

Sorghum has a primary and secondary root system. The primary roots are those which appear first from the germinating seed. The primary roots provide the seedling with water and nutrients from the soil. Primary roots have limited growth, and the secondary roots soon take over their functions. Secondary roots develop from nodes below the soil surface. The permanent root system branches freely, both laterally and downwards, into the soil. If no soil impediments occur, roots can reach a lateral distribution of 1 m and a depth of up to 2 m early in the plant's life. The roots are finer and branch approximately twice as much as roots from maize plants.

Sorghum leaves are typically green, glasslike, and flat and have a smaller leaf area than maize. The leaf blade is long, narrow and pointed. Young leaves have upright leaf blades; however, the blades tend to bend downwards as the leaves mature. A unique feature of sorghum leaves is the rows of motor cells along the midrib on the upper surface of the leaf. These cells can roll up leaves rapidly during soil moisture deficit. Leaves are covered by a thin wax layer and develop opposite one another on either side of the stem. Number of leaves vary from eight to 22 leaves depending on environmental conditions.

Stems are solid, dry, succulent and sweet. Under favorable conditions more internodes develop, together with leaves, producing a longer stem. The stem consists of internodes and nodes. Stem diameter varies between 5 mm and 30 mm. The internodes are covered by a thick waxy layer, giving it a blue white colour. The waxy layer reduces transpiration and increases the drought tolerance of the plants. The root band of nodes below or just above the soil surface develops prop roots. The growth bud develops lateral shoots. Sometimes the growth buds higher up the stem may also develop lateral shoots.

The inflorescence of sorghum is a compact panicle. The shape and colour of the panicle varies between cultivars. Heads are carried on a main stem or peduncle with primary and secondary branches on which the florets are borne. The peduncle is usually straight and its length varies from 75 to 500 mm. Each panicle contains from 800 to 3 000 kernels, which are usually partly enclosed by glumes. Glume colour may be black, red, brown or tan. The flowers of sorghum open during the night or early morning. Those at the top of the panicle open first and it takes approximately 6 to 9 days for the entire panicle to flower. Seed are oval to round and the colour may be red, white, yellow, brown or shades. They are partially enclosed by glumes, which are removed during threshing and/or harvesting. The sorghum grain consists of the testa, embryo and endosperm.

1.1.2 Agroecology

Figure 2 presents the results of the analysis of sorghum suitability based on MCDA-AHP and OWA operators. These results show the existing distribution of the land suitability classes, excluding areas where present land use is nature conservation, plantation, urban and water. Results indicated that about 2% of the land is highly suitable (S1) for the production of sorghum. Moderately suitable (S2) land constitutes the most substantial proportion (61%) of the calculated arable land of South Africa (12 655 859 ha) while marginally suitable (S3) and unsuitable (N1) constitutes 33% and 4%, respectively of calculated arable land (Figure 12). Large areas suitable (S1 and S2) land was concentrated in eastern provinces, and suitability intensity decreased towards western provinces (Figure 12). A total of 60 GPS location was used to confirm the presence of sorghum within selected locations in KwaZulu Natal province.

Sorghum yields are expected to decline for most growing areas along the eastern seaboard of the country, with the highest yield losses (> 50%) predicted for the Limpopo and eastern Mpumalanga provinces. Yield increases may occur in the central parts of the Eastern Cape and western regions of the Free State (Figure 13). In contrast, taro yields should improve for most growing areas in Limpopo, North West and KwaZulu-Natal (except in the north-east and along the coast) provinces. However, taro is not suited to the central and western parts of Mpumalanga, central and southern regions of the Free State, south-western KZN and northern areas of the Eastern Cape province. The review by Franke (2021) showed that changes in sorghum yield across southern Africa are highly variable and exhibit inconsistent patterns.

A comparison of Figure 13 with for Figure 14 sorghum revealed that certain areas have changed from a yield decrease to a yield increase. Examples can be found in the north-eastern regions of Limpopo and Mpumalanga, northern and eastern regions of Free State and north-eastern KZN. Overall, areas where more than a 50% decrease in yield have reduced in spatial extent, particularly in the North West, Limpopo and Mpumalanga provinces. For sorghum, no noticeable expansion in suitable growing areas was simulated by the model from present to near future, except in the higher altitude zones in Lesotho.

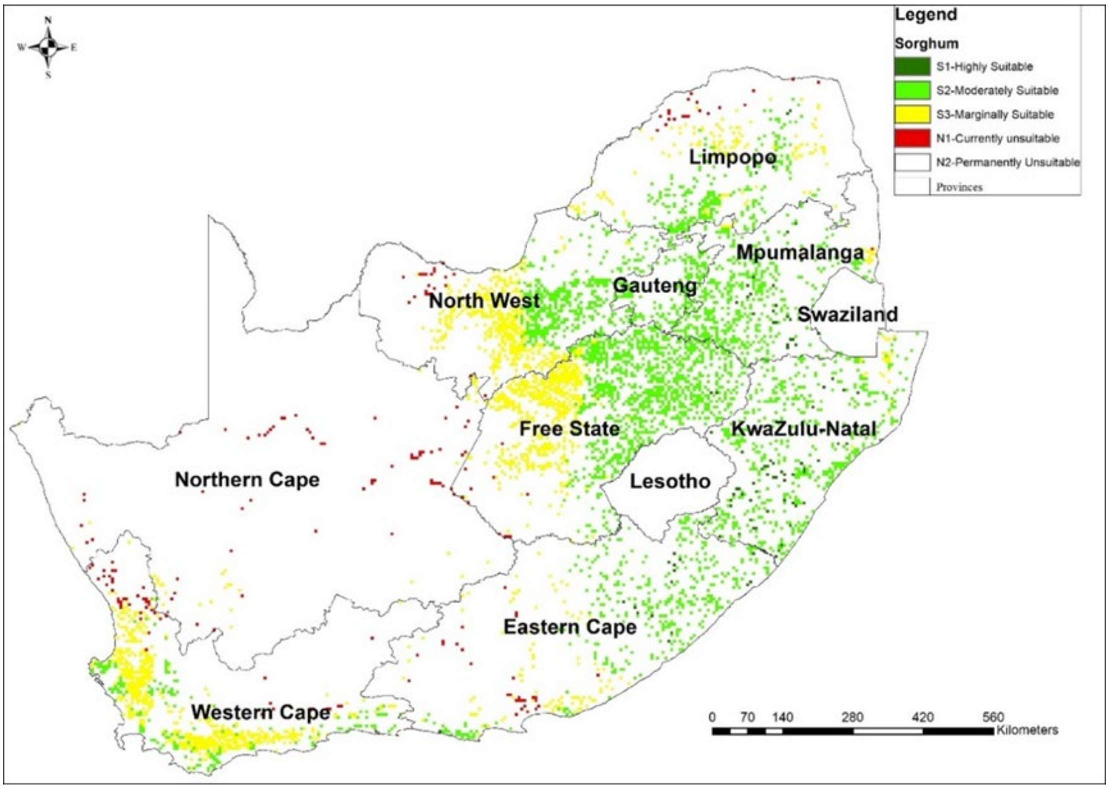


Figure 12. Suitability map for sorghum production in South Africa computed using MCDA-AHP and OWA operators [Source, *South African Quaternary Catchments database, (*https://doi.org/10.6084/m9.figshare.13179881*), in ArcGIS 10.5]*

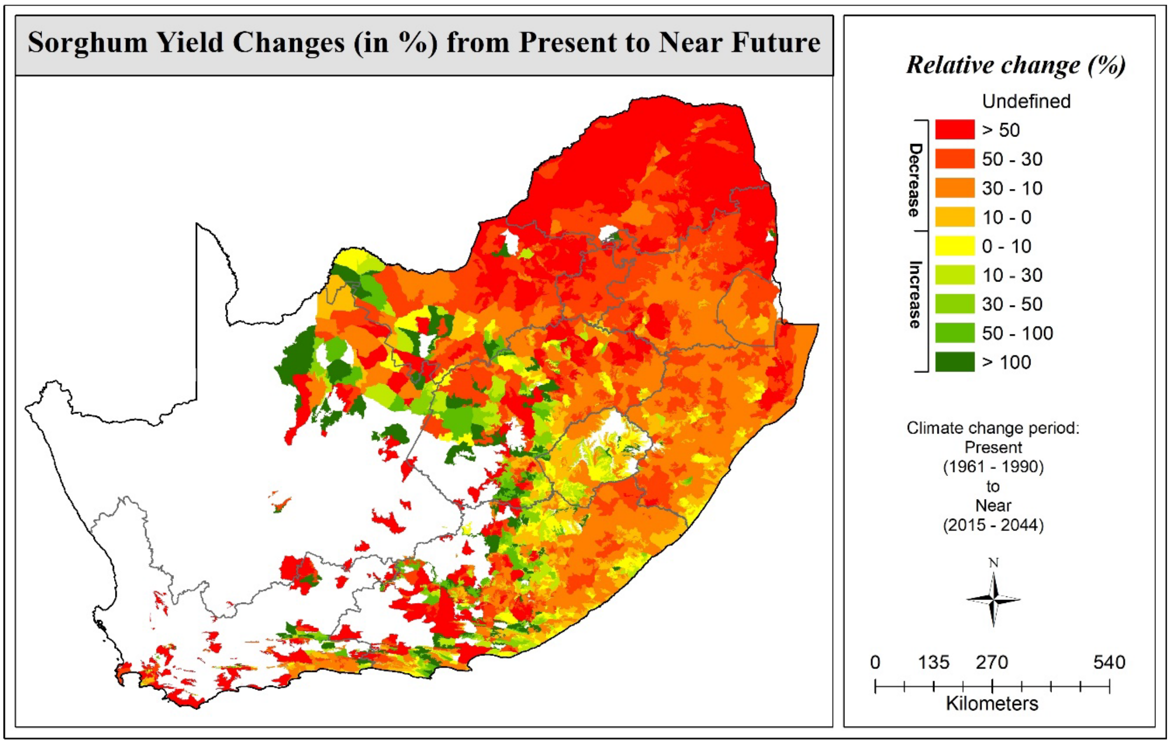


Figure 13: Change in mean dry yield (as %) from present to near future for sorghum

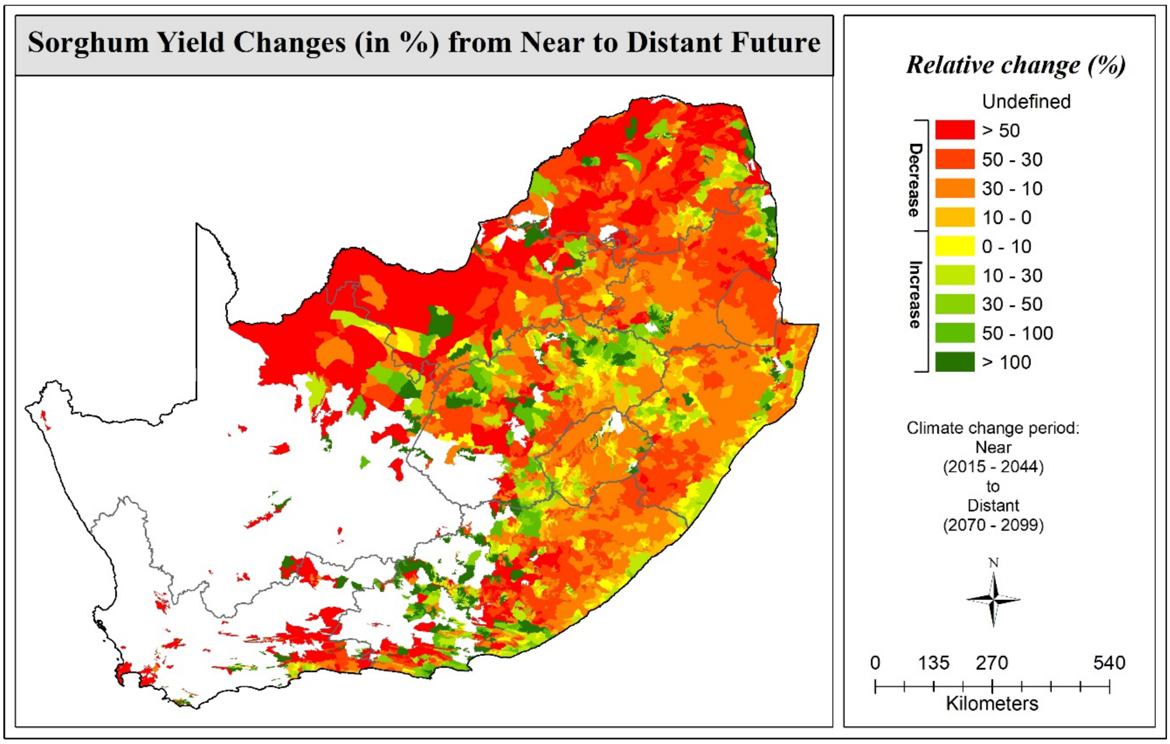


Figure 14: Change in mean dry yield (as %) near to distant future for sorghum

1.1.3 Drought tolerance

Sorghum can respond to drought stress using 3 drought resistance mechanisms:

1. Drought Avoidance: which is defined as the ability of plants to conserve water at the whole plant level through decreasing water loss from the shoots or by more efficiently extracting water from the soil. Most sorghum genotypes have a thick waxy cuticle that limits water loss during drought stress period. Sorghum plants have the ability to change their root length as an avoidance mechanism to drought stress. Sorghum has an exceptionally well developed and finely branched deep root system which is very efficient in the absorption of water. The deep root system enables the plant to extract water from deeper soil areas. The cell architecture of mesophyll tissue of C4 plants allow them to accumulate CO_2 in the bundle sheath cells, reducing photorespiration, reducing stomatal conductance to preserve water without decreasing carbon fixation rates. Leaf abscission, dormancy, and any other mechanisms that reduce water loss by transpiration are considered drought avoidance mechanisms. Stomatal conductance and leaf rolling have also been found to be reliable physiological indicators of drought resistance in sorghum plants. The rolling of leaves usually occurs following the reduction in leaf water potential. Leaf rolling has positive effects on reducing leaf temperature and loss of water by decreasing the incident irradiation.

2. Drought escape: is defined as a mechanism by which plants grow and complete their life cycle before severe drought stress occurs for example some plants are able to produce flowers with a minimum vegetative growth before the onset of water stress, which enables them to produce grains with a limited water supply. Some early maturing sorghum genotypes adopt this strategy to avoid water deficit periods that could occur during the growing season in some regions.

3. Drought tolerance: defined as the ability of plants to withstand water deficit while maintaining appropriate physiological activities to stabilize and protect cellular and metabolic integrity at tissue and cellular level. In order to lower the osmotic potential and maintain turgor, drought tolerant plants can accumulate compatible solutes including sugars, organic acids, amino acids, sugar alcohols or ions. Osmotic adjustment is important in the drought tolerance of many C4 species growing in arid

environments and allows the growth of sorghum when leaf water potential is low. Sorghum bicolor accumulates glycine betaine and proline in response to water deficit.

1.1.4 Crop management

Based on results from Ukulinga, as part of another WRC project (Modi and Mabhaudhi, 2017) and other literature, the following best management practices for grain sorghum are recommended:

For smallholder farmers, suggested and affordable strategies to help reduce runoff through improved infiltration capacity and soil transmission characteristics are low-cost mulching and low-tillage practices.

Contour farming, ridge and mound tillage, strip farming and terrace farming are options that are suggested to reduce runoff loss, particularly when farming sorghum outside optimal planting dates, as recommended next.

Early- and mid-season plantings are recommended for rainfed sorghum cultivation in agro-ecologies like Ukulinga.

Late-season planting exposes the crop to frequent intermittent stress episodes and is thus recommended in areas where farmers have access to irrigation to supplement rainfall.

