DROUGHT IMPACTS ON POTENTIAL MAIZE YIELD IN THE FREE STATE PROVINCE, SOUTH AFRICA

By

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DECLARATION STATEMENT

I hereby declare that this thesis entitled "Drought Impacts on Potential Maize Yield in the Free State Province, South Africa" is my original work, completed under the guidance of Dr W Tesfuhuney (supervisor), Dr ME Moeletsi, and Dr ZA Bello (co-supervisors), and submitted in partial fulfilment of the requirements for the Master's degree in Agriculture, majoring in Agrometeorology at the University of the Free State.

I assert that:

The work presented in this thesis is the result of my independent research and investigation, except where otherwise acknowledged in the text. Any assistance received in preparing this thesis and sources of information has been acknowledged appropriately. All secondary sources used in this thesis have been duly cited and referenced. The content of this thesis has not been submitted for any other degree or qualification in any other university or institution. Any material previously published or written by other authors used in this thesis has been properly attributed, cited, and referenced. I understand that any act of plagiarism or academic dishonesty in this thesis is considered a serious violation of academic integrity and may result in severe consequences. I grant the University of the Free State a non-exclusive license to use this thesis for academic purposes, archiving and online dissemination.

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DEDICATION

This work is dedicated to my daughter, Mukonazwothe Angelica and my family, who have been my rock and my guiding light throughout my academic journey. Your unwavering support, encouragement, and sacrifices have been instrumental in my success. I am forever grateful for your love and inspiration; this thesis is a testament to your belief in me. Thank you for everything.

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"For I can do everything through Christ who gives me strength" Philippians 4:13-NLT

ARTICLES/PUBLICATIONS, CONFERENCES AND AWARDS BASED ON THIS RESEARCH

CONFERENCES

- Poster presentation at the 5th National Global Change Conference (https://gcc5.org.za/) under the topic "**Drought Impacts on Maize Yield in Major Maize-Producing Areas in the Free State Province Between 1990 and 2020**" held at the University of the Free State, Bloemfontein Campus on the 30th January - 2nd February 2023
- Poster presentation at the Annual Early Career Researchers Conference (https://sites.google.com/view/ecr-conference-2023/home) under the topic "**Planting dates as an Adaptation Strategies for Rainfed Maize under Climate Change**" held at Double Tree Conference Hotel in Cape Town on the 9th - 10th March 2023
- Oral presentation at the Society of South African Geographers (SSAG) conference (https://ssag2023.org.za/) under the topic "**Assessing Area-Specific Planting Dates as Adaptation Strategy for Rainfed Maize under Climate Change using AquaCrop model in the Free State Province, South Africa**" held at the University of the Free State, Qwaqwa campus on the 2nd - 4th of October 2023
- Poster presentation at the World Climate Research Programme (WRCP) conference (https://wcrp-osc2023.org/hybrid-platform) in Rwanda (Kigali) under the topic "**Utilizing Planting Dates as an Adaptation Strategy for Rainfed Maize in Response to Climate Change: A Case Study of the Free State Province, South Africa**", held on the 23rd -27th October 2023, presented virtually (Poster 1032)

AWARDS

- **Best Presented Poster** at Annual Early Career Researchers Conference (https://sites.google.com/view/ecr-conference-2023/home) – Appendix 1
- **2nd Prize for the Best Oral Presentation under the Masters' category** at the Society of South African Geographers (SSAG) conference (https://ssag2023.org.za/) **–** Appendix 2

ARTICLES/PUBLICATIONS

- **Assessing the Impact of Agricultural Drought on Yield over Maize Growing Areas, Free State Province, South Africa, Using the SPI and SPEI-** Published (https://www.mdpi.com/2071-1050/16/11/4703)
- **Assessing Area-Specific Planting Dates as Adaptation Strategy for Rainfed Maize under Climate Change using AquaCrop model in the Free State Province, South Africa-** under review at Elsevier Journal of Agricultural and Forest Meteorology

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ABSTRACT

Maize (*Zea mays* L.) is the most-grown rainfed crop in South Africa and is consumed by most people as their staple food. However, due to recurring droughts, which are predicted to intensify in severity and occurrence, its production is challenged, leading to lower yields. In order to address this issue, the study pursued two specific objectives. Objective a) analyzed the impacts of drought on maize yield, focusing on the selected maize-producing areas (Bethlehem, Bloemfontein and Bothaville) within the Free State Province over the historical period (1990-2020). In pursuit of this objective, the study employed widely used methodologies, including the Standardized Precipitation Index (SPI) and Standardized Precipitation Evapotranspiration Index (SPEI), to dissect the temporal-seasonal variations in drought occurrence and severity. Additionally, the coefficient of variation (CV) was used to measure the variability in seasonal climate patterns, providing insights into erratic climate patterns. The modified Mann-Kendall trend test was applied to pinpoint drought trends in the maize growing season (at monthly and seasonal scales). The correlation between drought indices (SPI and SPEI) and maize yield was systematically explored using the Pearson correlation coefficient to evaluate drought impact. The utilization of yield loss rate further enhances the understanding of the detrimental impact of drought on maize production, highlighting the urgency of effective adaptive strategies. The study results indicated that the highest variability in rainfall, maximum and minimum temperatures was 46.62%, 5.31% and 22.66%, respectively. Based on SPI and SPEI, drought frequently occurred in Bethlehem than Bloemfontein and Bothaville, particularly during the ONDJFM season. Regarding drought severity, the moderate droughts were prevalent in Bethlehem, while severe droughts were common in both areas (Bethlehem, Bloemfontein and Bothaville) and extreme droughts in Bloemfontein. Trends indicated that significant decreasing trends (indicating drier conditions) on monthly and seasonal scales were prevalent over Bethlehem under SPI and over Bloemfontein under SPEI. The impact of drought on maize was different during different growing seasons across all areas, where a strong relationship ($r = 0.82$, $p = 1.3e^{-08}$) was noted between SPEI and maize yield over Bloemfontein during the ONDJFM season. Regarding calculated yield loss, the highest maize yield loss recorded was -83.86% for Bethlehem, while Bloemfontein and Bothaville were -75.26% and -58.93%, respectively due to extreme drought. In tandem with these findings, the study objective b) evaluated planting dates as an adaptation strategy under changing climate for the mid-century period (2040-2069) using the AquaCrop model. The AquaCrop model, calibrated and validated with meticulous attention to detail, emerges as a robust tool for assessing the potential outcomes of adjusted planting dates. Ensemble climate projections sourced from multiple climate models under Representative Concentration Pathways (RCP) 4.5 and 8.5 were harnessed to decipher shifting rainfall and temperature patterns in the mid-century (2040-2069). These projections unveiled a complex landscape of shifting climatic conditions, with an overall increase in seasonal rainfall, except for some months with a decline in rainfall across all study areas. Moreover, the anticipated rise in maximum and minimum temperatures across the maize growing season reinforces the urgency of proactive measures. A noteworthy aspect of the study is its elucidation of projected maize yield changes under RCP 4.5 and 8.5 scenarios. The anticipated changes in yield, ranging from positive to negative, were contextualized for each study area, offering valuable insights into the intricate interplay between changing climate and agricultural outcomes. The study identified optimal planting dates for each study area and RCP scenario by analyzing model simulation outputs (i.e. yield). The study results revealed that the optimum planting dates could be 1st November for RCP 4.5 and 15th November (conventional planting date) for RCP 8.5 in Bethlehem, 29th December for both

RCPs in Bloemfontein, and 13^{th} December for both RCPs in Bothaville. These insights not only provide a practical roadmap for adapting maize production to changing climate conditions but also contribute to the broader discourse on sustainable agricultural practices in the face of a changing climate. In essence, this study underscores the imperative of proactive, science-driven strategies to safeguard South Africa's maize production and food security in the years ahead.

Keywords: Climate variability, SPI, SPEI, Drought severity, Drought trends, Maize yield loss, Model evaluation, Climate change, RCPs 4.5 and 8.5, Maize yield change, Planting dates

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LIST OF ACRONYMS

BFN- Bloemfontein

BTM- Bethlehem

BTV- Bothaville

EM-DAT- Emergency event database

FAO- Food and Agriculture Organization

GCMs- Global Climate Model

M.a.s.l -Metres above sea level

RCPs- Representative Concentration Pathways

SPEI- Standardized Precipitation Evapotranspiration Index

SPI- Standardized Precipitation Index

SSA- Sub-Saharan Africa

SST- Sea-Surface Temperature

T/ha- Ton per Hectare

CHAPTER 1: INTRODUCTION

1.1 Background

Among the most pressing concerns of climate change, drought poses significant challenges to agricultural systems worldwide, affecting crop production and food security (Food and Agriculture Organization (FAO), 2017b; 2019; 2021). Hamdy (2004) aptly described drought as a hazardous natural event associated with less-than-average rainfall and high temperatures over a prolonged period in a particular area. Its deleterious effects on agriculture are particularly pronounced, as it compromises the yield potential of staple crops upon which people depend. Among various crops, maize emerges as the third-most vital cereal crop alongside rice and wheat in the global agricultural landscape (Darekar and Reddy, 2017). This prominence is particularly pronounced in Sub-Saharan African (SSA) countries, where maize is mainly grown for human consumption (Tallury and Goodman, 2001; Orhun, 2013). For instance, in countries such as South Africa, Nigeria, Ethiopia, Tanzania, Kenya, and Malawi, maize is a staple food for over 50% of the population (Badu-Apraku *et al.*, 2017; Khojely *et al.*, 2018). Thus, more than 300 million people depend on maize as their basic food for survival (Macauley and Ramadjita, 2015; Badu-Apraku *et al.*, 2017). Maize remains a cornerstone with its multifaceted significance, ranging from food security to economic stability.