Low-cost mulching (e.g. dry grass) should be explored by smallholder farmers. In regions that experience high wind speeds, the growing of windbreaks (and effective weed control) should be explored as a long-term strategy to help reduce evaporation loss.

A recommended long-term strategy for water capture is rainwater harvesting for the supplementary irrigation of sorghum during dry spells and for the late planting of sorghum.

1.1.4.1 Cultivars

Cultivar selection aims to reduce risks by avoiding drought periods during the most critical growing stages of the plant growth, such as flowering and seed set (ARC, 2003; Du Plessis, 2008), as well as cold temperatures during the flowering stage (PANNAR, 2013b). Factors that should be considered when selecting a suitable cultivar include low-tannin cultivars, seed availability, growing season length, cold tolerance and drought tolerance.

Low-tannin cultivars

According to the South African list of cultivars (DAFF, 2018e), there are currently 23 registered grain sorghum hybrids and four open pollinated varieties. Seven of the 23 hybrids are sold by PANNAR. There are two types of sorghum: bitter and sweet sorghum. Bitter sorghum (high tannin) is planted in areas where birds are a major problem.

Kotze (2012) reported that PAN8625 is a tannin sorghum used mainly for malting and is not suitable for ethanol production. However, PANNAR supplies three grain sorghum hybrids suitable for ethanol production:

PAN8816, a tannin-free sorghum currently used by 85% of the market for malting and milling

PAN8906, a new hard-seed hybrid suitable for milling and ethanol

PAN8909, which is similar to PAN8906 (Kotze, 2012)

Both PAN8816 and PAN8906 are bronze-grained, medium- to late-maturing, and low-tannin sorghum hybrids. Flowering occurs at approximately 80 days after planting (

Table 6). The hybrids are well known for good leaf disease and head smut resistance. PAN8816 is used by 85% of the market for malting and milling, with yields ranging between 2-5 t ha^{-1} under optimum conditions. PAN894 is another zero-tannin cultivar and suitable for ethanol production (classified as genetically modified (GM), which indicates tannin-free, and good for malting and milling). This cultivar has a shorter growing season than PAN8816.

Table 6 Agronomic characteristics of grain sorghum hybrids available from PANNAR (PANNAR, 2018)

General characteristics	PAN8944	PAN8816	PAN8906	PAN8625
Growing season	Medium-early	Medium-late		Late
± days to 50% flowering	60-65	79-81	78-81	82-85
± days to harvest	120-130	135-142	135-142	140-145
Plant height (cm)	105-110	112-117	110-115	120-130
Uniformity (1 = excellent; 9 = poor)		2	1	3
Standability (1 = excellent; 9 = poor)		2	2	2
Threshability (1 = excellent; 9 = poor)		2	2	4
Head smut (1 = excellent; 9 = poor)		2	2	3
Plant colour		Purple	Purple	Purple
Grading	GM	GM	GL	GH
Seed colour	Red	Red	Red	Brown

Macia was developed by the International Crop Research Institute for the Semi-arid Tropics (ICRISAT). Macia is a low-tannin, open-pollinated variety. It is an early- to medium-maturing (60-65 days to heading and 115-120 days to maturity), semi-dwarf (1.3-1.5 m tall with thick stem) variety. However, Hadebe et al. (2017a) concluded that Macia is a late-maturing genotype with a consistently longer growing cycle compared to PAN8816. Macia has a wide growing rainfall range (250-750 mm) during the growing season, with stay green characteristics extending beyond harvest. However, the extractable starch content of Macia is much lower than that of PAN8816 and PAN8906, which is less desirable for ethanol production.

Based on results from the Swayimane trial, the following best management practices for grain sorghum are recommended:

PAN8906 outperformed PAN8816 and Macia in terms of final yield and is thus highly recommended for biofuel production.

The late (i.e. January) planting at Ukulinga resulted in cold and water stress and is thus not recommended in similar agroecologies.

Grain yield is an important factor influencing biofuel production. PAN8906 produced more theoretical biofuel due to its higher yield.

Macia produced a relatively high proportion of biomass to grain and may thus not be a suitable feedstock for biofuel production.

1.1.4.1 Seed availability

In order to meet the projected demand for ethanol production from sorghum, 60,000 to 70,000 bags of 25 kg seed will need to be supplied to the market, which is about five times that supplied in the 2012/13 season (Kotze, 2012). Due to various issues, including seed availability, South African farmers will not be able to realistically expand ("ramp up") sorghum production to meet the immediate demand created by biofuel manufacturers. Therefore, Lemmer and Schoeman (2011) noted that sorghum will initially be imported for a number of years to meet the increased demand. Over time, imports of sorghum are predicted to drop as local production increases.

1.1.4.2 Planting date

Under rainfed conditions, rainfall variability is an important determinant of crop yield. Thus, planting date selection is critical to ensure that critical growth stages do not coincide with dry spells. Based on an analysis of 50 years of rainfall and temperature data for each quinary sub-catchment, the first planting date:

could not be determined for 26.2% of the quinary sub-catchments, thus indicating their unsuitability for crop production;

occurs in either November or December for most quinary sub-catchments; and

occurs in October and January in a few quinary sub-catchments.

Maps showing the spatial variability in planting date are presented in this report. However, weather is known to vary between growing years, affecting the selection of planting dates. Hence, it is acknowledged that planting dates should be determined using climate forecasts, rather than using historical data. Access to seasonal weather forecasts is recommended to aid farmers' management practices, planning and the selection of planting dates.

Short-season cultivars take 90 to 110 days to mature and are best suited to areas where daily average temperatures exceed 20 °C. When the average daily temperature drops below 20 °C, the growth period is lengthened by 10 to 20 days for each 0.5 °C fall in temperature (Steduto et al., 2012; WMO, 2012). Medium-duration cultivars take 110 to 140 days to mature. At an average temperature of 15 °C, grain sorghum takes 250 to 300 days to mature. In cool climates, sorghum is grown mostly as a forage crop (Steduto et al., 2012).

Based on the results from a scenario analysis reported by Modi and Mabhaudhi (2017) for two sorghum genotypes (PAN8816 and Ujiba) across 10 different planting dates and three agroecologies (Deepdale, Richards Bay and Ukulinga), the following best management practices for grain sorghum are recommended:

Sorghum farmers in Richards Bay would benefit most from strategies that maximise transpiration (i.e. rainwater harvesting for supplemental irrigation).

Sorghum farmers in Deepdale and Ukulinga can explore increasing planting populations, together with appropriate soil fertilization mechanisms.

Intercropping sorghum with a legume could be recommended to effectively use evaporated water in all three agroecologies. Ideally, the legume of choice should have low water requirements and a short growing season (≈90 days).

1.1.4.3 Intercropping

Based on scenario analyses conducted with the Agricultural Production Systems sIMulator (APSIM) and AquaCrop models, Modi and Mabhaudhi (2017) suggested the following best management practices for sorghum in a sorghum-cowpea intercrop system:

To achieve high water use efficiency (WUE), early planting (15 September) and late planting (15 January) in low-rainfall and high-rainfall areas, respectively, is recommended.

The ideal plant population of sorghum should be 39,000 plants·ha^{-1} in combination with 13,000 plants·ha^{-1} of cowpea.

When yields of both crop species are desired, increasing the cowpea plant population to 19,500 plants·ha^{-1} is recommended.

1.1.4.4 Plant spacing

Seeds should be planted to a depth of 1.5 to 5 cm (DAFF, 2009b). A planting depth of 5 cm is recommended for drier or sandy soils, compared to 2.5 cm for clayey soils (ARC, 2003; Du Plessis, 2008; DAFF, 2010b). The DAFF (2009b; 2010b) also recommends that when planting in dry soils, soil compaction may be necessary to ensure moisture absorption by the seed. After germination, thinning is required to establish an in-row spacing of 15 to 20 cm before tilling begins (usually four weeks after emergence). However, gap filling may be required if the seed does not germinate or seedlings are affected by disease.

1.1.4.5 Fertilizer

The nutrient requirements of grain sorghum are similar to those of maize, i.e. similar quantities of nitrogen, phosphorus and potassium are removed from the soil by these two crops. To maintain phosphorus and potassium levels in the soil, approximately 15 kg nitrogen, 3 kg phosphorus and 4 kg potassium should be added to the soil per ton of harvested crop (PANNAR, 2013b; Steduto et al., 2012). However, SEEDCO (2018) stated that 7 kg of phosphorus is removed from the soil per ton of grain produced ().

Table 7: Nutrient removal and uptake per ton of harvested sorghum grain (SEEDCO, 2018)

Nutrient	Removal	Uptake
Nitrogen	18 kg	30 kg
Phosphorus	7.2 kg	10 kg
Potassium	5.4 kg	30 kg

For the growth and development of sorghum, nitrogen is considered critical (Ruthrof et al., 2018). Soils with a low nitrogen content result in delayed crop development, thus increasing the risk of drought exposure and subsequent yield loss prior to physiological maturity (Buah et al., 2012). Recommendations for nitrogen application are usually based on the target yield, with more fertilizer required for sandy soils and for crops grown in the wetter (eastern) growing regions, when compared to the drier (western) regions. Buah et al. (2012) determined the response of grain sorghum to applications of nitrogen and found that an application of 40 kg nitrogen ha^{-1} resulted in yield increases of 47% relative to no nitrogen. Nitrogen increases early seedling vigour, LAI, chlorophyll concentration and plant height. In addition, nitrogen catalyses the conversion of carbohydrates into protein and protoplasm, resulting in increased biomass and grain yield (Buah et al., 2012).

In general, sorghum is sensitive to low phosphorus and potassium levels in the soil, which should thus be corrected with fertilizer application (DAFF, 2010b). Phosphorus is also usually applied in the band, except where the required quantity exceeds the amount applied in the fertilizer mixture. The optimal phosphorus concentration under conditions where 5-11 kg of phosphorus ha^{-1} is applied in the band at planting was determined as approximately 17 mg of phosphorus kg^{-1} for most regions. In order to raise the “phosphorus requirement” or soil phosphorus concentration by 1 mg phosphorus kg^{-1} (Bray 1 test), 5, 7 and 9 kg of phosphorus ha^{-1} should be applied on soils with clay contents less than 10%, 10-20% and 21-35%, respectively (PANNAR, 2013b).

For potassium, analyses should be undertaken to determine the status of the soil. The optimum concentration is at least 80 mg of potassium kg^{-1} of soil. If the topsoil potassium concentration is low (less than ~40 mg of potassium kg^{-1}), then 12-50 kg of potassium ha^{-1} is recommended. If the soil is sandy (less than 10% clay) and the topsoil potassium concentration is low, the subsoil potassium concentration should also be determined. Potassium is normally placed in the band using fertilizer mixtures.

However, high, mixed applications of potassium and nitrogen in the band should be avoided and should thus not exceed 70, 50 and 30 kg ha^{-1} for row widths of 0.9, 1.5

and 2.1, respectively. If potassium requirements are too high to place in the band, a portion can be spread before planting (PANNAR, 2013b).

Rotation with leguminous crops (e.g. soybean) may provide low-cost nitrogen addition and fertility build-up. Low grain protein can result when nitrogen deficiency occurs between anthesis and maturity. The crop thus responds well to nitrogen application (DAFF, 2009b; WMO, 2012). If fertilizer is applied in the band at planting, levels should not exceed the following (PANNAR, 2013b):

40 kg nitrogen ha^{-1} for 0.9 m row widths

30 kg nitrogen ha^{-1} for 1.5 m row widths

20 kg nitrogen ha^{-1} for 2.1 m row widths

Overall, sorghum responds well to a low application (100 to 300 kg ha^{-1}) of basal fertilizer, followed with a top dressing of 100 to 200 kg ha^{-1} of 28 to 34% nitrogen fertilizer. Before planting, the basal fertilizer is broadcast, then incorporated into the soil by disking (SEEDCO, 2018).

1.1.4.6 Pest and disease

Insect pests: Cutworms, several species may attack sorghum. They remain in the soil and feed at night where they cut off seedling plants at or near ground level. Plants cut above the main growing point may regrow. Heavy infestations usually kill the main stem or completely destroy plants. Risk of cutworm damage is greater in reduced tillage systems. **Control:** Control weeds several weeks before planting. Cutworms can be controlled preventively using at planting soil insecticides or by pre-plant or post at-planting or postemergence foliar sprays. **Maize Stalk Borer and Grain Sorghum Stalk Borer:** the larvae of the grain sorghum stalk borer differ from those of the maize stalk borer in that they are slightly smaller, pale white in colour, with pigmented spots. The stem borers tunnel into the stem of the plant feeding on the internal tissues and causing the plant to weaken. **Control:** Cultural approaches: Plant early to avoid a serious infestation of stem borers. Applying nitrogen, either a commercial product or manure or compost, enhances the crops tolerance to an attack. Intercropping with non-host plants, such as cowpeas or cassava, will also reduce the damage. Adult moths will lay eggs on the non-host plants, but the larvae are unable to feed on them and will die. Chemical approaches: Chemical control should only be used when the infestation is severe. Spraying a pesticide early over the plants might be more effective; however, once the larvae have bored into the stem of the plant, pesticides are no longer effective. **Aphids:** Grain sorghum is affected by three types of aphids, the most important of which is the honeydew aphid. The other two are known as the "wheat aphid" and the "maize aphid". The aphid feeds mainly on the underside of the leaves and lives off the sap of the plant. They absorb mainly the protein and nitrogen particles of the sap and excrete excess sugars known as "honeydew", a sticky, gummy secretion which appears on the leaves. A fungus grows on this honeydew, giving infected plants a typical black colour. **Control:** application of an insecticide is able to control aphid infestation. **Black Maize Beetle:** The beetles feed on young plants near the soil surface, resulting in the death of the plant or damage to its growth point. Damaged plants that recover produce ears mainly on suckers. **Sorghum Midge:** This pest feeds on the developing florets and results in poor seed development. **Control:** plant resistant hybrids, apply insecticide, following helps to reduce the build op of midge in the field. **Spotted Maize Beetle**: This yellow and black beetle sometimes attacks sorghum and feeds on the ears while the grain is still in the milk stage. **Control:** Spraying with a registered chemical is recommended as soon as the number of beetles reaches serous proportions. **Fall Armyworm:** Small larvae will feed on leaves causing windowpane type feeding before moving into the leaf whorl. There they will feed until full size when they leave the whorl and pupate in the soil. Feeding can cause large irregular holes in leaves as they unroll from the whorl. Sometimes the main vein is cut causing the entire leaf tip to die. Fall armyworm populations increase as the season progresses. This is why late planted or double cropped sorghum is at greater risk of defoliation than early-planted sorghum. Control: application of registered insecticide is recommended to control FAW populations.

Birds: Isolated or small areas of sorghum are prone to bird damage (ARC, 2003). The African Centre for Crop Improvement (ACCI, 2018) states that "birds love sorghum and are very problematic because they can decimate a field". Kunz et al. (2015a) also noted that small stands of zero-tannin cultivars of grain sorghum are cause for concern due to possible bird damage. Grain sorghum trials conducted at Ukulinga and Hatfield in the 2012/13 season and at Ukulinga in the 2013/14 season were severely affected by feeding birds at both establishment and grain filling. Modi and Mabhaudhi (2017) stated that short genotypes (e.g. PAN8816) were susceptible to panicle destruction by large birds (e.g. guinea fowls) as the panicle was within reach. Rethman et al. (2007) also reported that sorghum grain was consumed by birds during the 1999/2000 season at Hatfield.