In South Africa, maize production plays a pivotal role in the agricultural sector, contributing substantially to the national economy through exports and employment opportunities and exerting substantial influence on critical aspects like food security (Republic of South Africa National Treasury (RSANT), 2003; Meza *et al.*, 2021). The maize sector is recognized by both commercial and small-scale farmers across the country (Department of Agriculture Land Reform and Rural Development (DALRRD), 2021). The total maize production by commercial farmers accounts for approximately 98% and 2% by small-scale farmers (Simanjuntak *et al.*, 2022); collectively, these farmers account for approximately 45% of the gross domestic product of the agricultural sector (Adisa *et al.*, 2019). The Free State, North West, Mpumalanga and KwaZulu-Natal are the central maize-producing provinces in South Africa, accounting for about 83% of the total country's production (Adisa *et al.*, 2019). In 2020, South Africa was ranked 9^{th} among the world's largest maize-producing countries and top in the African continent; it is an essential regional exporter in the continent often depended upon to ensure food security throughout the Southern African region (Bradshaw *et al.*, 2022). The country's agricultural production within the Southern African Development Community (SADC) region contributes notably to the Gross Domestic Product (GDP), with its share ranging from 4% to 27% (Muthelo *et al*., 2019). Nonetheless, due to its heavy reliance on rainfed agriculture, maize harvests in South Africa have been severely reduced by extreme weather events such as droughts over the years (Rey *et al*., 2017). A stark illustration of this unfolded during the 2015 severe drought in South Africa, which was attributed to the El Niño weather phenomenon, where maize production experienced a substantial decline of approximately 8.4%, concurrently affecting the national livestock herd by around 15% (Agri SA, 2016; Mare *et al*., 2018). Drought conditions have intensified in recent years, largely attributed to climate change and variability. These adverse weather patterns not only jeopardize crop yields but also disrupt the entire agricultural value chain, affecting both smallholder farmers and commercial agricultural enterprises. The implications extend far beyond the agricultural sector, affecting food security, socio-economic stability, and environmental sustainability.

Specifically, the Free State Province, renowned as one of the country's breadbaskets, plays a pivotal role in maize production. The province is the leading maize producer in the country, with approximately 44% of the overall production (Meyer *et al.*, 2019). The potential maize yield in the province is not only essential for local consumption but also contributes significantly to the broader national and international maize supply (DALRRD, 2021). However, the relentless and intensifying frequency of drought events in the province casts a pall over its agricultural productivity and economic sustainability. This vast and agriculturally rich province, often called the "Granary of South Africa," plays a crucial role in South Africa's food security. In the 2019/20 season, approximately 45% of the total commercial maize in South Africa was produced in the Free State province (DALRRD, 2021). As one of the most water-intensive crops, maize is particularly susceptible to the adverse effects of prolonged drought events (Zhao *et al.*, 2016). Due to the predominantly semi-arid climate in the Free State Province (Department of Environmental Affairs (DEA), 2016a), the province has been grappling with the intensified effects of drought over the past decades, driven by erratic rainfall (Eckardt, 2020), which have dire consequences for maize production, as it is a highly water-sensitive crop. For example, in the Free State and North West Provinces, the 2015-2016 agricultural season was marked by a severe drought induced by El Niño, which significantly affected white maize yields. During this period, the provinces experienced extended dry spells that reduced maize yield by approximately 53% (Ramugondo, 2020). The agricultural landscape of this province predominantly consists of rainfed maize production systems. Any disruption in maize production within the province can reverberate through the national food supply chain, affecting prices and food availability for millions of South Africans (Department of Agriculture, Land Reform and Rural Development (DALRRD), 2023). Moreover, variations in maize yields stemming from drought events have profound ramifications not only on local food security but also on the broader regional and national economies.

The impact of drought on potential maize yield encompasses a wide range of factors, including altered rainfall patterns, increased temperatures, soil moisture depletion, and the prevalence of water stress during critical growth stages. These climatic and environmental stressors can disrupt the physiological processes of maize crops, such as photosynthesis and transpiration, ultimately leading to diminished yields (Ramirez-Cabral *et al*., 2017; Zhao *et al.*, 2020; Waqas *et al.*, 2021). By conducting a comprehensive analysis that amalgamates historical meteorological data, agronomic variables, and cutting-edge modelling techniques, a nuanced understanding of the challenges posed by drought and identifying potential strategies for mitigating its effects on maize production can be gained. In doing so, this will contribute valuable insights that can inform policy decisions, support adaptive agricultural practices, and promote the long-term sustainability of maize farming in this vital region of South Africa. Droughts have been understood in terms of their severity, duration and Spatio-temporal in agriculture (Rouault and Richard, 2003; Van Loon and Laaha, 2015; Orimoloye *et al.*, 2019; Mengistu *et al.*, 2020); however, their impacts need urgent attention. The impacts become complicated in semi-arid areas with a high dependency on agriculture (Van Loon, 2015). Identifying the relationship between drought and maize yield allows the better formulation of adaptation strategies for overcoming the upcoming agricultural challenges caused by drought.

1.2 Problem statement

The Free State Province of South Africa is one of the key contributors to the country's agricultural sector, particularly in maize production. However, the region has been grappling with the recurring challenge of drought, which poses significant threats to maize yield and overall food security (Botai *et al.*, 2016; Simanjuntak *et al.*, 2022). Drought in the Free State Province is characterized by irregular rainfall patterns (Botai *et al*., 2018), leading to prolonged periods of water shortage. As a predominantly rainfed agriculture region, maize production is particularly vulnerable to variations in precipitation, making it susceptible to yield fluctuations and even complete crop failures. The changing climate patterns in recent years have further exacerbated the frequency and intensity of drought events, posing a considerable threat to the livelihoods of farmers and the broader agricultural economy. Existing studies have primarily focused on analyzing, monitoring, and mapping drought in relation to maize production in the Free State Province (Botai *et al.*, 2016; Adisa *et al.*, 2019). Other studies focused on assessing and characterizing drought occurrence, severity and duration (Phaduli, 2018; Mbiriri *et al*., 2019; Abubakar *et al*., 2020). However, there are limited studies that explicitly focused on drought impacts on maize yield, especially in the main areas producing maize in the Free State Province. Moreover, most of these studies have predominantly focused on the provincial scale, with limited studies at a local scale. In addition, these studies lack a holistic perspective on the adaptation strategies that farmers can employ to increase their production. Given these knowledge gaps, the current study aims to analyze drought impacts on maize yield and assess adaptation strategies in the major areas producing maize in the Free State Province, South Africa.

1.3 Aim

This study's main aim was to analyze the impact of drought on maize yield from 1990 to 2020 and evaluate adaptation strategies for mid-century (2040-2069) in the selected main maize-growing areas in the Free State Province, South Africa.

1.4 Specific objectives

a) To assess the impact of drought on the major areas producing maize in the Free State Province over the historical period (1990-2020).
b) To evaluate different planting dates as adaptation strategies under changing climate for mid-century (2040-2069) using the AquaCrop model.

1.5 Research questions

a) How have drought events affected maize yield in the Free State Province from 1990 to 2020?
b) Are there any effective adaptation strategies that can enhance maize production in the future under changing climate?

1.6 Significance of the study

One of the Sustainable Development Goals (SDGs) is to eradicate hunger by 2030; this study will serve as the reference point for decision-makers who solely focus on drought matters to advise on better management and adaptation strategies to increase maize production and ensure food security. The study results intend to play a role in helping to understand drought behaviour for better management of agricultural activities. In the same vein, this research anticipates playing a role in helping governments, non-profit organizations and policy and decision-makers specializing in drought monitoring matters, thus assisting them in reviewing and prioritizing their actions based on the area's susceptibility level to drought in an informed manner. Moreover, it will guide policymakers in building agricultural adaptation programs and encouraging effective adaptation. Understanding extreme events such as drought is essential because it determines adaptation development and implementation. The findings will also serve as a foundation for subsequent research by other interested researchers.

1.7 Thesis outline

This thesis is organized into five chapters:

- **Chapter 1** is the general introduction; it provides an overview of the research topic, problem statement, research objectives, significance of the study, and the structure of the thesis.
- **Chapter 2** is the literature review; it comprehensively reviews existing literature on drought impacts on maize production, climate change in South Africa, drought monitoring indices, adaptation strategies and crop modelling.
- **Chapters 3 and 4** individually present the objectives; thus, these chapters describe the research methodologies, data sources, and analytical techniques used in this study and present the empirical findings and discussion.
- **Chapter 5** is the conclusion and recommendations; it summarizes the key findings, draws conclusions, and provides recommendations for policymakers, farmers, and future research directions.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

Drought is a recurrent natural phenomenon that significantly affects agricultural productivity worldwide (FAO, 2015; Orimoloye, 2022). It is considered an environmental disaster by environmentalists, ecologists, hydrologists, meteorologists, geologists, and agricultural scientists (Mishra and Singh, 2010; Belal *et al.*, 2014). Drought, a complex and multifaceted phenomenon, can be classified into four main types: meteorological, hydrological, agricultural, and socio-economic (Figure 2.1). In South Africa, one of the regions vulnerable to drought due to its semi-arid climate and reliance on rainfed agriculture is the Free State Province, known for its substantial maize production. This chapter aims to synthesize and analyze existing research on drought and climate change, the impacts of drought on maize yield, drought monitoring indices, adaptation strategies and crop modelling.

2.2 Definition of drought by types

2.2.1 Meteorological drought

Meteorological drought occurs when there is a prolonged period of abnormally low precipitation or moisture in an area (Hisdal *et al.*, 2000; Wang *et al.*, 2016). The meteorological drought is characterized by reduced precipitation, which reduces the water seeping into the ground and higher temperatures, winds, and lower relative humidity, resulting in increased water loss from plants, land and ocean (Figure 2.1). There are drought indices developed to monitor meteorological drought across areas/regions with different climates. For instance, SPI is widely used to characterize meteorological drought on various timescales. It measures precipitation anomalies at a given location by comparing observed total precipitation amounts for an accumulation period (Wang and Asefa, 2019).

2.2.2 Hydrological drought

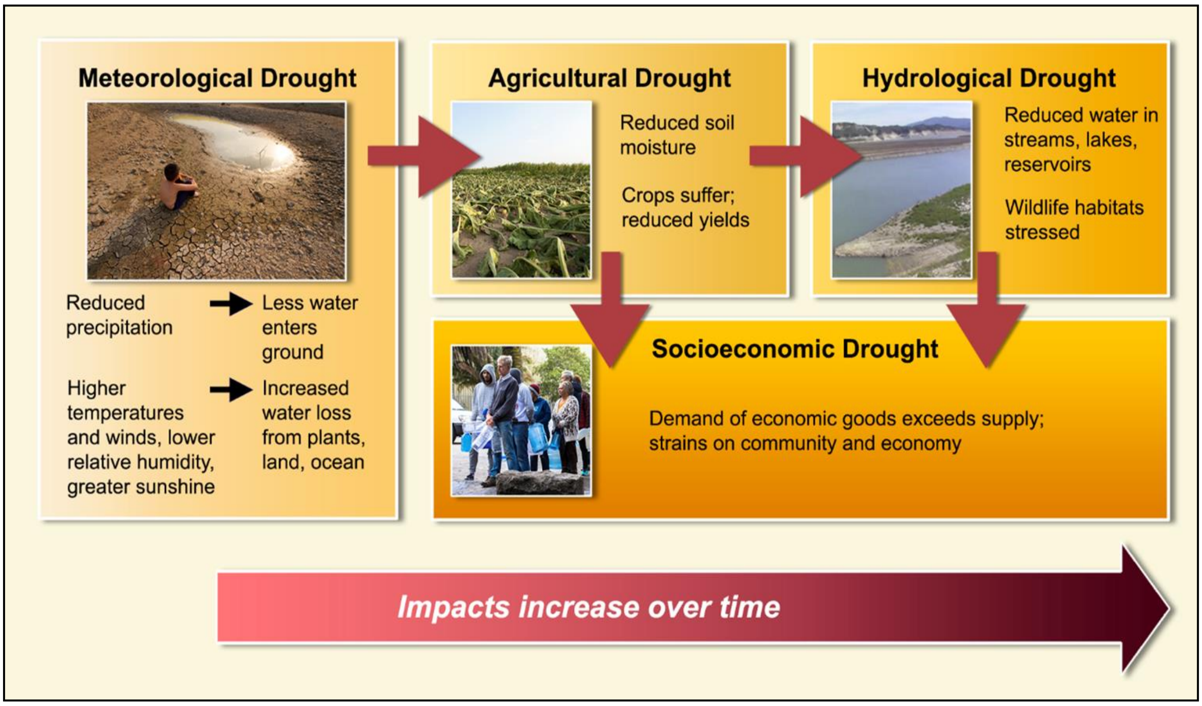
Hydrological drought occurs when the water reserves available in sources such as aquifers, lakes, and reservoirs fall below a significant threshold (Wang and Asefa, 2019). Hydrological drought is characterized by reduced water from streams, lakes and reservoirs (Figure 2.1). Indices such as the Standardized Streamflow Index (SSFI) (Vazifehkhah and Kahya, 2019), Standardized Flow Index (SFI) (Wen *et al.*, 2011) and Surface Water Supply Index (SWSI) (Rad *et al.*, 2017) are widely used to monitor and detect hydrological drought.

2.2.3 Agricultural drought

Agricultural drought results when meteorological drought persists for a prolonged period (Heim, 2005). As a result, a lack of rainfall combined with higher evaporation rates circulates through the water cycle, causing soil moisture reduction, crop failure and reduced yields, resulting in agricultural drought (Wang *et al.*, 2016) (Figure 2.1). Due to less productivity, food prices increase, and the demand for food by the population escalates, with fewer people being able to afford putting strain on people. Drought indices such as the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano *et al*., 2010) and Normalized Difference Vegetation Index (NDVI (Mullapudi *et al.*, 2023) are widely used in monitoring and detecting agricultural drought.

2.2.4 Socio-economic drought

According to Mishra and Singh (2010), socio-economic drought is a prolonged dry spell associated with the failure of water resources to meet water demands. Furthermore, it also occurs when demand for economic goods exceeds supply due to a weather-related shortfall in the water supply (Madani *et al*., 2016) (Figure 2.1). Economic sectors such as agriculture also require water for irrigation; the water deficit pressures the economy by reducing productivity, leading to socio-economic drought (Shew *et al.*, 2020). Socio-economic drought is monitored and detected using various indices that consider changes in precipitation, temperature, and surface and groundwater supplies1. For instance, a novel socio-economic drought index (SeDI) has been developed to monitor the severity of drought in certain ecosystems. This index utilizes the domestic water deficit index, bareness index, normalized difference vegetation index, and water accessibility index as input variables (Kimwatu *et al*., 2021). Understanding these different types of droughts and their impacts is crucial for effective drought management and mitigation.



Adopted from https://lsintspl3.wgbh.org/en-us/lesson/kend19-il-droughtbasicsil/7.

Figure 2.1. Development of different types of drought.

2.3 Overview of Climate Change and Drought in South Africa

Climate change is a global phenomenon with far-reaching implications for ecosystems, economies, and societies (Abbass *et al.*, 2022). Like many other countries, South Africa is experiencing the effects of this phenomenon, which manifest in altered weather patterns, rising temperatures, and shifts in precipitation (Nkhonjera, 2017). Human-induced greenhouse gas emissions, deforestation, and industrialization have contributed significantly to the changing climate (Okolie *et al*., 2023). The impact of climate change on drought dynamics in South Africa is a subject of growing concern. Studies indicated that rising temperatures and changing precipitation patterns contribute to altered food security, health, infrastructure, ecosystem services, and biodiversity (Ziervogel *et al.*, 2014). Moreover, other impacts include reduced runoff and streamflow, heightened fire risk and reduced crop yields (Phaduli, 2018). Over the past century, a warming trend has been observed in South Africa, with increases in temperature being particularly pronounced in arid and semi-arid regions. Over the past five decades, there has been a notable augmentation in mean annual temperatures by 1.5°C across the country, surpassing the recorded global average of 0.65°C (Ziervogel *et al.*, 2014; United States Agency International Development (USAID), 2015). Climate change contributes to altered rainfall patterns, longer dry spells, and reduced water availability, all of which exacerbate drought conditions (Department of Environmental Affairs (DEA)), 2012).

South Africa has a history of experiencing recurrent drought events. Historical records indicate several significant droughts, including 1982-1983 (Edossa *et al*., 2014), 1991-1992 (Hlalele *et al*., 2016), and 2015-2017 events (Otto *et al.*, 2018) that significantly impacted South Africa's economy and agricultural sector. These droughts have been associated with a climatic driver known as El Niño-Southern Oscillation (ENSO). The El Niño-Southern Oscillation (ENSO) phenomenon plays a pivotal role in modulating drought occurrence in South Africa (Reason and Rouault, 2002). El Niño events are associated with reduced rainfall (Malherbe *et al.*, 2016). In general, the impacts of drought in South Africa are multifaceted, affecting water availability (Schreiner *et al*., 2018), agriculture (Chami and Moujabber, 2016), biodiversity (Hoffman, 2009), and socio-economic systems (Ruwanza *et al*., 2022). Reduced water availability leads to decreased crop yields, increased competition for water resources, and heightened vulnerability of marginalized communities. Previous droughts in the country have led to considerable economic, environmental, and socio-economic consequences (Meza *et al.*, 2021), often resulting in crop failure, unemployment, and even the need to import staple foods like maize from other countries. For instance, in a typical year, South Africa produces enough maize to feed itself. It exports surplus maize (Agri SA, 2016) to other countries such as China (9.7% of total exports), the United States (7.5%), Germany (7.1%), India (4.7%), Japan (4.7%) and Botswana (4.3%). Others include the United Kingdom (UK), Namibia, Netherlands, and Mozambique (South Africa Exports, 2022). However, during the 2016/17 drought, South Africa moved from a net maize exporter to a net maize importer (Schreiner *et al*., 2018). For instance, Grain SA utilized the market pricing approach, estimating that between May 2016 and April 2017, South Africa imported a record 3.8 million tons of maize at the cost of almost R3 800 per ton, which decreased the country's GDP since money is going out instead of coming in (Agri SA, 2016). The economic impacts can result in social impacts because they affect the economy essential for the survival of people.