Possible damage from red-billed queleas (*Quelea quelea*) is a serious threat to grain crops in South Africa (Oschadleus and Underhill, 2006). Hence, queleas were declared pests in the Agricultural Pests Act, Act No. 36 of 1983. Steyn (2011) reported that queleas can eat around 10 g of grain per day, which means an average quelea flock can rapidly decrease sorghum yields from 5 to 1 t ha^{-1}. The birds have recently expanded into regions where previous sightings were uncommon. For example, Oschadleus (2015) recorded the first breeding of quelea in the Western Cape near Worcester. Coleman (2017) reported that all grain producers are urgently required to report quelea breeding and roosting spots to the Department of Agriculture, Land Reform and Rural Development.

Fungal diseases: Seedling blights are often referred to as "**damping off diseases**." Seedling diseases may be caused by soil-borne pathogens. The primary seedling disease pathogens are: *Pythium*, *Fusarium*, *Aspergillus*, and *Rhizoctonia*. These pathogens may occur independently or in combinations to cause seedling disease problems. **Symptoms:** first symptom of seedling blight is failure of the seed to germinate which results in rotted seed. In other cases, necrotic tissue may be present, seeds may germinate, or the young roots or leaves may have a water-soaked appearance. In other cases, seedlings may emerge and then begin to die. **Control:** Using high quality seed and use of appropriate seed treatments will minimize seedling disease concerns. **Sorghum leaf blight** is a foliar disease caused by *Exserohilum turcicum*. **Symptoms:** infected seedlings develop small reddish or tan spots on the leaves. As the disease progresses, these spots enlarge, the leaves wilt and turn purplish grey, and the seedling ultimately may die. In more mature plants, long elliptical lesions develop on older leaves and may be reddish-purple or yellowish tan. These lesions vary in colour and size according to varying levels of resistance. Most of the lesions occur on older leaves, and then progress to younger leaves. Lesions on older plants have yellowish to grey centres and reddish margins**. Control:** Sorghum leaf blight can be controlled by rotation to non-susceptible crops and foliar applications of labelled fungicides. Planting resistant hybrids is the most effective management strategy for sorghum leaf blight. **Head smut** is caused by the soil borne fungus *Sporisorium reilianum*. **Symptoms:** pores will actively invade the sorghum plant in the nodal region of the shoot apex. The disease will continue to grow in the plant, actively destroying the reproductive tissues. A black mass of spores replaces some or all of the sorghum head. When infected, some hybrids are dwarfed and will tiller profusely. Control: Crop rotation and fungicides cannot control this disease. Head smut can only be effectively managed genetically by planting resistant varieties. **Sorghum ergot** is a fungal disease formerly confined to the African and Asian continents. It is caused by a fungus *Claviceps Africana*. **Symptoms**: fungus infects the ovaries of sorghum flowers and often converts them into a white, fungal mass. The most obvious external symptom of infection is the abundant exudation from infected flowers of an amber-coloured, sticky fluid, or “honeydew,” which often drips onto the leaves and soil. Spores of the fungus are contained within the honeydew, and when these germinate, they produce secondary spores on the surface of the honeydew, giving it a white-scum to powdery appearance. **Control:** chemical control measures that have been used successfully in sorghum seed production consist of a 5-7 day interval of 3-4 applications of a triazole fungicide such as propiconazole. Seed treatment fungicides can disinfect seeds that have some ergot residue on the seed coat. Conventional topical treatments such as captan and fludioxonil will control the spores present on ergot-encrusted seeds.

There are many other fungal diseases on sorghum including: Leaf rust and grey leaf spot which can be economically damaging in sorghum, especially in moist environments. These foliar diseases are often associated with late planting and ratoon sorghum. Sorghum downy mildew caused by the fungal pathogen *Peronosclerospora sorgi*. Downy mildew spores germinate and invade the roots of sorghum seedlings. This type of infection is systemic, in that most of the plant will eventually be infected. Infected seedlings may become chlorotic and die.

Bacterial diseases: Bacterial Leaf Spot caused by *Pseudomonas syringae pv. Syringae*. **Symptoms:** Spots first appear on lower leaves with infection moving up the plants as they approach maturity. Spots are circular to elliptical and 1-10 mm in diameter. Initially spots are dark green and water soaked but soon become tan with a red border. Small lesions may be entirely red with somewhat sunken centres. Sometimes spots are so numerous that they coalesce to form large diseased areas, resulting in the death of the whole leaf. Lesions may also occur on leaf sheaths and seeds. **Control:** Plant healthy seed that has been treated with a seed-protectant fungicide. Rotate sorghum with nonsusceptible crops. Plow under infected residue where soil erosion is not a problem. **Bacterial Leaf Streak** caused by *Xanthomonas campestris pv. Holcicola*. **Symptoms:** Streaks occur on leaves of plants of all ages as water soaked and translucent, about 3 mm wide and 25-150 mm long. Initially only light-yellow drops of bacterial exudate are present on the translucent streaks. This will eventually dry to thin white or cream-colored scales. Later, red-brown blotches appear that eventually enlarge and become red throughout the streak, causing the water-soaked and translucent areas to disappear. Portions of the streaks may broaden into elongated oval spots with tan centres and narrow red margins. Numerous streaks may join to form long, irregular areas that cover a large area of the leaf with necrotic tissue bordered by dark narrow margins between the red-brown streaks. **Control:** Rotate sorghum with other crops. Plow under infected residue where erosion is not a problem. Plant healthy seed that has been treated with a fungicide. **Bacterial stripe** caused by *Pseudomonas andropogoni*. **Symptoms:** Initial symptoms are small (1 cm long), linear, interveinal lesions. Lesions on leaves and sheaths are purple, red, yellow or tan, depending on the host reaction. Under favourable conditions, lesions may exceed 20 cm in length and they usually coalesce along the width of the leaf. Water soaking of tissue adjacent to a lesion is usually not observed under field conditions. Bacterial exudates are usually observed from infected portions of the leaf under microscopic observation. Lesions may also occur on the kernel, peduncle, and rachis, and in the pith of the stalk. **Control:** No suitable treatment is available for eradication of this bacteria.

Viral diseases: The two primary viruses infecting sorghum are maize dwarf mosaic virus (MDMV) and sugarcane mosaic virus. Aphids transmit both diseases after feeding on plant reservoirs containing the virus. **Control:** control of insect vectors and alternate hosts of the diseases will provide some suppression. Genetic resistance offers the best control of these diseases.

1.1.4.7 Weed control

Weed control: Weed control during the first 6-8 weeks after planting is crucial, as weeds compete vigorously with the crop for nutrients and water during this period. The root parasite Striga asiatia (L.) Kuntze or witchweed (rooiblom) can damage the crop and mainly occurs under low-input farming conditions. The parasitic plants are single stemmed with bright red flowers. Most of the damage is done before the parasite emerges from the soil. The symptoms include leaf wilt, leaf roll, and leaf scorch, even though the soil may have sufficient water. The tiny seeds are disseminated by wind, water and animals, and remain viable in the soil for 15-20 years. Rotation with cotton, groundnut, cowpea and pigeon pea will reduce the incidence of Striga. Hand pulling the plants before flowering could be used. Weeds can be removed mechanically, using manual labour or implements. Ploughing during winter or early spring is an effective method of controlling weeds. Chemicals formulated as liquids, granules or gasses can be applied to kill germinating, growing weeds or seeds. Control of nut-grass with pre-emergence herbicides is not effective when applied after emergence. It is important to cultivate fields before applying herbicides. Wild sorghum in sorghum fields can only be controlled mechanically or by hand hoeing.

1.1.4.8 Harvesting

When seeds reach the milk to dough stage, sorghum can be harvested manually (cutting by hand) or mechanically (with a combine harvester). Panicles are dried in heaps on the ground or threshing floor for 10 to 14 days. Sorghum grain can only be threshed when seed moisture is below 20 to 25%, even though the seed is physiologically mature at higher moisture levels of 30 to 35% (Steduto et al., 2012). Once the seed moisture content is 12 to 13% (or less), permanent storage in silos is recommended (DAFF, 2009b; DAFF, 2010b).

For seed drying, the absolute maximum air temperature is 40 °C. However, in order to reduce the risk of heat damage to the seeds, drying temperatures should be lower than 40 °C. If seed moisture is more than 18%, maximum drying temperature should be 32 °C, and if lower than 18%, 40 °C is the recommended temperature for drying (Reddy et al., 2008).

Sorghum’s harvest index is more variable than that of maize, mainly because of variable tilling in sorghum. Generally, reported harvest index values are low (0.3 to 0.4), but higher harvest index values (more than 0.5) have been observed and may be the result of vegetative (tiller) growth, which is affected by cultivar-specific water stress (Steduto et al., 2012).

1.1.5 Nutritional Value

The sorghum bran is low in protein and ash and rich in fibre components. The germ fraction in sorghum is rich in ash, protein and oil but very poor in starch. Over 68% of the total mineral matter and 75% of the oil of the whole kernel is located in the germ fraction. Its contribution to the kernel protein is only 15%ew2. Sorghum germ is also rich in B-complex vitamins. The endosperm, the largest part of the kernel, is relatively poor in mineral matter, ash and oil content. It is, however, a major contributor to the kernel's protein (80%), starch (94%) and B-complex vitamins (50-75%). Sorghum also supplies a lot of minerals – one cupful contains 55% of the recommended daily allowance (RDA) of phosphorus, 47% of iron, 19% of potassium, 5% of calcium and even some magnesium and zinc. A cup of sorghum contains -30% for thiamine, 28% for niacin and 16% for riboflavin. Sorghum is low in sodium and saturated fat and completely cholesterol free.

1.1.6 Food preparation – Sorghum Parfait (serves 1)

Ingredients

1/4 cup uncooked coarse grain sorghum

½ cup milk

½ cup water

A pinch of salt to taste (optional)

1 Tbsp. sugar

A pinch of cinnamon

4 Tbsp. yogurt (optional)

½ cup chopped strawberries (fresh or frozen)

Method

In a cup, mix the sorghum, salt, and a dash of liquid (water and milk) and stir to a paste.

In a heavy saucepan, boil the liquid of choice (water or milk), and add the sorghum paste.

Lower the heat to simmer, and stir the pot to prevent boiling over or bottom sticking, for 10-20 minutes, until the liquid is absorbed.

Remove from the heat, and stir in the sugar and cinnamon.

In a serving bowl or mason jar add ½ of the sorghum and spread across bottom.

Add 2 tablespoons yogurt, then strawberries, and repeat the layering of sorghum, yogurt and strawberries.

Nutritional Value per serving

Energy: 234 calories

Total Carbohydrates: 37.2 g

Total protein: 8.9 g

Total fat: 8.4 g

Fibre: 6.5 g

1.2 Bambara groundnut

1.2.1 Crop physiology and morphology

Bambara groundnut is an annual herbaceous plant bearing bunched leaves arising from creeping stems that grow close to the ground. The growth habit of the crop may be bunched (erect), semi-bunched or spreading. It is naturally self-pollinated. The leaves are trifoliate, forming a cluster arising from branched stems that are either purple or green in colour and are borne on a long, erect and glabrous petiole, thickened at the base. Stem branching begins early, about one week after germination. Up to 20 or more branches may be borne on a single plant, depending on the genotype. Stem colour may be pigmented green, or partial or wholly red. Flowers are normally carried in pairs on short peduncles by a pedicle which arises from the axis formed by the petioles and the stem. Flowers produced on the same peduncle do not open synchronously, although they will open within a 24-hour intervals. Delayed flower opening may be caused by low temperatures and cloudy skies. After fertilization, the flower stem elongates. During this time, the peduncle elongates to bring the ovaries to the soil level and the pedicels penetrate the soil surface after fertilization to form the pods The sepal enlarges and the fruit develops above or just below the soil surface. Pod development lasts up to 30 days after fertilization and the seed develops over a further 10 days. The pod is small, round or slightly oval shaped and wrinkled. Generally a single seed is produced in the pod, although two seeds per pod have been reported. The unripe pod is yellowish green, while the mature pods may be yellowish green or purple. Seeds are mature when the parenchymatous layers surrounding the embryo have disappeared and the pods become a light brown. The seeds are round, smooth and very hard when dried, with highly variable testa colours, including cream, brown, red and blotched. The plant has a well-developed tap root with abundant lateral roots of around 20 cm long on the lower part that grow geotropically. The roots form nodules for nitrogen fixation, in association with suitable Rhizobium bacteria, which makes them useful for crop rotation and intercropping.

1.2.2 Agroecology

Under historical climatic conditions (represented by the 50 year period 1950-1999) the AquaCrop model used shows relatively few areas (in red) that are climatically totally unsuitable for Bambara groundnut production, but that over 80% of South Africa the yields of < 1 t/ha/yr imply that the crop is neither economically, nor from a livelihoods perspective, viable there. It is only really in KwaZulu-Natal, the north-eastern parts of the Eastern Cape, and parts of Mpumalanga and Limpopo, plus parts of Swaziland and Lesotho, that yields increase up to 3 t/ha/yr (Figure 15).

For bambara groundnut (Figure 16), there is a marked increase in areas deemed suitable for crop production, especially in Mpumalanga and Free State. Most of these “new” areas show a doubling of yield (> 100%) from the near to distant future (dark green). Furthermore, there is large reduction in areas where the yield is expected to decline by 50% or more (red). Hence, this crop is expected to benefit from climate change.

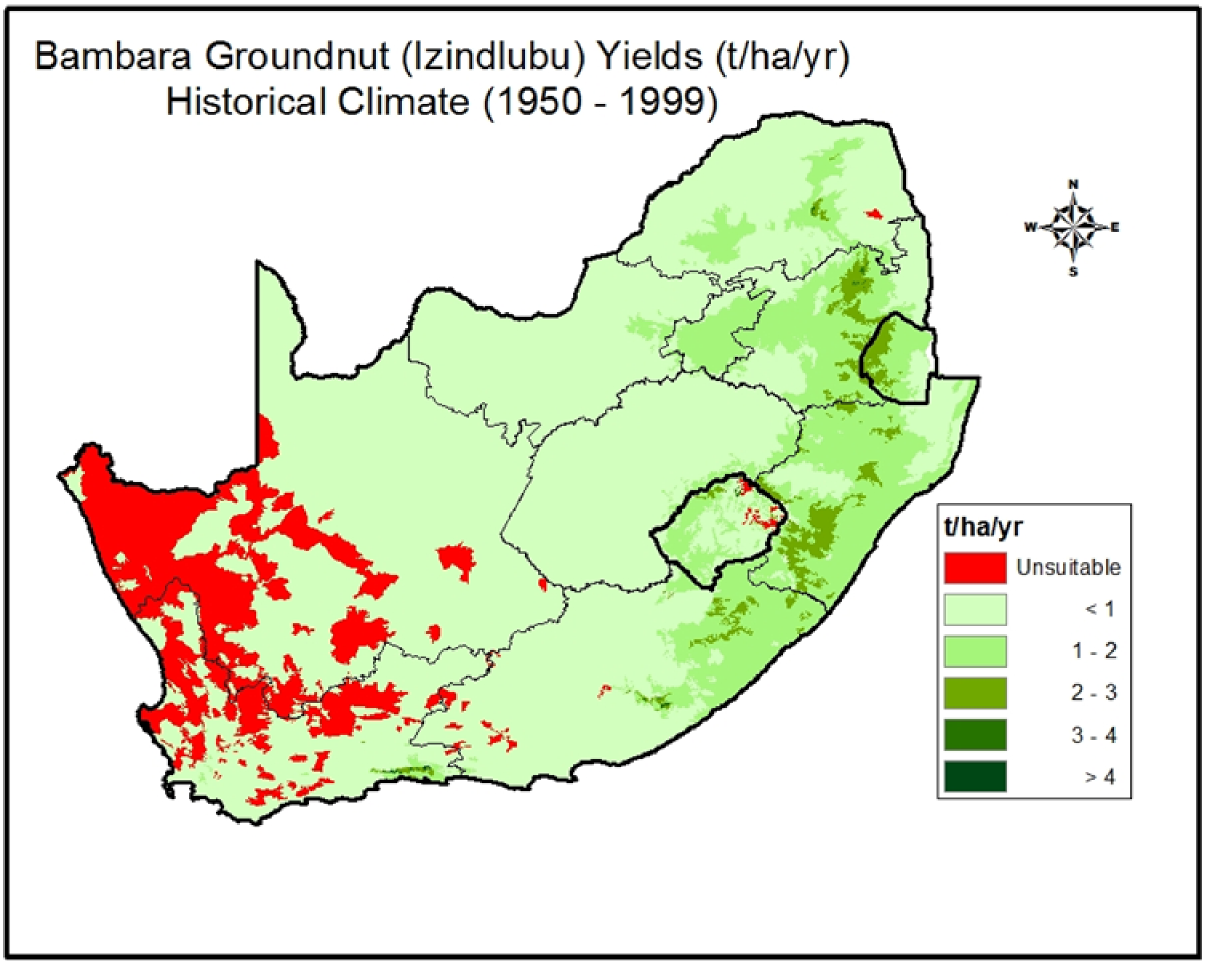


Figure 15: Mean annual Bambara groundnut yields (t/ha/yr) over South Africa under historical climatic conditions