The need for accurate drought monitoring and prediction becomes paramount as the global climate continues to change. Global climate models (GCMs), which simulate complex interactions among the atmosphere, ocean, land surface, and ice, have emerged as essential tools for understanding future climate scenarios (Yang *et al.*, 2021). GCMs incorporate physical principles governing atmospheric and oceanic behaviour to project how climate variables will change under different greenhouse gas emissions scenarios (Santoso *et al*., 2008). While GCMs have inherent limitations in resolving regional-scale features (Shashikanth *et al.*, 2014), they provide valuable insights into large-scale atmospheric patterns (such as temperature) that influence droughts (Jiang *et al*., 2023). By analyzing GCMs outputs for key drought-related indicators like precipitation, temperature, and soil moisture, researchers can identify shifts in climatic conditions that lead to drought emergence. For instance, Feng et al. (2014) forecasted shifts in climate regimes due to future global warming using CMIP5 simulations involving multiple models and scenarios. They reported that under the Representative Concentration Pathway (RCP) 8.5 scenario, models predict a temperature increase of 3-10°C globally by the 2100s. This warming will be more pronounced in the high latitudes of the Northern Hemisphere, while the tropics and Southern Hemisphere will experience milder warming. Projections for precipitation changes are spatially diverse and come with higher model uncertainties.

Generally, the models agree on higher precipitation in the high Northern Hemisphere latitudes, but reduced rainfall is anticipated in regions like the Mediterranean, south-western North America, and northern and southern Africa and Australia. While Global Climate Models (GCMs) are indispensable tools for predicting future climate patterns, their limitations include coarse spatial resolutions and inherent biases (Sachindra *et al.*, 2014). In order to tackle the issues mentioned above, downscaling techniques are employed to enhance the applicability of GCMs outputs to local scales (Keller *et al.*, 2022). Regional Climate Models (RCMs) nested within GCMs provide higher-resolution simulations, capturing finer-scale features crucial for drought prediction (Diallo *et al.*, 2012). Dynamic downscaling uses high-resolution regional climate models (RCMs) to bias-correct and refine GCMs outputs, yielding more accurate temperature and precipitation patterns information (Flato *et al.*, 2014). For example, Pavlik et al. (2012) conducted dynamic downscaled global climate projections for Eastern Europe at a 7 km horizontal resolution. They used a two-tier nesting approach within the Regional Climate Model CCLM (COSMO-Climate Local Model). The initial nesting spanned central Europe, while the secondary nesting focused on parts of Poland, Belarus, and Ukraine. The study successfully replicated long-term area mean temperatures. However, both nesting levels exhibited an overestimation of long-term annual precipitation means. Seasonal analysis of the first nesting indicated positive precipitation biases in spring and winter and negative biases in summer. Notably, disparities in spatial precipitation patterns emerged, particularly in the Carpathian high mountain region. In contrast, the second nesting demonstrated overestimations in spring and summer precipitation, albeit with smaller biases than the first.

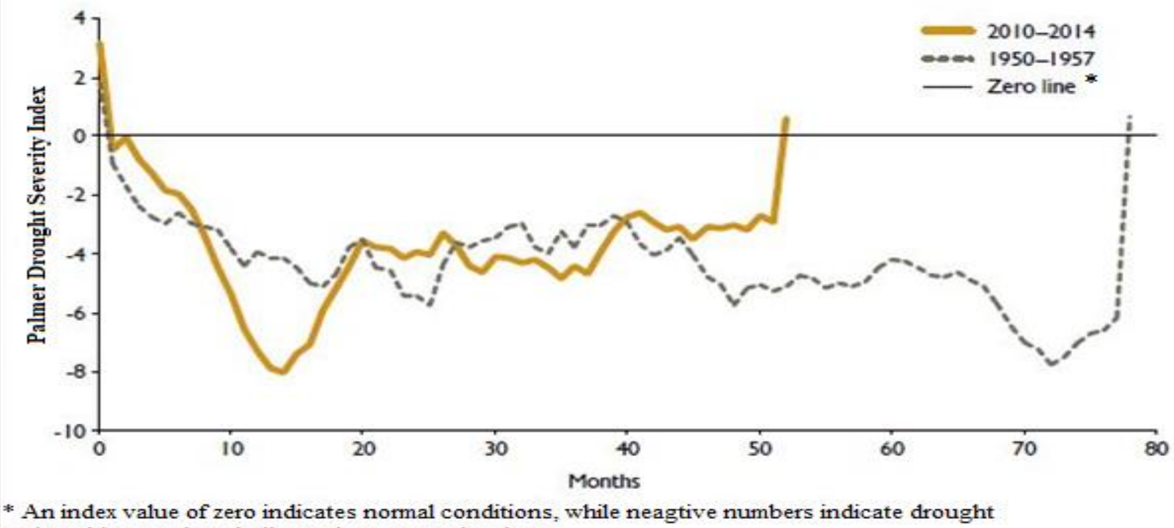
Statistical downscaling techniques, such as weather generators and quantile mapping, further refine GCMs outputs (Ugolotti *et al.*, 2023), improving the representation of extreme events like droughts. For instance, in a study by Tang *et al.* (2016), China’s regional climate was downscaled both statistically and dynamically. They found that the Statistical Downscaling Model effectively reproduces current surface temperature patterns in China, while the Weather Research and Forecasting model tends to underestimate temperatures across the country. Furthermore, they indicated that both models need refinement to enhance their precipitation downscaling capabilities. Both methods diverge notably from historical norms when projecting surface temperatures for 2041-2060. Notably, the two approaches differ in their projections of precipitation changes, introducing considerable uncertainties regarding the direction and extent of future precipitation changes in China. In an intriguing study, Ali *et al.* (2019) undertook an assessment of climate extremes within future projections that were downscaled using multiple statistical downscaling methods specifically applied to Pakistan. The study found that among the applied methods, Quantile Delta Mapping effectively preserves the long-term climate change signal from 1976 to 2095. During 1976-2005, observed average and maximum temperatures increased by 0.5°C and 0.8°C, respectively. CMIP5 models projected consistent increases in warm extremes under RCP 4.5 and RCP 8.5 across Pakistan. Conversely, cold extremes are decreasing in frequency and magnitude across the country and sub-regions. While downscaling techniques have been utilized for rainfall and temperature projections in Europe and China, their application in Africa, especially South Africa, remains limited. This is a significant gap, given that Africa is one of the continents most vulnerable to climate change, and accurate local climate projections are crucial for effective adaptation and mitigation strategies. Although downscaling techniques are limited in Africa, initiatives like the Coordinated Regional Climate Downscaling Experiment (CORDEX) and tools like Rossby Centre regional climate model version 4 (RCA4) have been implemented. CORDEX is an international initiative aimed at producing high-resolution climate projections for all land regions worldwide, including Africa (Climate System Analysis Group (CSAG), 2015). This is achieved by downscaling the output from a number of Global Climate Models (GCMs) under varying greenhouse gas concentration scenarios (CSAG, 2015). RCA4 is a dynamical downscaling tool that uses physical equations to simulate how large-scale climate conditions affect local climates (Giorgi and Gutowski, 2015). The RCA4 (Rossby Centre regional Atmospheric model version 4) is a regional climate model that has been used in the downscaling of Coupled Model Intercomparison Project Phase 5 (CMIP5) simulations for the Coordinated Regional Downscaling Experiment (CORDEX) for Africa (Rana *et al.*, 2016; World Climate Research Programme (WCRP), no date). This model comes with predefined regions and grids, as well as established experiment protocols, output variables, and output formats. These features facilitate a more streamlined analysis of potential future regional climate changes (Nikulin *et al.*, 2012). Further research and investment in this area (Africa) could significantly enhance our ability to predict and respond to climate change in Africa. The interplay between drought and climate change presents a critical challenge for South Africa. The complex relationship between altered precipitation patterns, temperature extremes, and their cascading impacts underscores the urgency of comprehensive mitigation and adaptation strategies. Effective policy implementation, community engagement, and international collaboration are essential to safeguarding South Africa's ecosystems, livelihoods, and future generations from the adverse effects of drought and climate change.

2.4 Drought Impacts on Maize Yield

Drought exerts significant impacts on agricultural productivity and food security. A particularly vulnerable crop to the adverse effects of drought is maize, which plays a crucial role in global food systems. This vulnerability arises from maize's relatively high water requirement for optimal growth and yield production. Scientific literature, such as the study by Matiu *et al.* (2017), highlights the profound implications of drought-induced stress on maize yield, thereby affecting food security and livelihoods. Maize's susceptibility to drought stress is underscored by its reliance on adequate water availability for its growth and development. In this context, Alqudah *et al.* (2011) emphasize that drought conditions, characterized by deficient rainfall and soil moisture, can substantially impede maize growth, leading to decelerated or halted growth rates and reduced crop yields. Beyond yield reduction, drought stress imparts further deleterious effects on maize quality. Leng and Hall (2019) outlined that the physiological changes induced by drought on maize crops encompass reductions in photosynthetic activity and alterations in nutrient uptake and allocation. These changes synergistically contribute to diminishing maize yields. Overall, the impacts of drought on maize yield depend on the severity and duration of the drought (Moeletsi and Walker, 2012), as well as the stage of maize growth when the drought occurs (Potopová *et al.*, 2016).

2.4.1 Globally

Drought has become an enormous problem in the face of the world's agricultural spaces (Despommier, 2010; Forni *et al*., 2017). According to drought impact estimates published by EM-DAT (2014), between 1900 and 2013, 642 droughts occurred worldwide. These droughts resulted in the mortality of about 12 million people and affected over 2 billion people. China is one of the countries where agricultural drought is the most natural hazard that causes crop failure (Ashton *et al.*, 1992; Simelton, 2011; Zhang *et al.*, 2019). Due to the monsoon climate, China has regularly suffered drought disasters over the last decades. However, China has found little evidence of expanding the area affected by droughts over the last 50 years (1961-2012) (Wang *et al.*, 2015). Severe droughts in South-Western China and the middle/lower Yangtze Basin and Huaihe River Basin in 2010 and 2011 brought heightened attention from the scientific community, the general public, and governments to the impacts and problems of drought (Wang *et al*., 2017). Additionally, in 2014, rainfall decreased in Liaoning Province, China. The precipitation was 20% to 50% below the normal average rainfall, resulting in maize production declining by 3.93 million tons. On the other hand, Ray *et al*. (2018) study showed that Texas had experienced an agricultural drought resulting in inadequate water and soil moisture available for crop growth. Consequently, there was a reduction in maize production and other crop yields. Additionally, the rainfall pattern has also changed due to drought. The crops are said to be more sensitive to precipitation than to temperature. Maize crops are mainly cropped in highlands. During the 2011-2013 drought, maize yield deteriorated by approximately 18% per 536 km^2 in high plain climate zones. Furthermore, between August 2010 and October 2014, the drought lasted for 51 months. The Palmer Drought Severity Index (Figure 2.2) indicated that Texas's drought between 2010 and 2014 was the second-worst and longest state-wide drought. The extreme drought conditions of PDSI of less than or equal to -4 during the 2010/14 period continued for about 45% of the time (Texas Water Development Board, 2017). The low state-wide record of the drought measured -8.05 after 14 months. From October 1950 to February 1957, the PDSI indicated that the drought lasted for 77 months (Texas Water Development Board, 2017). After 72 months, the lowest state-wide measurement was -7.7 from 1950 to 1957.



* An index value of zero indicates normal conditions, while neagtive numbers indicate drought and positive numbers indicate above normal moisture

Adopted from Texas Water Development Board (2017) report.

Figure 2.2. Palmer Drought Severity Index of Texas drought.

The impacts of drought on maize yield are a complex interplay of physiological responses, yield reduction mechanisms, genetic variability, and potential adaptation strategies. Understanding these intricate dynamics is essential for devising effective strategies to enhance maize yield stability in the face of changing climate patterns. Continued research efforts, guided by insights from studies such as those by Harrison *et al.* (2014), Liu *et al.*

(2020) and Potopová *et al.* (2023), are critical to ensuring global food security and sustaining agricultural systems amidst growing drought challenges.

2.4.2 Africa

Agriculture is the predominant primary activity in Africa, especially in rural areas. Due to erratic rainfall and temperature patterns, Africa is prone to extreme weather conditions, such as droughts (Mutekwa, 2009; Masih *et al.*, 2014). Owing to extreme temperatures and deficit rainfall, this phenomenon negatively affects social, economic, and environmental sectors such as rivers, land, and vegetation. Most of the African studies address various drought issues on a regional level; thus, southern Africa (Thomson *et al.*, 2003), eastern Africa, Horn of Africa (Endris *et al.*, 2019), and north-western Africa (Nguvava *et al.*, 2019). However, fewer studies attempted to cover more than one region (Masih *et al.*, 2014; Rovere *et al.*, 2014; Ayugi *et al.*, 2022) study showed that the Greater Horn of Africa had encountered agricultural drought; crops failed dismally in Tanzania. Bazza *et al.* (2018) indicated that the Sahel is one of the areas in Africa that are more prone to drought; hence, Mauritania and other countries have been affected by severe drought. In 2011, a drought resulted in poor maize production and food prices escalating. Approximately 20% to 30% of the population suffered food insecurity due to drought. Masih *et al.* (2014) conducted a study that reviewed and analyzed droughts from 1900 to 2013 in Africa. The continental droughts of 1972-1973, 1983-1984, and 1991-992 were unprecedented in recorded history. In addition, many severe and long-term droughts have occurred recently. This includes droughts in north-west Africa that occurred between 1999 and 2002. Western Africa in the 1970s and 1980 and Eastern Africa in 2010-2011. In Southern and South-eastern Africa, they occurred between 2003 and 2013. Past evidence strongly suggests that severe and widespread droughts will befall the African continent in the future. This concern is expected to rise due to slow progress in drought risk management, rising population and water demand, and land and environmental deterioration. As a result, more major and comprehensive drought adaptation measures are needed to alleviate the adverse effects of future droughts.

2.4.3 South Africa

South Africa is susceptible to droughts, affecting the agricultural sector negatively (Baudoin *et al.*, 2017; Hove and Kambanje, 2019; Ngcamu and Chari, 2020). The local communities and the national economy of South Africa have been affected by droughts for many years (Meza *et al.*, 2021). The drought has strained South Africa's agro-economic system, resulting in increased unemployment, adverse effects on increasing debt servicing costs for farming firms, and negative consequences on upstream economic activities (Schreiner *et al*., 2018). South Africa's reduced agricultural productivity affects citizens of neighbouring countries such as Zimbabwe, Lesotho, Namibia, Botswana, and Swaziland, who rely on South African food imports, especially maize (van Koppen *et al*., 2015; Ainembabazi, 2018). Food insecurity in southern Africa is exacerbated by a lack of essential foods such as maize meals and rising prices (Baudoin *et al.*, 2017). Moreover, maize is the staple food for most of the population in South Africa and its neighbouring countries, such as Zimbabwe (Muyambo and Shava, 2021) and Mozambique (Cunguara and Hanlon, 2012).

South Africa is the largest producer of maize on the African continent (Mohlala *et al.*, 2016; Chukwudum and Dioggban, 2022). However, drought is one of South Africa's most common natural disasters that affect crop production. It results in crop failure and low production. Extreme droughts that last for several years are occasionally caused by the El Niño Southern Oscillation (ENSO) (Nhamo *et al.*, 2019). For example, South Africa experienced a severe drought between 2015 and 2016, associated with an extreme El Niño event; the drought was the worst since the 1990s (Baudoin *et al.*, 2017). In a typical year since 1904, all South African provinces average approximately 608 mm of rainfall annually (Muofhe *et al.*, 2020; Pretorius *et al*., 2022). However, in 2015, it was different, where the country had about 403 mm of precipitation. The drought was historic because it surpassed the lowest rainfall recorded in 1945 at approximately 437 mm (Maritz, 2018). According to FAO (2016), in the five years leading up to 2014, the average annual national production of maize was 12.345 million tons; nevertheless, the drought has caused a drastic decline in maize production. In 2015, there were 10.629 million tons of maize produced; by the end of July 2016, there were 7.597 million tons. Moreover, Bazza *et al.* (2018) reported that white maize decreased in 2015 by approximately 29.9% (1.448 million ha). Conversely, yellow maize declined from 1.205 million ha to 932 000 ha. The 2015/16 drought also affected other Southern African countries' maize production. Thus, in Botswana, Lesotho, Swaziland, and Zimbabwe, productivity declined by approximately 78%, 67%, 63%, and 56%, respectively (Ainembabazi, 2018). In the same vein of drought impacts in 2017/18 growing season drought decreased maize by nearly 21.4% in (DALRRD, 2019). Drought management and mitigation have become a significant concern in South Africa due to the enormous impacts of drought (Figure 2.3). The impacts of drought on maize yield in South Africa are influenced by the country's diverse climate, physiological responses of maize crops, genetic variability, and agricultural practices. As the frequency and intensity of drought events continue to escalate, sustained research efforts, combined with informed policy decisions and innovative farming approaches, are crucial to ensuring food security and sustainable agricultural systems in South Africa.

Adopted from Ka'Nkosi and Faku (2015) article.

Figure 2.3. The 2015 drought impacted maize at Ryan's Matthews farm in Lichtenburg, North-West Province, South Africa.

2.4.4 The Free State Province

The Free State Province is one of the main maize-producing regions in South Africa, contributing substantially to national and regional supplies. However, the province's susceptibility to recurring droughts has raised concerns about its ability to maintain consistent maize yields. Studies such as Adisa *et al.* (2019) and Simanjuntak *et al.* (2023) have highlighted the historical patterns of drought occurrence in the province and their correlation with fluctuations in maize yield. On the other hand, research by Botai *et al.* (2016) provides insights into the historical trends of drought events in the province, highlighting the need for understanding the risks of drought and determining the impacts of droughts on agriculture and water resources. Historical meteorological data reveal increased drought frequency and intensity over the decades, imposing strain on water availability for maize production (Botai *et al.*, 2016). The yield reduction in the Free State is solely driven by variations in rainfall patterns and rising temperatures attributed to climate change. A study by Simanjuntak *et al.* (2022) examined how agrometeorological factors impacted yield variability over 31 years (1990/91-2020/21) in major maize-producing provinces of South Africa. Notably, yield fluctuations in the Free State exhibited a significant positive correlation ($r > 0.43$) with agrometeorological variables. The study also highlighted that temperature, precipitation, solar radiation, and wind speed were the primary drivers influencing yield variability in the Free State.