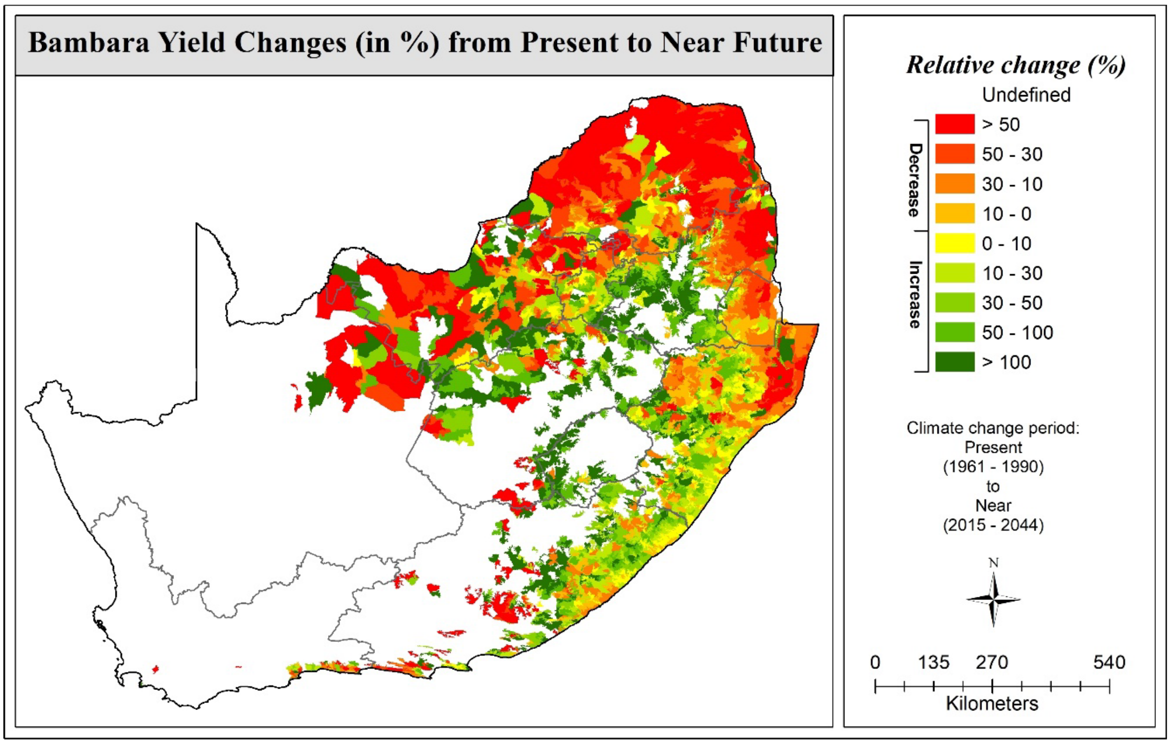


Figure 16: Change in mean dry yield (as %) present to near future for bambara groundnut

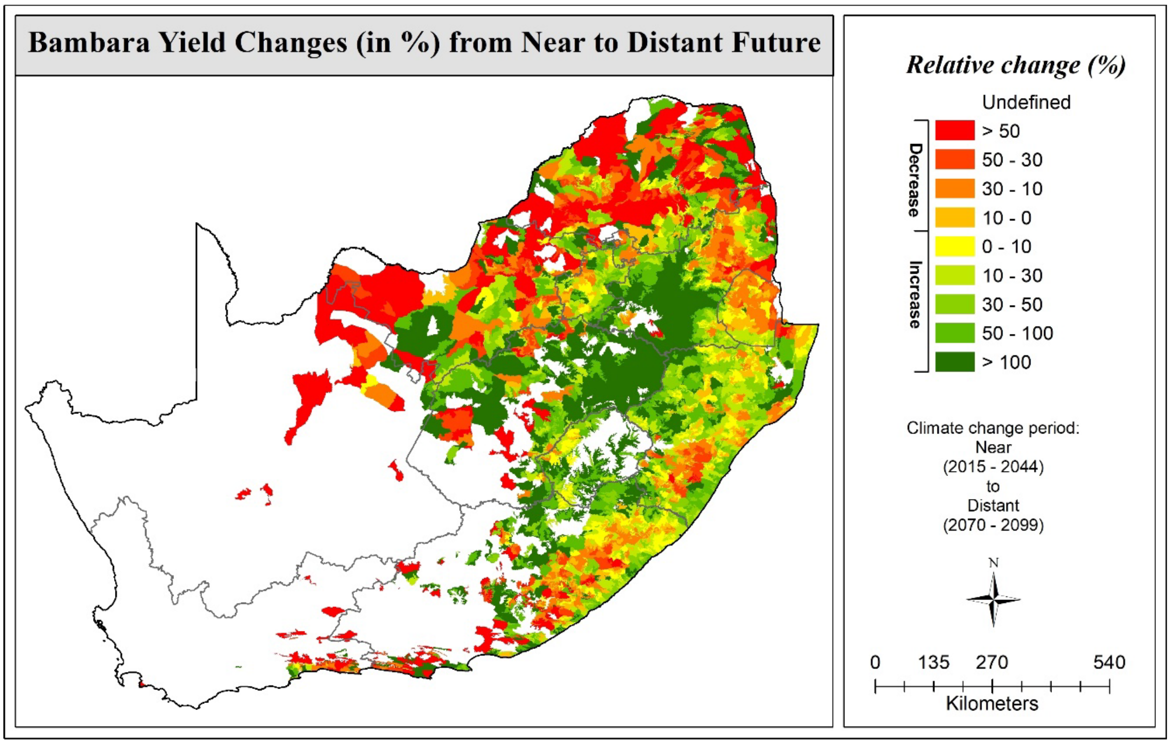


Figure 17: Change in mean dry yield (as %) near to distant future for bambara groundnut

For bambara groundnut (Figure 17), yield declines exceeding 50% are expected across the majority of Limpopo and eastern Mpumalanga, as well as the north-eastern parts of KwaZulu-Natal and North West provinces. However, the central and western parts of Mpumalanga and Free State can expect yields to more than double (> 100% change), as well as certain parts of KwaZulu-Natal and Eastern Cape. A review by Franke (2021) of 20 climate change studies over southern Africa cited the work of Mabhaudhi et al. (2018) that showed yields of bambara groundnut (including potato and sugarcane) are expected to increase. The bambara groundnut study was undertaken using AquaCrop for only one location in KwaZulu-Natal with climate scenarios from five CMIP3 GCMs (A2 CO_2 trajectory). Hence, this work is superseded by that presented here.

For bambara groundnut (Figure 17), there is a marked increase in areas deemed suitable for crop production, especially in Mpumalanga and Free State. Most of these “new” areas show a doubling of yield (> 100%) from the near to distant future (dark green). Furthermore, there is large reduction in areas where the yield is expected to decline by 50% or more (red). Hence, this crop is expected to benefit from climate change.

1.2.3 Drought tolerance

Bambara groundnut is an underutilised crop grown by subsistence farmers in Africa and is considered to be drought resistant. It is known to be more drought tolerant than other legume crops. Bambara groundnut has shown to adopt drought-escape mechanisms, including a reduced vegetative growth period, early flowering, a reduced duration of the reproductive stage, and early maturity under dehydration stress. Such responses are likely to be employed where the initial plant growth is based on stored soil water, but further rain is unlikely. Bambara groundnut responds to water stress by partitioning more assimilate into the root, relative to the shoots, so that a greater soil volume can be exploited. The plant commits a greater supply of assimilates to root growth, irrespective of the soil moisture status. This strategy may have clear advantages when water becomes limited, however, this could compromise on yield. Other drought-avoidance traits such as stomatal regulation of water loss, osmotic adjustment and a reduction in leaf area to maintain plant water status during periods of drought have been reported in Bambara groundnut.

1.2.4 Crop management

1.2.4.1 Cultivars

Bambara groundnut is primarily grown using landraces or farmers' varieties. Farmers grow local landraces from previous harvests, or buy from local markets, because there are no available improved varieties of the crop for small- or large-scale production. Initial collections and evaluations of Bambara groundnut landraces were carried out by the International Institute of Tropical Agriculture (>2000), Ibadan, Nigeria. In South Africa, there are approximately 300 accessions kept at the Agricultural Research Council – Grain Crops Institute, Institute for Veld and Forage Utilisation and Department of Agriculture. The large collections are found at the IRD (Institut de Recherche pour le Développement), Montpellier, France (about 1200 cultivated and 60 wild accessions from Cameroon, of which 50 were morphologically characterized), the University of Zambia, Lusaka, Zambia (460 accessions), the Plant Genetic Resources Centre, Accra, Ghana (170 accessions). In many African countries smaller collections are maintained. In studies of genetic diversity in cultivated bambara groundnut with RAPD and AFLP markers, considerable genetic variation was found, with accessions clustering mainly according to their geographical origin. Sometimes, e.g. in Swaziland, farmers sow a mixture of landraces as a buffer to biotic and abiotic stresses, thus helping to maintain the diversity of the crop.

Bambara groundnut breeding has mainly been confined to selection between and within populations for yield, disease resistance (Fusarium wilt and Cercospora leaf spot) and drought tolerance. From the IITA germplasm collection genotypes have been identified with a longer and denser root system, which may be useful in breeding for drought tolerance. Breeding of genotypes with a shorter growth period also seems useful for drier regions. Selection of the most effective combinations of genotypes and rhizobial strains seems promising to improve nitrogen fixation and increase crop yields. Artificial hybrids between cultivated genotypes and between cultivated and wild accessions have been made in the United Kingdom and Swaziland, but success rates are generally low. A genetic linkage map of bambara groundnut using AFLP markers is being developed in the United Kingdom as well. Micropropagation of bambara groundnut is possible using stem nodal cuttings or embryo axes.

The ARC recognizes 5 distinct accessions namely

Black: Early maturing, usually small to medium-sized kernels. Mainly one-seeded

Red: Late maturing. Kernels are large. A good yielder, however, it is prone to rotting onsite

Cream/black eye: A large kernel and a good yielder

Cream/brown eye: A moderate kernel and a good yielder

Cream/no eye: Very small pods and kernels. It mainly produces one seed and yields are lower.

Mabhaudhi and Modi (2013) segregated three accessions (cream, red and brown) in the landrace Jozini. Other popular landraces include Diphiri cream and Uniswa red.

1.2.4.2 Planting date

For optimum yield, cowpea should be planted late November to early December in the lower rainfall areas of South Africa. However, in areas with rainfall above an annual mean of 700 mm, planting dates can extend into January, but this produces low yields. The seed should be planted at 3 to 4 cm deep. The early-sown crops tend to have elongated internodes, are less erect, more vegetative and lower yielding than those sown at the optimum time. Planting date manipulation is utilised by farmers for various reasons. The reasons include escape from periods of high pest load or planting bambara at such a time that harvesting of the crop would coincide with the period of dry weather.

1.2.4.3 Intercropping

Simultaneous intercropping of taro and Bambara groundnut has been shown to be more productive compared to sole crops of either crop (Mabhaudhi, 2012). Especially the 1:1 (taro: Bambara groundnut) intercrop has indicated huge advantages to intercropping. In addition, intercropping taro and Bambara groundnut at a ratio of 1:1 had no negative effect on growth of either taro or Bambara groundnut landraces.

Intercropping taro with Bambara groundnut was shown to be highly productive, in terms of additional output per unit area of land accrued from Bambara groundnut. Intercropping taro with Bambara groundnut also showed no significant negative effect on yield of taro as the main crop. Inclusion of Bambara groundnut (a legume) in taro cropping systems may be complementary in that it improves the overall water use of the farming system through greater capture of water in the horizon. Furthermore, the fact that taro and Bambara groundnut roots extract water from different depths of the soil profile would imply reduced drainage losses. Therefore, intercropping taro with bambara groundnut is productive, sustainable and beneficial in that it has potential to improve farmers' nutritional productivity per unit area, bolster food security and enhance resilience of farmer's cropping systems

1.2.4.4 Plant spacing

The recommended spacing is 50 to 75 cm between rows and 20 to 40 cm between plants for spreading varieties and 50 cm between rows and 10 to 25 cm for erect and semi-erect varieties

1.2.4.5 Fertilizer

Chemical fertilisers are not usually applied on the land. Because the nitrogen requirement is met by natural N2 fixation, seed should be inoculated. When nitrogen content is high in the soil, bambara groundnut usually produces mostly only a few pods and seeds on the top surface. It is always advisable to conduct soil tests and apply fertiliser according to the recommended rates. Fertiliser usage may be linked to the development of certain diseases.

1.2.4.6 Pest and disease

Insect pests: Leafhoppers, *Hilda patruelis* and the larvae of *Diacrisia aculosa* and *Lamprosema indicata*. In storage, bruchids (*Callosobruchus maculatus*) are the most important pest attacking the seeds of the crop. When the crop is stored whilst damp, mould sets in and weevils are able to attack the seeds. Most of the cultivars are resistant to weevil attack.

Fungal diseases: The most important fungal diseases are cercospora leaf spot (*Cercospora* spp.), powdery mildew (*Erysiple polygoni*) and Fusaruim wilt (*Fusarium oxysporum*).

Nematode diseases*: Meloidogyne incognita* and *Meloidogyne javanica* are the most parasitic nematodes on bambara groundnut. The symptoms of nematode infestation include stunted growth, leaf chlorosis and yield losses. About 10 weeks after planting, the leaves turn yellow and the plants become stunted and die.

Virus diseases: Peanut Clump Virus (PCV) which persists in soil even for several years as its fungal vector, *Polymyxa graminis*, is capable of producing highly resistant resting spores. PCV can be transmitted by planting seeds. The crop is susceptible to viruses such as cowpea mottle virus, cowpea mild mottle virus, Voandzeia necrotic mosaic virus and white clover mosaic virus

1.2.4.7 Weed control

Weed control: Weed control is done mechanically or by hand. Care should be taken when weeding around the plant, especially at flowering as the flower stalks are fragile and may break with rough handling. There are no registered herbicides for bambara now, but those registered for cowpea could be used for bambara groundnut.

Annual grasses and some broadleaf weeds can be controlled by a pre-sowing application of herbicide. Row crop cultivation may be necessary with cowpeas, depending on the weed pressure, soil conditions, and rainfall. Preplant tillage can assist greatly in reducing early weed pressure, and the use of cover crops. *Striga gesnerioides* and *Alectra spp*. are the principal parasitic weeds attacking cowpeas, particularly in the semiarid regions. The following three are the most common Striga species that are a pest to cowpea: S*. hermonthica, S. asiatica* and *S. gesnerioides*.

Control of Striga is difficult and time consuming. At present, chemical control is not recommended, as the chemicals are expensive, handling them is very difficult and no research results are available to support chemical treatment. Farmers are advised to improve soil fertility where this weed is a problem. Soil fertility has an effect on Striga infestation; more fertile soils are less infested with Striga. Use of manure and/or small quantities of fertiliser may reduce the infestation, when combined with weeding of plants before seed setting. Hand weeding of the infested areas before Striga sets seeds is the most important control method at present. Striga should be weeded out as soon as any flowering is observed, as the development of seeds takes only a few weeks. It may be necessary to weed the area twice in a season.

1.2.4.8 Harvesting

A growth period of 110 to 150 days is required for the crop to develop fully. However, it can be ensured by checking the plant and seed appearance. Seeds are mature when the parenchymatous layer sur-rounding the embryo has disappeared and brown patches appear on the outside of the pod. Plants are harvested as the plants turn yellow or die, or when about 80% of the pods have matured. Pods can also be harvested while they are still green before they reach maturity as they are more palatable at this stage. Pods are removed as they mature to restrict losses by rotting and premature germination. Harvest bambara groundnut by hand lifting and pulling the plant or the taproot can be cut, using a groundnut harvester or ploughed out or hoed out. The nuts are then pulled off the plant, dried and stored or eaten raw. Harvesting small plots is often done over a period of time. Bambara pods can break off very easily and up to half of the pods can remain in the soil, requiring collection by hand.

1.2.5 Nutritional Value

Bambara groundnut seeds are highly nutritious containing protein (19%), carbohydrate (63%) and fat (6.5%) for a nutritionally balanced diet. Mineral content was also estimated for 100g seed, giving; iron 59 mg, potassium 1240 mg, phosphorus 296 mg, sodium 3.7 mg and calcium 78 mg. In addition it has high protein quality with a good balance of essential amino acids, compared to most of other grain legumes, with relatively high lysine (6.8%) and methionine (1.3%). which are often only available at low levels in legumes.

1.2.6 Food preparation – Bambara groundnut curry (Serves 2**)**

Ingredients

½ cup dry bambara soaked for 8 hours or overnight (yields 1 ½ cup-soaked bambara)

3 Tbsp. cooking oil

1 ½ Tsp, salt

1 Tsp. mustard seeds (optional)

½ Tsp. turmeric

½ Tsp. cumin (optional)

1 Tsp. ginger, smashed

1 Tsp garlic, smashed

5 curry leaves (optional)

1 medium onion chopped

1 medium tomato chopped

1 cup water

½ Tsp. chilli powder

Coriander or parsley to garnish (optional)

Method

In a pot, bring the soaked bambara to a boil, add ½ teaspoon salt, and simmer for 15-20 minutes until al dente.

In a saucepan, heat oil on a low flame, adding ½ teaspoon each of turmeric and cumin, and 1 teaspoon each of mustard seeds, ginger, garlic, and the curry leaves.

Add the chopped onion and tomato, increase the heat to high, and fry for 5 minutes, stirring continuously.

As the spice, onion, and tomato mixture starts to sweat, add the boiled bambara, 1 teaspoon of salt, and ½ teaspoon of chilli powder.

Add water (boiling or room temperature) to adjust curry consistency to your preference and lower the heat to simmer for 10 minutes.

Serve garnished with coriander or parsley, with rice, roti, or bread, or by itself.

Nutritional Value per serving

Energy: 276 calories

Total Carbohydrates: 12 g

Total protein: 2.7 g

Total fat: 23.6 g

Fibre: 3.5 g

1.3 Taro

1.3.1 Crop physiology and morphology

Taro is herbaceous perennial herb which grows to a height of 1-2 m. The main stem is an edible starch-rich underground structure. It is called the corm, from which leaves grow upwards, roots grow downwards while cormels, daughter corms and runners grow laterally. The root system is fibrous and confined mainly to the top layer of the soil. Corms in the dasheen type of taro are cylindrical and large, they are up to 30 cm long and 15 cm in diameter and constitute the main edible part of the plant. In the eddboe types, the corm is small, globoid and surrounded my several cormels and daughter corms. The cormels and the daughter corms constitute a significant portion of the edible harvest of eddboe taro. The shoots consist of mainly of the leaves which arise in a whorl from the apex of the corm. The terminal bud remains close to this apex. Each Leaf is made up on an erect petiole and a large lamina which is 20-50 cm long. The lamina is large, thick, entire (not serrated) and globous. Three main veins radiate from the point of attachment of the petiole, one going to the apex, and one to each of the two basal lamina lobes. The petiole is 0.5-2 m long and flared out at the base where it is attached to the corms. It is thickest at the base and thinner towards its attachment to the lamina. Internally, it is spongy in texture and has numerous air spaces which facilitate gaseous exchange when the plant is grown in swampy or flooded conditions. The overall leaf venation is reticulate however, there are some prominent veins that arise from the three main veins. The leaves are the most prominent aerial organ of the plant. Plant height is determined by the height of the leaves.

Flowering is sporadic but when it does occur, the flowers appear shortly after planting, sometimes before any of the leaves have expanded. The inflorescence arises from the leaf axil or the centre of the cluster of the unexpanded leaves. A plant may bear two or more inflorescences. The peduncle is stout and relatively short. The inflorescence consists of a cylindrical spadix of flowers enclosed in a spathe. The flowers are unisexual with the female flowers located at the base of the spadix and the male flowers at the top. Sterile flowers are located in between the pistillate and staminate flowers.

The inflorescence is protogamous and pistillate flowers are normally receptive 2-4 days before pollen is shed. The spadices are seldom fertile and produce few viable seed. Flowers are fragrant, and pollination is probably by insects, especially flies. Fruit and seed setting are even more uncommon than flowering. Many inflorescences wither without setting any seed. The fruits are clustered at the basal portion of the spadix. Each fruit is a berry about 3-5 mm in diameter. The seed is hard and contains endosperm and germinates with extreme difficulty.

1.3.2 Agroecology

Fig 4 presents the spatial distribution of the suitability scores for taro-based on MCDA-AHP method. The results indicated that there is about 0.4% of the land that is highly suitable (S1) for the production of taro. Moderately suitable (S2) land constitutes 28% of the calculated arable land of South Africa (12 655 859 ha) while marginally suitable (S3) constitutes the most substantial proportion 64% and (N1) 7% of calculated arable land. Taro suitability is high in KwaZulu Natal and Mpumalanga provinces. Limpopo, Northwest, Northern Cape and Western Cape are marginally suitable for taro (Figure 18). The distribution of taro suitability was consistent maximum temperature and length of the growing season and rainfall distribution.

The results presented in this study for taro also supersede those developed by Mabhaudhi et al. (2016a), who showed more than a doubling of yield for production areas along the eastern seaboard of South Africa (Figure 19). However, in this study, lower yield increases of 50% or less were simulated for the same areas, as well as significant increases in areas deemed suitable for taro production, particularly in the Limpopo and Northwest provinces. In the near to distant future there is a marked increase in areas deemed suitable for taro production, especially in the Mpumalanga, Free State and Eastern Cape provinces. Yields are expected to more than double in these "new" areas located in Mpumalanga and the Free State. However, in the western regions of the Eastern Cape and Northwest provinces, substantial reductions in yields were simulated, i.e. from increases to decreases in taro yield. Taro could benefit the most, with a large expansion in areas deemed suitable for crop production in the Mpumalanga and Free State provinces (Figure 20). These areas are likely too cold for crop production up to 2044, especially in the higher altitude zones. Of the four neglected and underutilised species, taro seems to benefit the most from climate change, particularly towards the distant future.

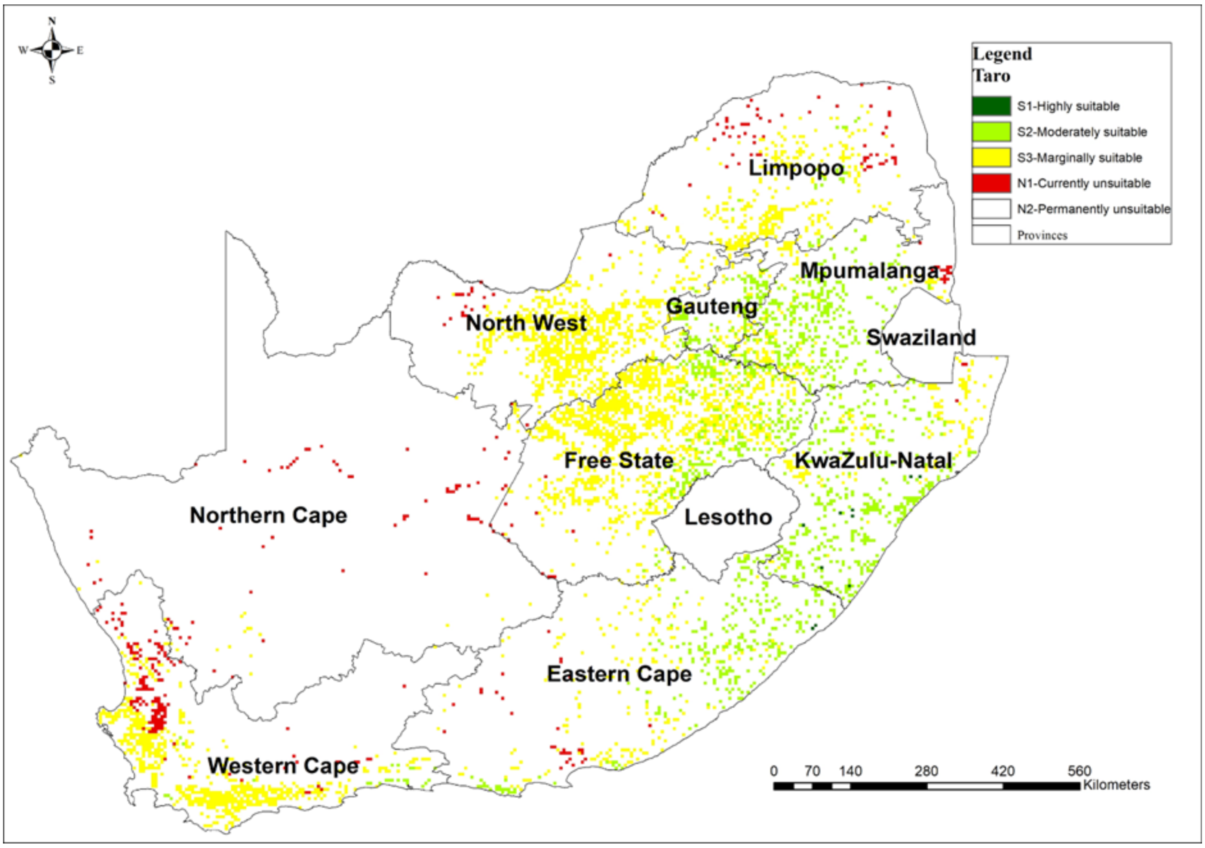


Figure 18: Suitability map for taro production in South Africa computed using MCDA-AHP and OWA operators.[Source, *South African Quaternary Catchments database,(* https://doi.org/10.6084/m9.figshare.13179881*), in ArcGIS 10.5]*

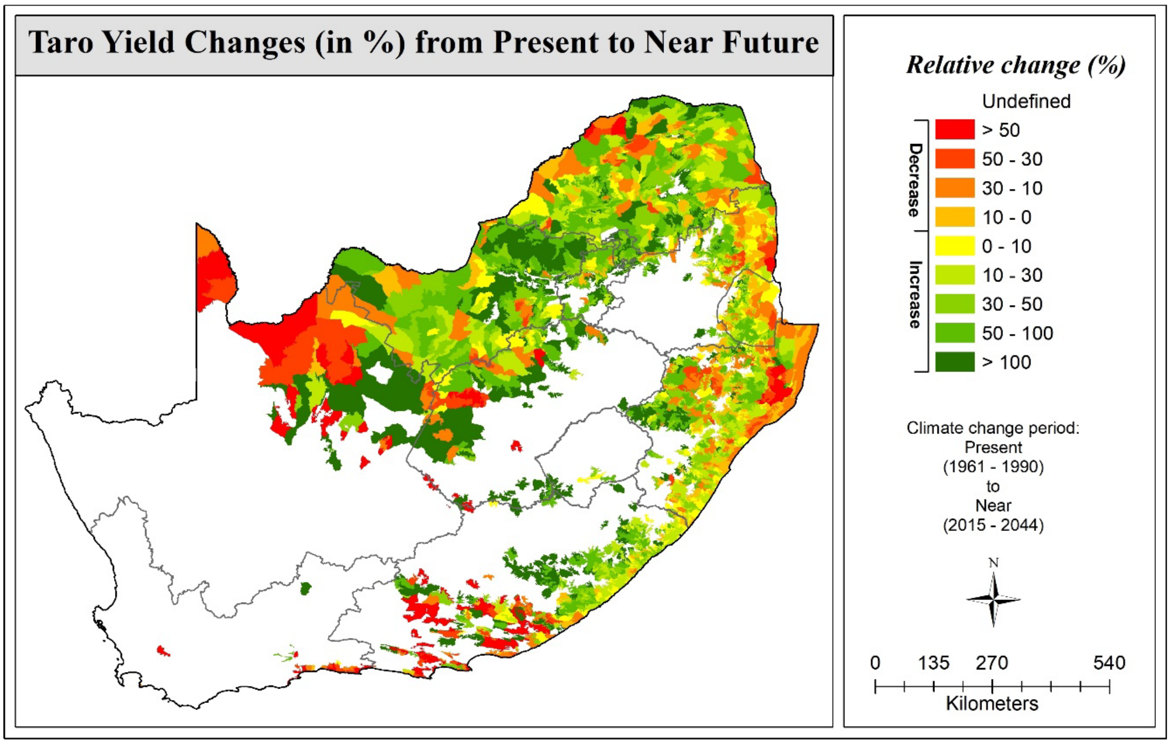


Figure 19: Change in mean dry yield (as %) from present to near future for taro

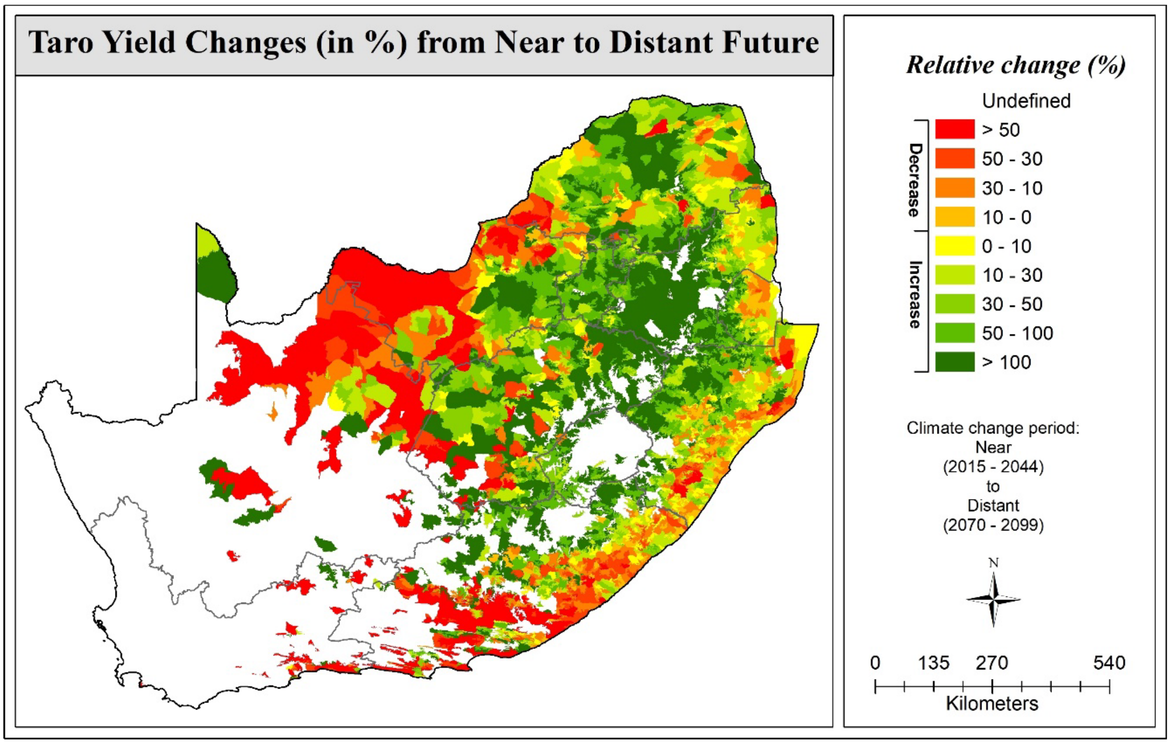


Figure 20: Change in mean dry yield (as %) near to distant future for taro

1.3.3 Drought tolerance

Taro is a wetland crop associated with high levels of water-use. Its production in South Africa is rain-fed and occurs inland under water-limited conditions. It has been suggested that, over the years, through natural and farmer selection and often under harsh conditions, local taro landraces may have “acquired” drought tolerance. However, information on the effect of drought on growth, development and yield of diverse taro landraces is lacking and research on drought tolerance is limited.