Drought stress triggers physiological responses in maize crops that impact growth and yield. The Free State's water-limited environment exacerbates these effects. Orimoloye *et al.* (2022) studied agricultural drought and its effects on maize and sorghum in the Free State Province. The research identified extreme drought events (<10%) in 2015 and 2018, significantly affecting most of the province. Severe drought (>30%) impacted the agricultural sector in 2011, 2016, 2018, and 2019. Notably, maize production hit record lows in 2014 (223 600 tons) and 2015 (119 050 tons). Their findings validated the influence of drought on maize production in 2015 and other years, with the lowest yields during periods of drought. The Free State's unique climate necessitates the cultivation of drought-tolerant maize varieties. The work related to the performance of various maize genotypes under drought conditions in the Free State Province is limited. Farmers in the Free State Province have adopted diverse strategies to mitigate drought. In a study conducted by Muthelo (2018), the focus was on investigating the implementation and effectiveness of diverse adaptation measures employed by farmers in Thaba 'Nchu, Free State Province, amid the challenging 2015/2016 drought period. Their findings indicated that technical measures were adopted by 2.7% of farmers, with 73.8% reporting effectiveness. Water-use efficiency was implemented by 4.7% of farmers, and 85.0% found it effective. Economic instruments were used by 2.3% of farmers, with 68.8% perceiving effectiveness. The water-use restriction was employed by 26.9%, and 57.8% found it effective. Only 2.3% implemented improved forecasting, but 83.1% found it effective. Similarly, only 2.0% adopted insurance scheme improvements, yet 82.1% deemed it effective.

Drought-induced impacts on maize yield in the Free State Province are a culmination of climate-driven stress. As drought events are projected to be more frequent and severe, ongoing research efforts and sustainable agricultural practices will play a pivotal role in ensuring food security and livelihoods in the Free State Province's maize-dependent agricultural landscape.

2.5 Drought monitoring indices

Indices are calculated numerical representations of drought severity based on climatic or hydro-meteorological inputs such as rainfall, soil moisture content, and temperature (Agwata, 2014; World Meteorological Organization (WMO), 2016). Drought indices are used to quantify drought events' severity, magnitude, location, and duration (Nandintsetseg and Shinoda, 2013). Climatologists, hydrologists, and meteorologists developed numerous drought indices, such as the Standardized Precipitation Index (SPI) and Standardized Precipitation Evapotranspiration Index (SPEI), to monitor and quantify drought (Fuchs, 2012; Zhu *et al.*, 2016; Bachmair *et al.*, 2018; Pathak and Dodamani, 2020). These indices serve as crucial tools for analyzing drought characteristics.

2.5.1 Standardized Precipitation Index

The Standardized Precipitation Index (SPI) is the most widely used index to quantify meteorological drought in a particular area (Svoboda *et al*., 2012). The SPI uses historical precipitation data for any location to generate a probability of precipitation that can be computed at any number of timescales ranging from 1 to 48 months or longer (Svoboda *et al*., 2012). Thus, the shorter timescales, such as 1 and 3-month timescales, assist in identifying drought early and gauging its severity. The longer timescales, such as 6, 9 and 12-month timescales, accentuate moisture deficit in the soil, groundwater and reservoir storage. The input parameter is only rainfall data (Svoboda *et al*., 2012; Poornima and Pushpalatha, 2019; Docheshmeh Gorgij *et al.*, 2022). SPI is probabilistic and has a historical context, which is optimum for decision-making (Svoboda *et al*., 2012). Its main shortcoming is that it solely considers precipitation, making it impossible to calculate ratios of evapotranspiration (ET) and potential evapotranspiration (PET) (Alsafadi *et al.*, 2020; Cerpa Reyes *et al*., 2022). The period of data used to calculate SPI, like other climatic indicators, should have a minimum period of 30 years, even when the data accounted for is missing (Hayes *et al.*, 2011). SPIs positive and negative intensity scale correlates directly to wet and dry events (Musonda *et al.*, 2020). Drought events occur when the results of SPI become continuously negative and reach a value of 1. Drought is considered continuous until the SPI reaches zero. Drought commences at an SPI of -1 or less. There is no standard in place, as some researchers select a threshold less than 0 but not quite -1, while others initially categorize drought at values less than -1 (Svoboda and Fuchs, 2016). Because of its utility and flexibility, SPI can be calculated with data missing from a location's period of record. SPI is typically computed for timescales of up to 24 months, and its flexibility enables a wide range of applications addressing events affecting agriculture, water resources, and other sectors (Fuchs, 2012). SPI is compatible in many research areas, such as agriculture, hydrology and meteorology (Zhang and Jia, 2013; Pramudya and Onishi, 2018; Rolbiecki *et al.*, 2022).

Numerous studies globally have harnessed SPI to assess drought characteristics. For example, Rolbiecki *et al.* (2022) used SPI to analyze drought during the maize-growing period in the three provinces of Turkey. Their SPI results clearly reveal a consistent pattern of drought occurrences across the Adana, Mersin, and Osmaniye provinces during various years, particularly in 1990, 1994, 2004, 2008, 2010, and 2012, as indicated by SPI values falling below 0. However, it is worth noting a few exceptional cases within this pattern. In the year 2004, the SPI values pointed to a severe drought in Adana and Osmaniye, whereas Mersin faced a moderate drought. Additionally, a remarkable deviation from the drought trend occurred in 2002, when Mersin Province witnessed an unusual situation with extreme wet conditions, as evidenced by an SPI exceeding 2.24. Interestingly, Phaduli

(2018) used SPI and SPEI to characterize drought in South Africa under changing climate from 1981 to 2015. The results indicated an overall increase in drought intensity, duration, severity and frequency during the two future periods, 2011-2040 and 2041-2070, under RCP 8.5.

2.5.2 Standardized Precipitation Evapotranspiration Index

For a broader perspective within agricultural domains, the Standardized Precipitation Evapotranspiration Index (SPEI) emerges as another widely employed multiscale index. Unlike SPI, the SPEI incorporates both precipitation and temperature data as input parameters (Ogunrinde *et al*., 2020). It accounts for the effect of temperature on drought development using a basic water balance calculation (Stagge *et al.*, 2014). Moreover, it considers temperature changes alongside rainfall and incorporates the influence of surface evaporation changes, making it more sensitive to drought responses caused by global temperature rise (Pei *et al.*, 2020; Liu *et al.*, 2021). While the mathematical underpinnings of SPEI and SPI are comparable, SPEI also integrates potential evapotranspiration (PET) (Vicente-Serrano *et al*., 2010; Ma *et al.*, 2015; Wilhite and Pulwarty, 2017). The SPEI intensity scale calculates positive and negative values, identifying wet and dry events, respectively. It can be calculated for time steps ranging from 1 month to 48 months or more (Vicente-Serrano *et al*., 2010). Monthly updates enable it to be used operationally, and the longer the data time series available, the more robust the results (Fuchs, 2012). By incorporating temperature data, the SPEI can capture the impact of temperature on water availability and demand, which is particularly important in regions where temperature plays a major role in the occurrence and severity of drought (Svoboda and Fuchs, 2016). One advantage of SPEI over other commonly used drought indices is that it considers PET's impact by including temperature and rainfall when determining drought severity due to its multiscalar properties, making it possible to identify various drought types and their effects in the context of global warming (Vicente-Serrano *et al*., 2010). Beyond the context of global warming, the SPEI can consider the potential consequences of temperature variability and temperature extremes. Because of this, the SPEI is preferred for identifying, analyzing, and monitoring droughts in all climate regions of the world (Vicente-Serrano *et al*., 2010).

Several research studies have used the SPI and SPEI to monitor drought worldwide. For instance, Yao *et al.* (2022) used SPEI to evaluate the responses of maize and wheat yields to agricultural and hydrological drought in China. Their findings unveiled varying drought conditions in different sub-regions during the spring maize growth phase (April-October). Sub-region I displayed normal conditions ($-0.5 < \text{SPEI} < 0.5$), sub-region III encountered moderately to extremely wet conditions (SPEI > 0.5), and sub-region IV experienced moderate to extreme drought ($-1 < \text{SPEI} < -4$) in May and June. On the other hand, Botai *et al.* (2016) characterized droughts in South Africa in the Free State and North-West provinces using SPEI and SPI between 1985 and 2015. The SPEI results showed that drought severity and frequency were more pronounced in the Free State, whereas drought intensity was more pronounced in the North West Province. Furthermore, SPEI showed moderate drought incidences increased from 1985 to 1994 and 1995 to 2004 in both provinces, then reduced from 2005 to 2015. Indices are critical for monitoring drought in agriculture worldwide.