Earlier studies by Snyder and Lugo (1980) revealed that drought tolerance existed in some wild relatives of taro, suggesting it was possible to develop drought tolerant hybrids. In India, Sahoo et al. (2006) evaluated a taro hybrid, along with its parents, for water stress tolerance. They reported significant variations for taro growth parameters (height, leaf number and leaf area), leaf relative water content, chlorophyll stability index and injury by desiccation in response to osmotic stress. The hybrid was observed to show tolerance to osmotic stress with minimum yield reduction. They concluded that the development of drought tolerant cultivars of taro was a possibility.

Local eddoe landraces have also been observed to be drought tolerant through a combination of drought avoidance and escape mechanisms. The observations also showed that the eddoe type landraces could be promoted further inland due to their adaptation to low levels of water use. Observed drought avoidance was achieved through stomatal regulation, energy dissipation and canopy size adjustment. Drought escape was demonstrated through phenological plasticity.

Taro is a drought-tolerant crop through a combination of drought avoidance and escape mechanisms, and it is somewhat adapted to low levels of water use. Drought avoidance is achieved through stomatal regulation, energy dissipation and smaller canopy size, resulting in lower crop water losses to transpiration. Drought escape is demonstrated through phenological flexibility, whereby under water-limited conditions taro matures earlier (Mabhaudhi, 2012) resulting in low yield. Yields are, however, relatively low when compared with those of central African countries, primarily in response to limited water availability.

1.3.4 Crop management

1.3.4.1 Cultivars

There are no commercial cultivar for taro and farmers growth and maintain local landraces. Lewu et al. (2017) assessed six accessions (Amadumbe 2914, Amadumbe 3053, Amadumbe 43, Amadumbe 56, Amadumbe Amzam 3553/5118 and Amadumbe 2919) of Colocasia esculenta (taro) were compared in the Western Cape Province of South Africa. These were obtained from the germplasm collection of the ARC-VOPI. Gerrano et al. (2019) identified 29 taro accessions from major taro producing areas in South Africa.

1.3.4.2 Planting date

The best planting time is between December and April, but plantings can be made any time during the year if moisture is adequate.

1.3.4.3 Intercropping

Simultaneous intercropping of taro and Bambara groundnut has been shown to be more productive compared to sole crops of either crop (Mabhaudhi, 2012). Especially the 1:1 (taro : Bambara groundnut) intercrop has indicated huge advantages to intercropping. In addition, intercropping taro and Bambara groundnut at a ratio of 1:1 had no negative effect on growth of either taro or Bambara groundnut landraces. Intercropping taro with Bambara groundnut was shown to be highly productive, in terms of additional output per unit area of land accrued from Bambara groundnut. Intercropping taro with Bambara groundnut also showed no significant negative effect on yield of taro as the main crop. Inclusion of Bambara groundnut (a legume) in taro cropping systems may be complementary in that it improves the overall water use of the farming system through greater capture of water in the horizon. Furthermore, the fact that taro and Bambara groundnut roots extract water from different depths of the soil profile would imply reduced drainage losses. Therefore, intercropping taro with bambara groundnut is productive, sustainable and beneficial in that it has potential to improve farmers' nutritional productivity per unit area, bolster food security and enhance resilience of farmer's cropping systems.

Intercropping taro with bambara groundnut in a 1 : 1 ratio has been shown in field experiments (Mabhaudhi, 2012) to be highly productive in terms of additional output per unit area of land accrued from Bambara groundnut. Intercropping taro with bambara groundnut also showed no significant negative effect on yield of taro as the main crop. Inclusion of bambara groundnut (a legume) in taro cropping systems may be complementary in that it improves the overall water use of the farming system through greater capture of water in the soil horizon. Furthermore, the fact that taro and bambara groundnut roots extract water from different depths of the soil profile would imply reduced drainage losses. Therefore, intercropping taro with bambara groundnut is productive, sustainable and beneficial in that it has potential to improve farmers' nutritional productivity per unit area, bolster food security and enhance resilience of farmer's cropping systems.

1.3.4.4 Plant spacing

The planting distance in commercial cultivation is 1,3 m between rows and 40 cm to 50 cm between plants. In small plantations, planting can be done in mounds spaced at 1 m x 1 m or 1,3 m x 1,3 m. Plant on the crest of the heaps or ridges at 1 m apart on rows. Planting is either done by hand labour or from a tractor-pulled planter. Plant 15 cm to 20 cm deep. The cut surface of the set should face upwards in a slanting position. Plant population is about 15 000 plants per hectare. The tubers have a large sink capacity and continue to grow and store food reserves throughout the year as long as conditions remain favourable. It is a fast-growing plant with a tendency to spread if conditions are favourable.

1.3.4.5 Fertilizer

Fertile soil may not need any fertiliser, but fertiliser may be needed if the soil has been depleted. Apply N.P.K. 15:15:15 at 5 to 6 Coke bottle capfuls in a ring about 10 cm around the plant. The applications are made at 2, 5 and 7 months after planting. The initial fertiliser application should include 1,5% Mg, 1% Mn, and 0,1% Zn.

1.3.4.6 Pest and disease

Pests and diseases of taro for local South African landraces have not been the focus of any studies. Studies to date have focussed on the agronomy, drought tolerance and water use as well as nutritional value of taro landraces. Although it is not well documented, *Phytophthora* leaf blight and corm rot have been observed. Aphids have been observed to be a major pest of taro with plant hoppers also observed, although the latter could be regarded a minor pest in South Africa.

Virus diseases: Numerous viral diseases are known to attack taro species. They are most serious viral pathogens with some infections resulting in severe yield reductions and even plant death. The most common world-wide is the Dasheen mosaic virus (DsMV). Taro Dasheen mosaic virus is caused by a stylet-borne, flexuous, rod-shaped virus that is spread by aphids. It is characterized by chlorotic and feathery mosaic patterns on the leaf, distortion of leaves, and stunted plant growth. The disease is not lethal, but yield is depressed. *Taro bacilliform* virus (TaBV) is a virus transmitted by the plant hopper, Colocasia bobone disease virus (CBDV) is a cytorhabdovirus

1.3.4.7 Weed control

Weeds should be controlled for the first three months after planting. Soil is moved up around the plant to control weeds and to enhance underground storage organ size. Weed at least three times per season. Weeding is done by cultivation with tractors and by hand. During the first four months of growth weeds are a particular problem. Weed competition during this period may reduce yields by as much as 43%.

1.3.4.8 Harvesting

Harvesting is done by uprooting when the leaves have turned yellow and are beginning to dry. The crop can be harvested by hand or by a semi-mechanised method. In small plantations, harvesting of the cormels begins four to six months after planting and is done without uprooting the plant. In the latter case, the tractor has an iron plate as wide as itself attached to it and has a central point which digs into the row of plants. It turns them over, and leaves the central stem and cormels free, which are subsequently collected by hand. Cormels that remain in the soil are dug out. Before harvest the foliage is cut with a rotary mower, and disc cultivation brakes down the furrow. A modified potato harvester is then used to lift the corms and cormels from the soil. The one-row potato digger brings the cormels to the surface where they are selected, cleaned and packed into 22,5 kg wooden boxes, all without the aid of machinery. The boxes are later hauled to the packing shed. The planting material is selected by hand and cut with a machete. It is then thrown into a box or piled for curing until the cut surface has suberised.

1.3.5 Nutritional Value

Taro corm has been reported to have 70-80% (dry weight basis) starch with small granules. Taro contains about 11% protein on a dry weight basis. In general, the fat contents of taro root range from 0.3-0.6%. Taro is a good source of minerals including iron (8.66-10.8 mg/100 g), calcium (31-132 mg/100 g), sodium (82-1521.34 mg/100 g), magnesium (118-415.07 mg/100 g), phosphorus (72.21-340 mg/100 g), zinc (2.63 mg/100 g), copper (1.04 mg/100 g) and an excellent source of potassium (2271-4276.06 mg/100 g). High potassium to sodium ratio food recommended for patient with high blood pressure. Vitamin C and vitamin B complex (niacin, riboflavin and thiamine) which are important constituents of human diet, are present in appreciable quantity in corms and leaves of taro.

1.3.6 Food preparation – Taro spicy fry (Serves 4)

Ingredients

12 medium sized Taro root

1 Tsp. turmeric powder

2 Tsp. chilli powder

1 Tsp. Kashmiri chilli powder

1 Tsp. black pepper

2 Tbsp. cooking oil

1 Tbsp. minced garlic

5 to 6 curry leaves

Method

In a pot, bring the washed Taro root to a boil. Boil for 1o minutes.

Let the boiled Taro root cool and then peel. Cut into small cubes.

Add turmeric powder, chilli powder, Kashmiri chilli powder and black pepper and mix well.

In a saucepan, heat 2 tablespoons of cooking oil and add minced garlic.

Add in the mixed Taro root and stir.

Add 5 to 6 curry leaves.

Stir and let it fry for 5 minutes.

Stir well and let it fry for a further 5 minutes.

Serve.

Nutritional Value per serving

Energy: 469.8 calories

Total Carbohydrates: 50 g

Total protein: 4.6 g

Total fat: 29.6 g

Fibre: 8.7 g

1.4 Amaranth

1.4.1 Crop physiology and morphology

Amaranth species are erect or spreading annuals with a rough appearance. Depending on the species, growth habitat and environment, height of the plant varies between 30 cm and 2 m. The species differ in flower, leaf and stem colour, with maroon and crimson being the most common plant colours. Flowers range from green to golden in colour. Deep crimson varieties tend to be very outstanding when in full bloom. Stems are usually longitudinally grooved. Grain amaranth plants are dicots plants with thick, tough stems similar to those of sunflowers. The leaves thin stalks and differ in size and colour. These are alternate, usually simple, with entire margins and diverse markings. Small green flowers are borne in dense, elongated clusters, usually on the branch tips. They are borne in spikes or plumes and are white, green, pink or purplish in colour. Seeds are very small and up to 3000 seeds weigh one gram. They are shiny black, dark red or cream in colour.

1.4.2 Agroecology

The land suitability analyses indicated that amaranth is highly suitable across South Africa. The results indicated that there is about 8% of the land that is highly suitable (S1) for the production of amaranth. Moderately suitable (S2) land constitutes the most substantial proportion with 81% of the calculated arable land of South Africa (12 655 859 ha) while marginally suitable (S3) constitutes 11% of calculated arable land (Figure 21). Amaranth is high suitable across South Africa in most cropping areas, even in the Western Cape, where the investigated crops had low suitability (Figure 21). The observed suitability could be associated with the growth requirements of the crops that allow for its production even under marginal conditions. From field visits, farmers confirmed that amaranth is suitable and grow naturally in KwaZulu-Natal environments.

In response to the projected warmer and drier climate conditions in the near future, amaranth yields are expected to decline by up to 10% across most of the Limpopo, Mpumalanga, Gauteng and Northwest provinces, including the northern regions of KwaZulu-Natal and Free State (Figure 22). In addition, yield declines of up to 30%

may occur in certain parts of the Limpopo and Northwest provinces. For the majority of KwaZulu-Natal and Eastern Cape, yield increases up to 10% were simulated, with larger improvements up to 30% in the western parts of the Free State and Eastern Cape provinces (Figure 23).

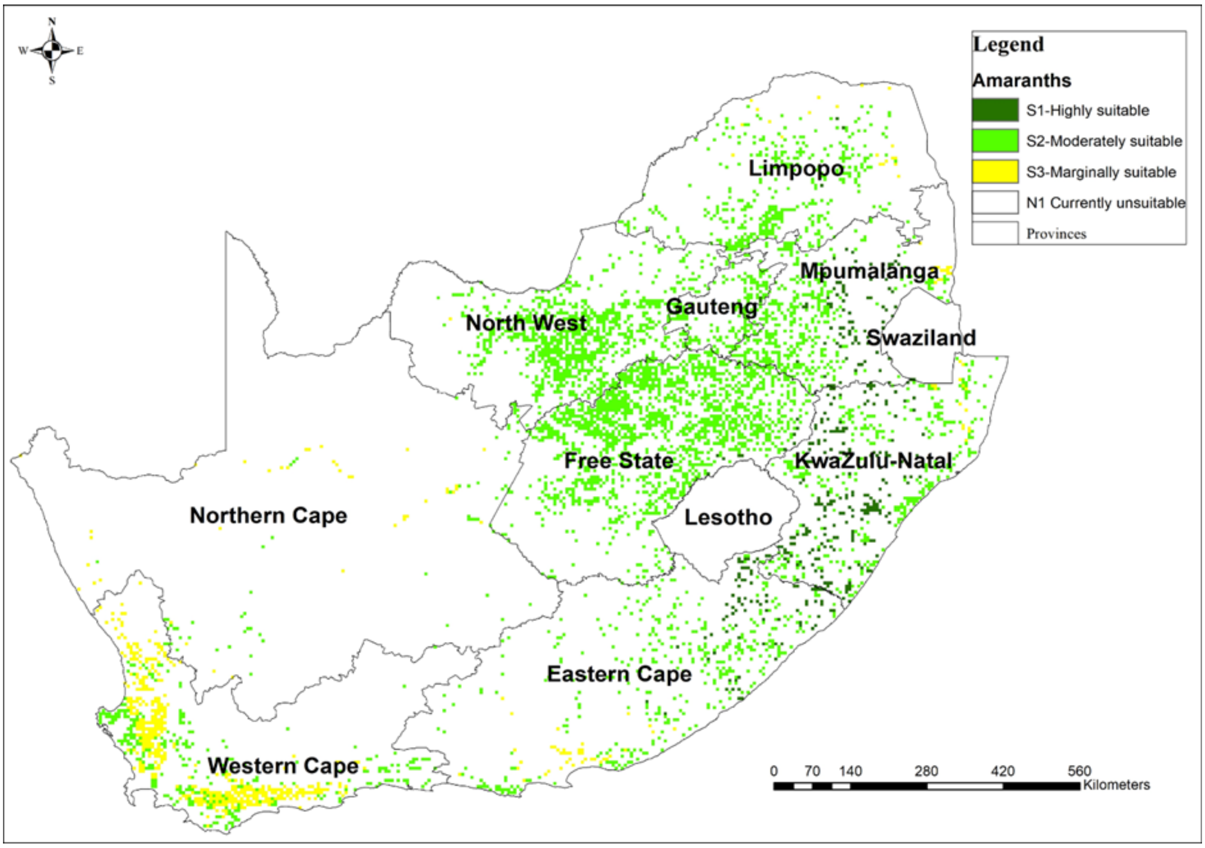


Figure 21: Suitability map for amaranth production in South Africa computed using MCDA-AHP and OWA operators. [Source, *South African Quaternary Catchments database, (* **https://doi.org/10.6084/m9.figshare.13179881***), in ArcGIS 10.5]*

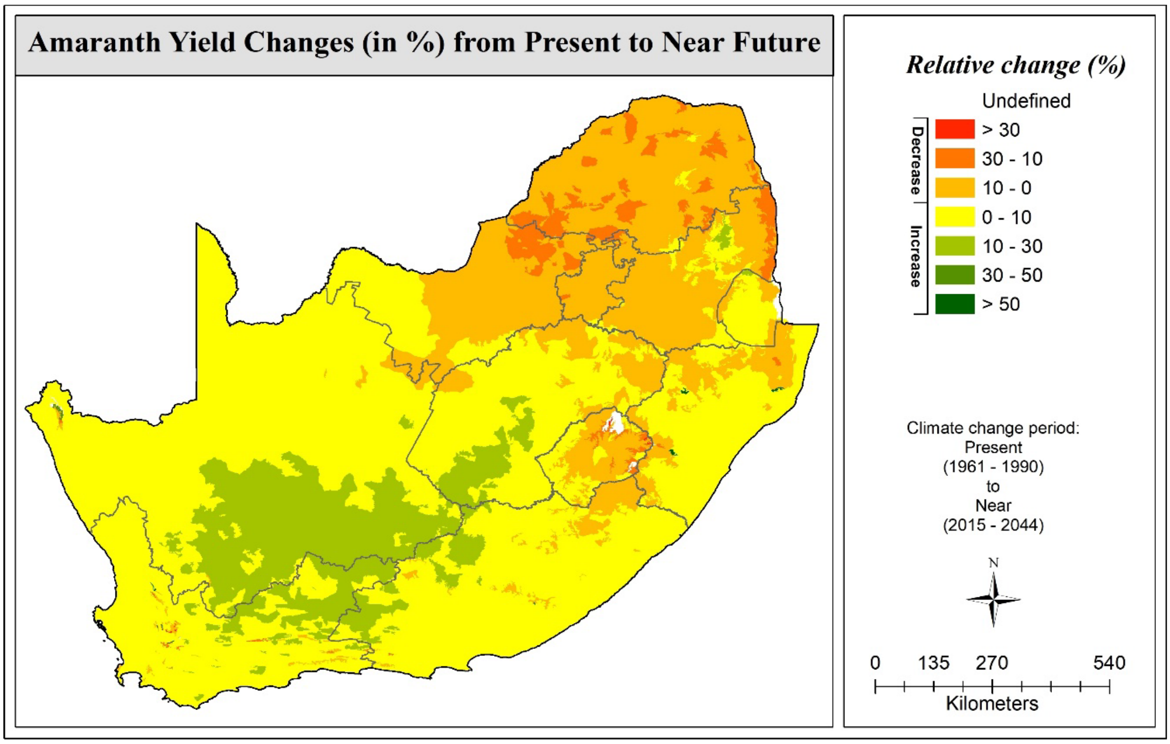


Figure 22: Change in mean dry yield (as %) from present to near future for amaranth

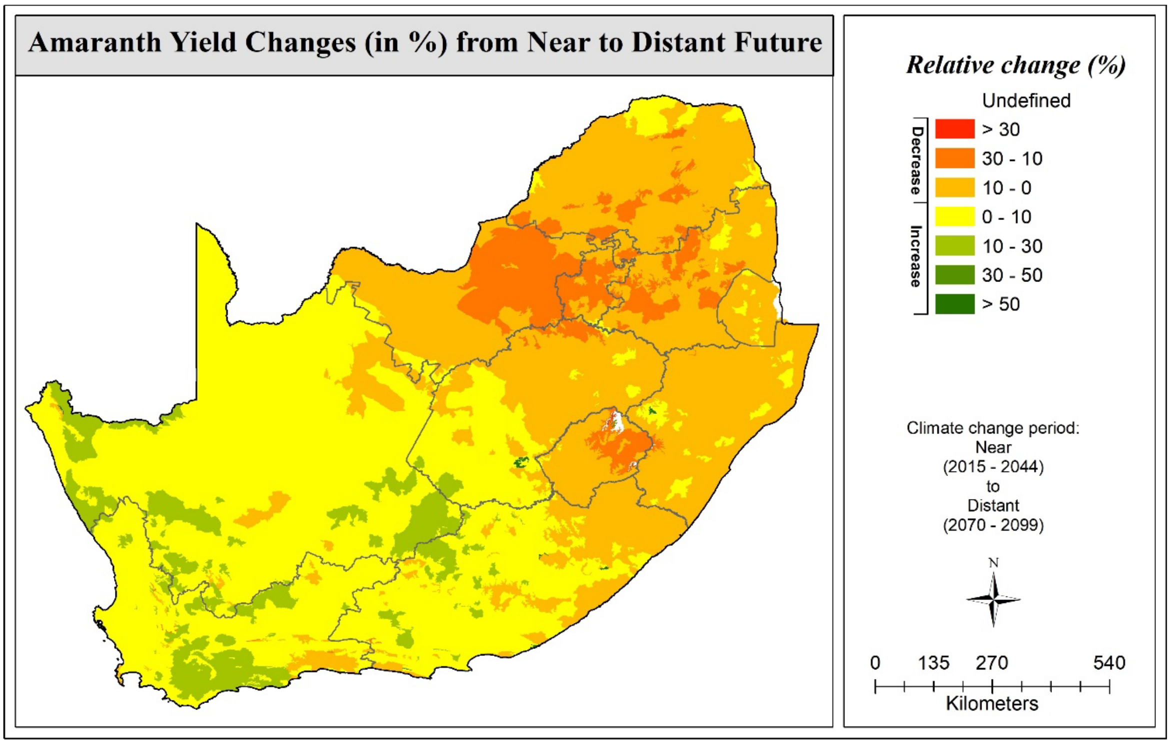


Figure 23: Change in mean dry yield (as %) near to distant future for amaranth

1.4.3 Drought tolerance

Amaranth is reported to be one of the most drought-tolerant vegetable crops. It is a C4 plant and it is capable of using solar radiation and nutrients at high temperatures similar to sorghum and millets One trait that helps it in extremely dry conditions is an ability to wilt temporarily and then revive after rainfall occurs. The exposure of the plant to severe drought induces early flowering and stops the production of leaves. The physiological basis of drought-tolerance in amaranth reveals a high capacity of osmotic adjustment which guarantees that the plant can continue to function under severe drought stress conditions.

1.4.4 Crop management

1.4.5.1 Cultivars

Amaranthus cruentus, A. hybridus, A. spinosus, A. caudatus and A. thunbergii, which are all indigenous to the country.

1.4.5.2 Planting date

Planting is done in September and October when the soil temperature is at least 18 °C and after early weed growth has been controlled by tillage or a contact herbicide. When planted early, amaranth will start flowering after it has accumulated enough growth and heat units; when planted later, flowering is triggered by photoperiod (day length).

Based on scenario analysis different planting date resulted in different responses to leaf number, leaf mass, leaf area index (LAI) and water productivity (WP) (*Figure 24*).

- Early planting 01-September (1) favoured a high number of leaves (123). Contrary to this, late plantings (01-March) resulted in a low leaf number (89).
- Results for leaf mass, LAI and WP showed an inverse relationship with leaf mass. The general observation was that late planting date gave the highest leaf mass, LAI and WP compared to early planting dates.
- Planting date 01-March (7) and 01-December (4) gave the highest (1 324 g plant^{-1}) and lowest (1 089 g plant^{-1}) leaf mass, respectively. Planting in March

resulted in the highest LAI (2.53) and WP (0.41 g m^{-3}) and while November planting had the lowest simulated values (1.90, 0.21 g m^{-3}, respectively).

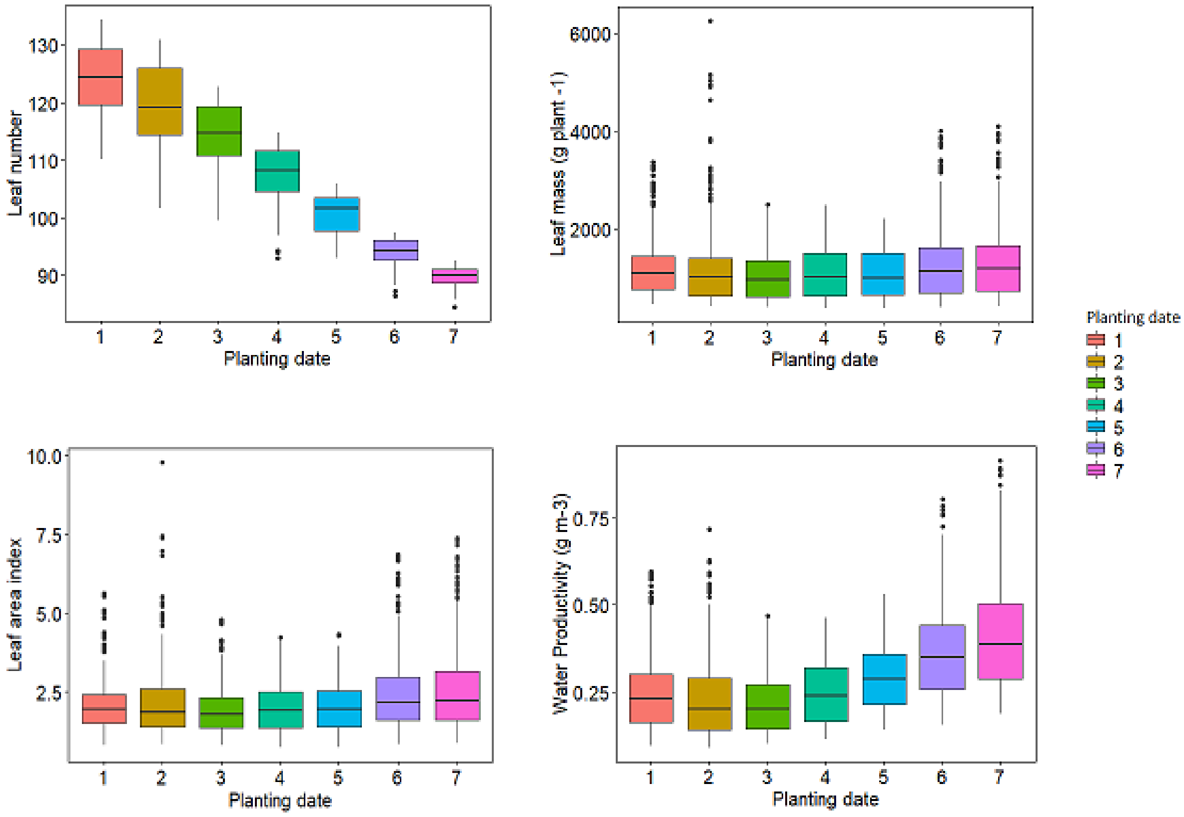


Figure 24: The effect of planting dates on leaf number, leaf mass (g $plant^{-1}$), leaf area index and water productivity (g m^{-3}) on growth and development of amaranth. Planting date 1 through 7 correspond to the 1st of September (1), October (2), November (3), December (4), January (5), February (6) and March (7), respectively.

1.4.5.3 Plant populations

The ideal plant population depends on environment, cultivar and management, According to Maboko and Du Plooy plant population of either 16 or 25 plants/m^2, harvested by cutting, increased production of amaranth, as a result of a reduced number of inflorescences and increased leaf area.

Using a modelling approach, Kunene (2021) observed

- a significant increase ($P<0.05$) in leaf number and LAI with increase in plant population. However, plant density did not affect leaf mass and water productivity.

- Optimum the leaf mass, LAI and WP were observed under medium plant density, 17.4 plants m^2
- Leaf mass was the highest (1193 kg $ha^{-1)}$ at medium plant density (17.4 plants m^2) and the lowest (1165 g $plant^{-1)}$ at low (8.7 plants m^2) plant density. At plant density, 26.1 plants m^2, the mean leaf mass was 1173 g $plant^{-1}$

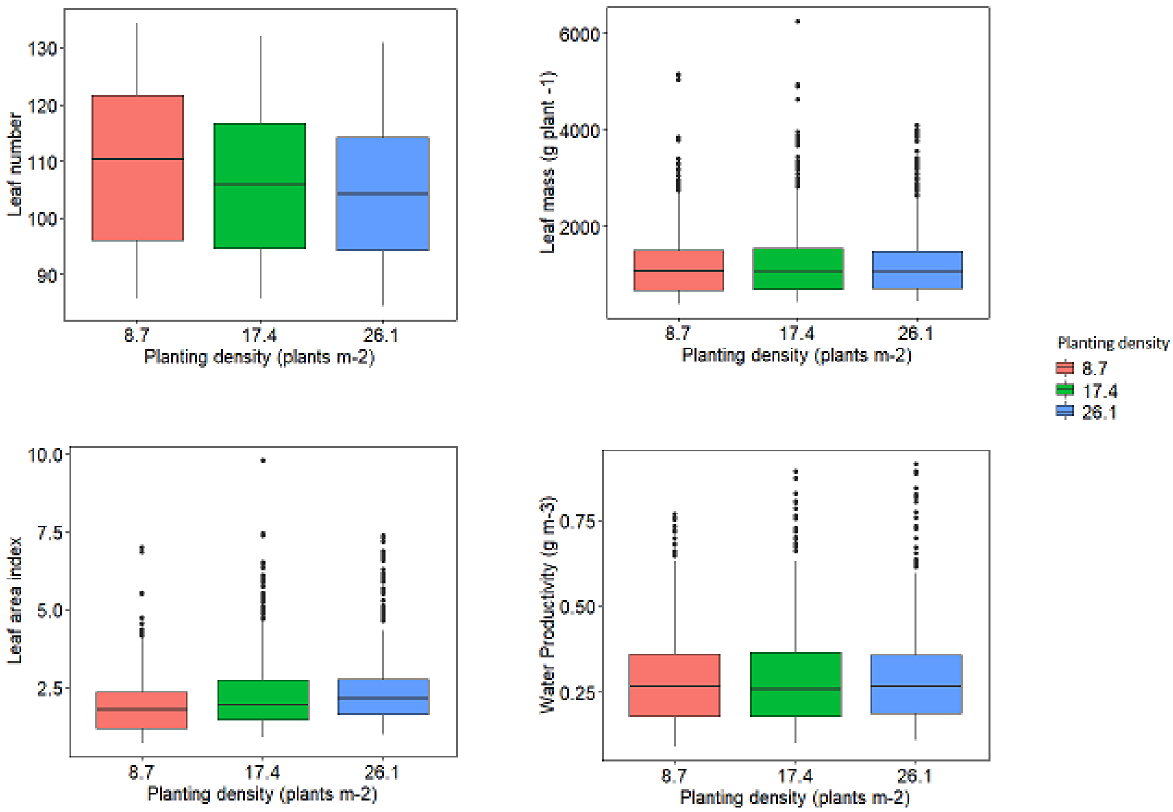


Figure 25: The effect of plant density (plants m^2) on leaf number, leaf mass (g $plant^{-1)}$, leaf area index and water productivity (g m^{-3}) on growth and development of amaranth

1.4.5.4 Fertilizer

One of the essential elements, and one which participates directly as an indispensable requirement for normal plant growth, is nitrogen. High levels of nitrogen are essential for the regrowth of leaves after harvesting. To promote better regrowth, a top dressing of LAN (limestone ammonium nitrate, 28 kg) can be given at monthly intervals. Nitrogen will be the most limiting nutrient in most environments. Nitrogen requirements may vary from 50 to 200 kg N/ha and the requirement also differs, depending on the species. Plants can be fertilised by using cow manure at 6 t/ha as well as commercial fertilisers with a high nitrogen content. Higher yields are also obtained from plots fertilised with composted chicken manure, which has considerable quantities of nitrogen, a mineral that plays a key role in the development of the plant (especially leaf growth). A side dressing of compost is sometimes applied during active growth, especially if plants are allowed to go to seed. If nitrogen is used, around 18 to 36 kg/acre, with the lower figure used after soya-beans or other legumes in a crop rotation system, the growth of vegetable amaranth is adversely affected by a soil pH of 5,3 and 4,7. A soil with a pH of 6, 4 could produce high yields and if the plants are treated correctly it should be possible to harvest leaves every two weeks. Phosphorus and potassium can be applied at soil-test-recommended levels.