2.6 Adaptation Strategies for Mitigating Drought Impacts on Maize Production

Adaptation strategies play a pivotal role in enhancing social, environmental, and economic resilience against the challenges of changing climate, which can result in drought. Given the significance of agriculture in global food security, the optimization of maize production under changing climate becomes paramount. Akinnagbe and Irohibe (2014) and Bahta and Myeki (2021) defined adaptation strategies as the responses to changes in the human and natural systems of current and anticipated climatic stimuli and their impacts to minimize damage and enhance benefits. In the same trace, adaptation strategies are actions taken by an individual, a government, an organization, or a community in response to climatic stimuli, either autonomous or planned (Smit *et al.*, 2000; Shackleton *et al.*, 2015). Autonomous adaptation refers to efforts made during or after being affected by climate change (Malik *et al*., 2010). Planned adaptation refers to the proactive measures taken to mitigate the impacts of climate change or extreme events before they occur (Smit *et al.*, 1999; Smit and Pilifosova, 2003). However, these decisions are difficult to make because climate change is uncertain (Cambodia, 2008). A plethora of adaptation strategies can be harnessed to maximize maize production under a changing climate (Rosenzweig and Tubiello, 2007). Such strategies include alternating planting dates (Basso *et al.*, 2015), sowing density (Parry, 2000), weather forecasting, introducing new cultivars, drought-tolerant varieties, vulnerability assessment, cultivation of low water-use crops, and sustainable and efficient water-use management practices, as highlighted by the World Bank (2006). As well as rotation of crops, development of new agricultural areas, and irrigation management (Tubiello *et al.*, 2002b; Chenu *et al.*, 2017). Developing a long-term adaptation strategy also requires knowledge of prior events, consequences, and responses, demonstrating a system's adaptive capacity (United Nations Framework Convention on Climate Change (UNFCCC), 2014). The adaptation measures help reduce drought-related losses and improve resilience and future risk reduction, which have long-term implications, particularly in the social and environmental sectors (Economic and Social Commission for Asia and Pacific (ESCAP), 2020).

Several studies have been conducted globally on different adaptation strategies as a measure to maximize maize production. For instance, according to Alam *et al.* (2017) study, rural households in Bangladesh prone to natural hazards developed a variety of farming and non-farming adaptation measures that differed significantly between farming groups. The most common techniques farming households implemented were crop varieties, modifying planting dates, and migrating. On the other hand, Rezaei and Lashkari (2019) indicated that in Iran, farmers employ different adaptation strategies ranging from introducing new, late-maturing cultivars, irrigation, a minor increase in fertilizer use, change of planting dates, and introducing heat-tolerant crop varieties to improve maize yield. Fascinatingly, Lin *et al.* (2017) conducted a study on adaptation strategies to enhance maize production in China. Their study indicated that farmers implemented three adaptation strategies to enhance maize production to varying degrees. Those adaptation measures were adjusting planting dates, switching to a later maturing cultivar with a more prolonged growth phase, and breeding cultivars with high thermal temperature requirements. The study indicated that moving to a later-maturing cultivar was the most effective method for dealing with the adverse effects of a future-changing climate. Moradi *et al.* (2013) carried out a seminal study in Iran's Khorasan Razavi province, where they explored the utilization of planting dates as an adaptation strategy in the context of changing climates. The researchers selected three distinct planting dates: 1 May (conventional planting), 10 May, and 20 May to discern the optimal alternative planting time amidst the anticipated changes in climate between 2020 and 2080. Their findings indicated that maize grain yields could potentially experience a decline ranging from 11.45% to 37.63%. Crucially, the study illuminated that early planting, as exemplified by the 1 May date, outperformed later planting (10 and 20 May) in yielding higher maize grain yields.

2.7 Crop modelling

Agricultural research has made considerable progress over the years, particularly in understanding the complex relationship between climate change and crop productivity. Crop simulation models have become instrumental in this field, providing a detailed analysis of the physical, chemical, and physiological processes that affect crops under varying climatic conditions (Tubiello and Ewert, 2002a; Inoue, 2003; Di Paola *et al.*, 2016; Islam and Hasan, 2021). These models, essentially software packages, simulate crop growth and development (United States Department of Agriculture (USDA), 2009). They provide valuable insights into both pre-season and in-season management practices, such as determining planting dates, fertilizer usage, irrigation strategies, and the selection of appropriate crop varieties, as highlighted by Boote *et al*. (1996). At their core, crop simulation models rely on intricate numerical equations that encapsulate the intricate relationships between diverse factors: crop development, growth, climate, and yields, as expounded by Ritchie *et al.* (1998). Through simulation, these models can predict the growth of different parts of a crop, such as roots, stems, grains, and leaves (USDA, 2009). Moreover, these models can predict the final state of crop yield or production and include quantitative data about important cycles involved in crop development and growth (Oteng-Darko *et al.*, 2013). The significance of crop models extends to the realm of cultivating sustainable land management across diverse agro-ecological and socio-economic contexts. The rationale behind this lies in the resource-intensive nature of field and farm experiments, which might fall short of furnishing comprehensive insights across spatial and temporal dimensions necessary for discerning effective management practices (Jones *et al.*, 2017). Crop models emerge as invaluable aids, empowering land managers and policymakers to pinpoint optimal management strategies that align with sustainability objectives across varying dimensions of space and time, contingent on the availability of essential data encompassing soil characteristics, management practices, climate influences, and socio-economic factors. In this capacity, they prove instrumental in identifying zones of potential risks that warrant more detailed on-field investigations (Jones *et al.*, 2017). The development of models for agricultural production systems dates back to the 1960s, with key contributions from physicist CT de Wit from Wageningen University and chemical engineer W.G. Duncan (Jones *et al.*, 2017). A notable example in the domain of crop models utilized in agriculture is the AquaCrop model.

AquaCrop is a crop model that is more straightforward and has fewer parameters than other models, making it easier to calibrate and potentially reducing the margin of error in parameter estimation (Ahmadi *et al.*, 2015). However, it is essential to note that the number of parameters does not necessarily determine the reliability of a model. The reliability of AquaCrop comes from its robust framework and ability to accurately simulate and predict crop growth, yield, and water requirements under varying climatic conditions (Alvar-Beltrán *et al.*, 2023). AquaCrop requires five weather input variables: daily maximum and minimum air temperatures, daily rainfall, daily evaporative demand of the atmosphere expressed as reference evapotranspiration (ETo), and the mean annual carbon dioxide concentration in the bulk atmosphere (Steduto *et al.*, 2009). In terms of management, the model emphasizes irrigation while also considering soil fertility, particularly nitrogen, and water-related factors such as soil bounds and mulches, which affect soil water balance, crop development, and growth. Forage crop cuttings are also under management (FAO, 2017). These variables allow AquaCrop to quantitatively analyze the potential impacts of climate change on different herbaceous crops, such as maize (Feleke *et al.*, 2023). This makes AquaCrop an invaluable tool for identifying optimal adaptation strategies, including alterations in planting schedules, irrigation practices, and crop selection. The AquaCrop model can be standardized as a model-linking technique to predict future maize yields for long-term production and drought adaptation (Abedinpour *et al.*, 2014). It is intended for a wide range of end-users, including educated farmers, extension officers, economists, water managers, practising engineers, and policymakers, to plan and analyze the effects of climate scenarios on crop water availability and sustainability (Kipkorir *et al.*, 2011; Adeboye *et al.*, 2019, 2021). The main assumption of the AquaCrop model is that it simulates yield responses to water of herbaceous crops, especially in situations where is the key limiting factor in crop production (Food and Agriculture Organization (FAO), no date). Other underlying assumptions of the AquaCrop model is that uses of canopy cover as the parameter characterizing crop growth instead of the leaf area index (LAI)(Salman *et al.*, 2021). AquaCrop also simulates the modulation of the response of the harvest index to water deficits in detail, an important requisite for a model that is focused on predicting yield as a function of the water supply available (Salman *et al.*, 2021). Overall, AquaCrop was specifically designed to pursue an optimum balance between simplicity, accuracy, robustness and wide applicability. To this effect AquaCrop uses only a relatively small number of explicit parameters and mostly-intuitive input-variables requiring simple methods for their determination (FAO, no date). Like any other model, the AquaCrop model has limitations: the model is designed to predict crop yields at the single field scale (point simulations). The field is assumed to be uniform without spatial differences in crop development, transpiration, soil characteristics or management. Only vertical incoming (rainfall, irrigation and capillary rise) and outgoing (evaporation, transpiration and deep percolation) water fluxes are considered (FAO, 2017a).

The AquaCrop model has been globally used in semiarid areas to simulate different parameters such as crop yield, growth, and crops' water use, as well as assessing different adaptation strategies. For example, Abedinpour *et al.* (2012) examined the performance of AquaCrop on maize in a semiarid environment at IARI, New Delhi, India. The results showed that the AquaCrop model predicted maize yield with acceptable accuracy under variable irrigation and nitrogen levels. Subsequently, Ahmadi *et al.* (2015) utilized AquaCrop to simulate maize yield and soil water content in semiarid experimental farms at Shiraz University, Iran, under both full and deficit irrigation conditions. The findings demonstrated AquaCrop's precise simulation of maize growth under deficit irrigation but noted poorer performance in simulating late-season biomass under such conditions. The model also showed limitations in accurately predicting ultimate grain output and biomass under moderate to severe water stress. In a study further afield, Nyakudya and Stroosnijder (2014) applied the AquaCrop model to estimate the impact of rooting depth, plant density, and planting dates on maize yield and water use efficiency in Zimbabwe's semiarid Rushinga District. Their research indicated that the model accurately simulated canopy cover development and biomass accumulation. Adjusting root depth from 0.40 m at 32,500 plants/ha to 0.60 m at 44,400 plants/ha resulted in increased grain yield (from 6.0 to 7.8 t/ha), enhanced transpiration by 26.8% and improvements in water use efficiency for grain and biomass. Saddique *et al.* (2020) employed multiple crop models, including AquaCrop, to assess these strategies, including irrigation, adjustments in planting dates, and combined modifications. The study projected future yield increases ranging from 1.1% to 23.2% under irrigation, 1.0% to 22.3% with delayed planting dates, and 2% to 31% with combined adaptation strategies. Bwambale and Mourad (2021) assessed different adaptation strategies: supplemental irrigation, changes in planting dates, soil fertility enhancement, and other field practices. Notably, enhancing soil fertility had a limited impact on maize yield in a changing climate, but a combination of supplementary irrigation and adjusted planting dates showed promise for increasing yields.