1.4.5.5 Pest and disease

Insect pests: There is a wide range of insects that attack amaranth in South Africa; various snout beetles, moth larvae, fleas, stinkbugs, aphids and blowflies. Tarnished plant bug and amaranth weevil are regarded as potentially significant insect pests of amaranth. The insect most likely to affect yields is the tarnished plant bug, a sucking insect which often reaches high populations in the seed head during the critical seed-fill stage. Flea beetles damage the young leaf tissue. The adult amaranth weevil feeds on leaves, but the larval stage is more damaging because they bore into the central tissue of roots and occasionally stems, causing rotting and potential lodging. There are no synthetic insecticides labelled for amaranth, but various organic insecticides can be used, including certain pyrethrum and BT products.

Fungal diseases: the most common disease infecting *Amaranthus* spp. are: **Anthracnose** caused by *Colletritrichum gloesporiiodes*. **Symtoms**: Necrotic lesions on leaves; dieback of leaves and branches. **Control:** Avoid damaging plants and creating wounds for pathogen to enter; plant resistant varieties. **Damping-off** caused by *Rhizoctonia* spp. And Pythium spp. **Symptoms:** Poor germination; seedling collapse; brown-black lesions girdling stem close to soil line; seedling fail to emerge from soil. **Control:** Avoid planting seeds too deeply; do not plant seeds too thickly to promote air circulation around seedlings; do not over-water plants. **Wet rot** caused by *Choanephora cucurbitarum*. **Symptoms**: Water-soaked lesions on stems; lesions have hairy appearance due to presence of fungal spores; may cause loss of leaves. **Control:** Plant varieties resistant to disease; only use certified seed; do not plant crop densely. There are no fungicides labelled for amaranth.

Nematode diseases: Amaranth is considered nematode tolerant and is thus recommended as a rotational crop to reduce nematode population for subsequent crops

Virus diseases: Curly top virus disease, which is transmitted by the beet leafhoppers (*Circulifer femellus*).

1.4.5.6 Weed control

Despite amaranth being often categorised as a weed, it is affected by other weeds such as lambsquarter, redroot pigweed, kochia, cheatgrass during growth. Early weeds are controlled by tillage or a contact herbicide prior to planting the amaranth. Amaranth grows slowly during the first several weeks, so three or four cultivations may be needed during this period to control weeds (no selective herbicides are labelled for use with amaranth). Once amaranth gets to be 15 cm tall, it will begin growing rapidly, and its shade can outperform late emerging weeds.

1.4.5.7 Harvesting

Most amaranth cultivars grow rapidly and may be harvested from 30 to 55 days from sowing, when they reach a height of 0,6 m. Timing of harvest is not as straightforward as with the commodity crops. Management during harvest is a most critical stage in grain amaranth production. Without careful harvest techniques it is possible to lose most of the seed. Before harvesting can begin a killing frost must occur, followed by a week of good drying weather to make the crop drier for harvest (there are no approved desiccants for amaranth).

The plants are harvested by hand only. Young plants can be pulled up or cut six to eight weeks after sowing when they are about 20 cm tall. This is done in cases where seeds were broadcasted. Plants may be cut back to 15 cm to encourage lateral growth for successive harvesting. When the plants are harvested at regular intervals, start picking the leaves eight weeks after sowing or four weeks after transplanting. Small quantities of leaves can be harvested on a daily basis. In the case of large quantities, intervals of two weeks are recommended. Leaf production can be sustained by the removal of flowers.

Leaves can be harvested in two ways:

• Picking of individual leaves when these are the size of the palm of your hand.

• Breaking off the leaves around the terminal growth tips of the stems. This is done by pulling one hand up towards the growth tip and breaking off the leaves with the other hand. Though amaranth can be harvested by hand, combine harvesters are also commonly used. A regular combine can be used if fitted with appropriately sized separator screens. When reel heads are used it may be helpful to remove several reel bats or raise the height of the reel. Row headers perform better at harvesting amaranth than reel heads do for combining amaranth. During harvest, if the stems and leaves are too wet, the seeds become sticky and adhere to the inside of the combine as well as the straw discharge. Shattering during the cutting process can also cause losses, so adjustment should be made to minimise shattering of the hands. Care should also be taken to balance against getting it combined before pre-harvest losses from lodging or seed shatter from wind occurrence.

Grain harvesting

Harvesting amaranth seeds is a basic process. Cut the seed heads just before these become dry and brittle. Lay the seed heads on a cloth or place them inside paper or cloth bags with the heads down and leave in the shade to finish drying. When the seed heads are dry, the seeds can be removed in several ways:

- by rubbing gently with your hands (wearing gloves is recommended);

- by enclosing the seed heads between two cloths and treading on them without shoes on.
- by beating the seed heads off a bag; or by beating them together over cloth.

1.4.5 Nutritional Value

Both the seeds and leaves of *A. tricolor* are known to contain protein of unusual high quality and are richer in vitamins and minerals than cereals. Amaranth leaves have protein content of 17-19% and have the advantage of having a more balanced composition of essential amino acids. Approximately 100 g of amaranth vegetable leaves cooked in the absence of oil makes up 45% of the daily vitamin A requirement. Amaranth has three times more vitamin C, niacin and calcium compared to other leafy vegetables like spinach.

1.4.6 Food preparation – Amaranth breakfast cup (Serves 1)

Ingredients

½ cup amaranth seeds

1 cup water

A pinch of salt to taste (optional)

1 Tbsp. sugar

1 Tbsp. chopped mixed nuts

½ cup chopped fruit

Method

1. In a heavy saucepan combine the amaranth and water and bring the mixture to a boil.
2. Whisking or stirring occasionally, reduce the heat to low and continue to simmer for about 20 minutes, until the liquid is absorbed.
3. Remove the pan from the heat and stir in salt (if adding) and sugar to attain preferred consistency.
4. Divide the mixture among bowls and top with nuts and fruit.

Nutritional Value per serving

Energy: 266 calories

Total Carbohydrates: 41 g

Total protein: 7.1 g

Total fat: 7.9 g

Fibre: 5.1 g

References

Abdelgadir, H.A., Kulkarni, M.G., Arruda, M.P. and Van Staden, J., 2012. Enhancing seedling growth of Jatropha curcas – A potential oil seed crop for biodiesel. South African Journal of Botany, 78, pp.88-95. ttps://doi.org/10.1016/j.sajb.2011.05.007

Adoukonou-Sagbadja, H., Wagner, C., Dansi, A., Ahlemeyer, J., Daïnou, O., Akpagana, K., Ordon, F. and Friedt, W., 2007. Genetic diversity and population differentiation of traditional fonio millet (Digitaria spp.) landraces from different agro-ecological zones of West Africa. Theoretical and Applied Genetics, 115(7), pp.917-931. https://doi.org/10.1007/s00122-007-0618-x

Berchie, J.N., Opoku, M., Adu-Dapaah, H., Agyemang, A., Sarkodie-Addo, J., Asare, E., Addo, J. and Akuffo, H., 2012. Evaluation of five bambara groundnut (Vigna subterranea (L.) Verdc.) landraces to heat and drought stress at Tono-Navrongo, Upper East Region of Ghana. African Journal of Agricultural Research, 7(2), pp.250-256.

Chibarabada, T.P., Modi, A.T. and Mabhaudhi, T., 2015. Bambara groundnut (Vigna subterranea) seed quality in response to water stress on maternal plants. Acta Agriculturae Scandinavica, Section B – Soil & Plant Science, 65(4), pp.364-373. doi:10.1080/09064710.2015.101397

Chibarabada, T.P., Modi, A.T. and Mabhaudhi, T., 2017. Nutrient content and nutritional water productivity of selected grain legumes in response to production environment. International Journal of Environmental Research and Public Health, 14(11), p.1300. doi:10.3390/ijerph14111300

Chimonyo, V.G.P., Modi, A.T. and Mabhaudhi, T., 2016. Water use and productivity of a sorghum-cowpea-bottle gourd intercrop system. Agricultural Water Management, 165, pp.82-96. https://doi.org/10.1016/j.agwat.2015.11.014

Chimonyo, V.G.P., Modi, A.T. and Mabhaudhi, T., 2016. Simulating yield and water use of a sorghum-cowpea intercrop using APSIM. Agricultural Water Management, 177, pp.317-328. doi:10.1016/j.agwat.2016.08.021.

Collinson, S.T., Clawson, E.J., Azam-Ali, S.N. and Black, C.R., 1997. Effects of soil moisture deficits on the water relations of bambara groundnut (Vigna subterranea L. Verdc.). Journal of Experimental Botany, 48(4), pp.877-884.

Department of Agriculture Forestry and Fisheries (DAFF)., 2011. South African Agricultural Production Strategy. http://www.nda.agric.za/docs/sectorplan/sectorplanE.htm

Faber, M., Van Jaarsveld, P.J., Wenhold, F.A.M. and Van Rensburg, J., 2010. African leafy vegetables consumed by households in the Limpopo and KwaZulu-Natal provinces in South Africa. South African Journal of Clinical Nutrition, 23(1). https://doi.org/10.1080/16070658.2010.11734255

Gerrano, A.S., Jansen Van Rensburg, W.S., Adebola, P.O., Manjeru, P., Bairu, M.W. and Venter, S.L., 2019. Evaluation and selection of taro [Colocasia esculentra (L.) Schott] accessions under dryland conditions in South Africa. Acta Agriculturae Scandinavica, Section B – Soil & Plant Science, 69(3), pp.219-227. https://doi.org/10.1080/09064710.2018.1530296

Giller, K.E., Witter, E., Corbeels, M. and Tittonell, P., 2009. Conservation agriculture and smallholder farming in Africa: the heretics' view. Field crops research, 114(1), pp.23-34. https://doi.org/10.1016/j.fcr.2009.06.017

Government of South Africa., 2015. Nine-Point Plan . Government of South Africa. http://www.gov.za/issues/nine-point-plan.

Hillocks, R.J., Bennett, C. and Mponda, O.M., 2012. Bambara nut: A review of utilisation, market potential and crop improvement. African Crop Science Journal, 20(1).

Hoffmann, T., Todd, S., Ntshona, Z. and Turner, S., 2014. Land degradation in South Africa.

http://www.botanicalsociety.org.za/ProjectsAndActivities/Shared%20Documents/3.%20Gardening%20with%20traditional%20plants.pdf

http://www.nda.agric.za/docs/Brochures/Amaranthus.pdf

http://www.newworldencyclopedia.org/entry/Amaranth

https://www.agmrc.org/commodities-products/specialty-crops/amaranth

https://www.farmersweekly.co.za/crops/field-crops/amaranth-farm-trial-high-potential-crop-marginal-land/

https://www.itis.gov/servlet/SingleRpt/SingleRpt?search_topic=TSN&search_value=20715#null

Khan, F., Chai, H.H., Ajmera, I., Hodgman, C., Mayes, S. and Lu, C., 2017. A transcriptomic comparison of two Bambara groundnut landraces under dehydration stress. Genes, 8(4), p.121.

Kipnyargis, A.C., 2016. Genetic Diversity of Aphid Species Attacking Amaranth and Nightshades in Different Agro-Ecological Zones of Kenya and Tanzania (Doctoral dissertation, University of Embu).

Kunene, T.G., 2020. Assessing nutritional water productivity of selected African leafy vegetables using the agricultural production systems simulator model (Doctoral dissertation).

Muinat, N.L., Mulidzi, A.R., Gerrano, A.S. and Adebola, P.O., 2017. Comparative growth and yield of taro (Colocasia esculenta) accessions cultivated in the Western Cape, South Africa. International Journal of Agriculture and Biology, 19(3). https://doi.org/10.17957/IJAB/15.0342

Mabhaudhi, T., Modi, A.T. and Beletse, Y.G., 2013. Growth, phenological and yield responses of a bambara groundnut (Vigna subterranea L. Verdc) landrace to imposed water stress: II. Rain shelter conditions. Water Sa, 39(2), pp.191-198. https://doi.org/10.4314/wsa.v39i2.2

Mabhaudhi, T., O'Reilly, P., Walker, S. and Mwale, S., 2016. Opportunities for underutilised crops in southern Africa's post-2015 development agenda. Sustainability, 8(4), p.302. https://doi.org/10.3390/su8040302

Mandiringana, O.T., Mnkeni, P.N.S., Mkile, Z., Van Averbeke, W., Van Ranst, E. and Verplancke, H., 2005. Mineralogy and fertility status of selected soils of the Eastern Cape Province, South Africa. Communications in Soil Science and Plant Analysis, 36(17-18), pp.2431-2446.

Mkandawire, C.H., 2007. Review of bambara groundnut (Vigna subterranea (L.) Verdc.) production in Sub-Sahara Africa. Agricultural Journal, 2(4), pp.464-470.

Modi, A.T. and Mabhaudhi, T., 2013. Water use and drought tolerance of selected traditional crops. Water Research Commission (WRC). Crop Science, School of Agricultural, Earth and Environmental Sciences, pp.140-168.

Mungofa, N., 2016. Attitude towards the cultivation and utilisation of indigenous leafy vegetables in rural communities(Doctoral dissertation).

National Planning Commission., 2013. National Development Plan Vision 2030. http://www.gov.za/issues/national-development-plan-2030

Paterson, G., 2015. The 'land question' from the point of view of the land – NEWS & ANALYSIS. Politicsweb. http://www.politicsweb.co.za/news-and-analysis/the-land-question-from-the-point-of-view-of-the-la

Schoeman, J.L., Van Der Walt, M., Monnik, K.A., Thackrah, J., Malherbe, J. and Le Roux, R.E., 2002. Development and application of a land capability classification system for South Africa. Agricultural Research Council (ARC) Institute for Soil, Climate and Water, Pretoria (GW/A/2000/57).

STATSSA., 2016. Statistics South Africa. http://cs2016.statssa.gov.za/

Vadivel, V. and Janardhanan, K., 2001. Nutritional and anti-nutritional attributes of the under-utilized legume, Cassia floribunda Cav. Food Chemistry, 73(2), pp.209-215. https://doi.org/10.1016/S0308-8146(00)00280-6

Van Averbeke, W., 2002, May. Indigenous Technology and technology-oriented research: implications for research methodology. In Proceedings of the 18th Annual Conference of the Association for International Agricultural and Extension Education, Durban, South Africa (pp. 26-30).

Wenhold, F.A.M., Faber, M., van Averbeke, W., Oelofse, A., Van Jaarsveld, P., Van Rensburg, W.J., Van Heerden, I. and Slabbert, R., 2007. Linking smallholder agriculture and water to household food security and nutrition. Water Sa, 33(3).