Nevertheless, combining supplementary irrigation and shifting the planting dates was a promising strategy as it indicated yield increment.

2.8 Conclusion

In conclusion, the comprehensive analysis of the literature pertaining to drought impacts on maize yield and adaptation strategies has provided valuable insights into the complex interplay between climate change and crop production. The findings from various studies underline the undeniable influence of drought events on maize production. The literature has consistently demonstrated that droughts lead to reduced maize yields, primarily attributed to diminished water availability and increased water stress on crops. These adverse effects are exacerbated by rising temperatures and changing precipitation patterns, which are characteristic of climate change. As a result, understanding and implementing effective adaptation strategies are imperative to ensure sustainable maize production and livelihoods for the local farming communities. By integrating scientific knowledge, community engagement, and innovative agricultural practices, the province can work towards safeguarding its food security, sustaining livelihoods, and fostering long-term agricultural resilience in an era of climatic uncertainty. As the province continues to grapple with the consequences of drought, the insights garnered from this literature review offer a foundation for future strategies and policies to ensure a more resilient and prosperous agricultural future.

CHAPTER 3: ASSESSING THE IMPACT OF DROUGHT ON MAIZE YIELD IN THE SEMI-ARID REGIONS OF THE FREE STATE PROVINCE, SOUTH AFRICA

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Abstract

Maize (*Zea mays* L.) is an essential crop in South Africa, serving as a staple food; however, drought threatens its production, resulting in lower yields. This study aimed to assess the impact of drought on maize yield in the Semi-arid Regions of the Free State Province, South Africa, from 1990 to 2020. The study used the Standardized Precipitation Index (SPI) and Standardized Precipitation Evapotranspiration Index (SPEI) to examine drought severity and occurrences during the maize growing season (October-March). The coefficient of variation (CV) assessed seasonal climate variability, and the modified Mann-Kendall trend test was used to identify drought trends at monthly and seasonal scales. The Pearson correlation examined drought effect on maize yield, and yield loss rate determined yield loss. The results indicated that the highest variability in rainfall, maximum and minimum temperatures was 46.62%, 5.31% and 22.66%, respectively. Based on SPI and SPEI, Bethlehem frequently experienced droughts than Bloemfontein and Bothaville, particularly during the ONDJFM season, such that moderate droughts were prevalent in Bethlehem, while severe droughts were common in both areas (Bethlehem, Bloemfontein and Bothaville) and extreme droughts in Bloemfontein. In terms of trends, significant decreasing trends (indicating drier/drought conditions), both on monthly and seasonal scales, were prevalent over Bethlehem under SPI and over Bloemfontein under SPEI. The strongest correlation of $r = 0.82$, $p = 1.3e^{-08}$ between drought and maize yield was observed in Bloemfontein during the ONDJFM season. This means that as the

severity or frequency of drought increases, the maize yield tends to decrease significantly. The highest maize yield loss of -83.86% was recorded in Bethlehem. The study findings offer essential guidance for agricultural researchers and policymakers in developing strategies to adapt to impending drought risks, a critical step in safeguarding food security, especially for maize production.

Keywords: Climate Variability, Maize growing season, Standardized Precipitation Index; Standardized Precipitation Evapotranspiration Index, Yield loss rate

3.1 Introduction

Drought, an increasingly prevalent consequence of climate change, has become a sinister force wreaking havoc on agricultural systems worldwide (Sharma, 2006; Meza *et al.*, 2021). Among the numerous crops affected by this climatic phenomenon, maize stands out as one of the most vulnerable in terms of its economic importance as a staple food crop (Lunduka *et al.*, 2019). Drought causes physiological and biochemical changes in maize crops, including reduced photosynthesis, decreased water uptake, and impaired nutrient uptake. These changes can result in stunted growth, reduced plant height, fewer tillers, and crop failures, ultimately reducing yields (Prasad *et al.*, 2008; Liliane and Charles, 2020), affecting food security, livelihoods, and the global economy. For instance, Zimbabwe imported approximately 50% of maize into the country between the 2011 and 2012 growing seasons due to extreme droughts, which affected their production and resulted in vast crop failures (Manyeruke *et al.*, 2013). As the world faces mounting challenges in ensuring food security, understanding the profound impacts of drought on maize yield becomes imperative.

South Africa is recognized for its semi-arid climate and frequent hydro-climatic extreme events such as droughts and floods (Adeola *et al.*, 2021). Droughts in South Africa are distinguished by fluctuations in rainfall patterns, which are influenced by the atmospheric circulation configurations and the interplay between westerly and easterly circulations (Tyson and Preston-Whyte, 2000; Adeola *et al.*, 2021). Drought is a primary environmental peril over the entire South African landscape that intermittently results in crop failures and low yields (Mugambiwa and Tirivangasi, 2017). In particular, the Free State province has experienced severe droughts in recent years that have significantly impacted maize production (Rabumbulu and Badenhorst, 2017; Muthelo *et al*., 2019). Droughts are prevalent in the Free State province because of its semi-arid climate; rainfall patterns are unpredictable and often erratic, defying crop production (Muthelo *et al*., 2019).

The Free State, Mpumalanga, and North West provinces are the leading areas producing maize in South Africa, accounting for approximately 73% of total production (Department of Agriculture Forestry and Fisheries (DAFF), 2017). The Free State Province accounts for approximately 35% of maize production yearly (Bello *et al*., 2020). Maize production holds a critical stand in South African agriculture, serving as a source of food and employment for the majority of people (Daya *et al*., 2006; Greyling, 2012; Department of Trade Industry and Competition (DTIC) and DALRRD, 2017). However, ongoing changes in climate patterns, including increased frequency and severity of drought events, pose significant threats to maize production (Masupha *et al*., 2016; Masereka *et al*., 2019). This is because it causes water stress during critical growth stages of maize, consequent to yield reduction. For instance, the Free State Province produced 7.3 million tons of maize in 2016/17; it declined to 5.2 million tons in 2017/18 to 4 million tons in 2018/19 because of drought (Diko and Jun, 2020).

Several drought indices have been developed to quantify, detect, and monitor the impacts of drought on crops. Indices such as SPI and SPEI have been established and used extensively to assess drought on maize and have proven effective, especially with long-term data (Dhakar *et al*., 2013; Tirivarombo *et al*., 2018; Liu *et al.*, 2021). Furthermore, these indices are practical tools for monitoring drought conditions and are widely used in agricultural spaces (Liu *et al.*, 2016; Pei *et al.*, 2020; Mohammed *et al.*, 2022). The SPI and SPEI indices were chosen in this study because they are standardized, adaptable, and simple to analyze drought over a range of timescales (Pei *et al.*, 2020). SPI uses only rainfall to quantify drought, while SPEI incorporates rainfall, temperature and potential evapotranspiration (PET) (Tirivarombo *et al*., 2018). Since evapotranspiration is the predominant type of water loss in dry locations with high temperatures, SPEI could be a helpful indicator of drought (Gurrapu *et al.*, 2014).

Previous studies conducted in the Free State Province solely focused on characterizing, assessing and monitoring drought (Botai *et al.*, 2016; Phaduli, 2018; Mbiriri *et al*., 2019), with few studies quantifying the impacts of drought on maize yield (Adisa *et al.*, 2019; Abubakar *et al*., 2020). Moreover, most of those studies were conducted at a provincial level, with limited studies at a local level. Hence, this study aimed to assess the impact of drought on maize yields in the main maize producing areas of the Free State province in South Africa. To achieve this objective, we assessed a) seasonal climate variability, b) temporal variation in drought occurrence and severity, c) trends during the maize growing season, d) impacts of drought on maize yield and e) maize yield loss. By comprehending the intricacies of drought, policymakers, researchers, and stakeholders can work collaboratively towards developing innovative solutions and ensuring a sustainable future for maize production in the face of an increasingly unpredictable climate.

3.2 Materials and methods

3.2.1 Study area

The Free State Province is situated at the centre of South Africa between latitudes of 26.6 °S and 30.7 °S and longitudes of 24.3 °E and 29.8 °E (Mbiriri *et al*., 2019). The main areas producing maize in the study area were Bethlehem, Bloemfontein and Bothaville. Bethlehem is located in the north-eastern part of the province, at coordinates of 28.2423° S and 28.3111° E, with an altitude of 1631 m above sea level (m.a.s.l). Meanwhile, Bloemfontein is found at 29.0852° S and 26.1596° E in the central part of the province, positioned at an elevation of 1304 m.a.s.l. Similarly, Bothaville is located at coordinates 27.3740° S and 26.6200° E, with an altitude of 1280 m.a.s.l (Figure 3.1). The annual mean rainfall in these semi-arid areas ranges from 545 to 845 mm (Table 3.1) (https://en.climate-data.org/). The climate of Bethlehem is temperate, with dry winters and warm summers (Cwb), while Bloemfontein has a cold semi-arid steppe climate (BSk) and a hot semi-arid steppe climate (BSh) in Bothaville based on the Köppen-Geiger system by Rohli *et al.* (2015). The most dominant soil types include sandy loams in Bethlehem and Bothaville and fine sandy loams in Bloemfontein (Du Preez *et al*., 2011) (Table 3.1).

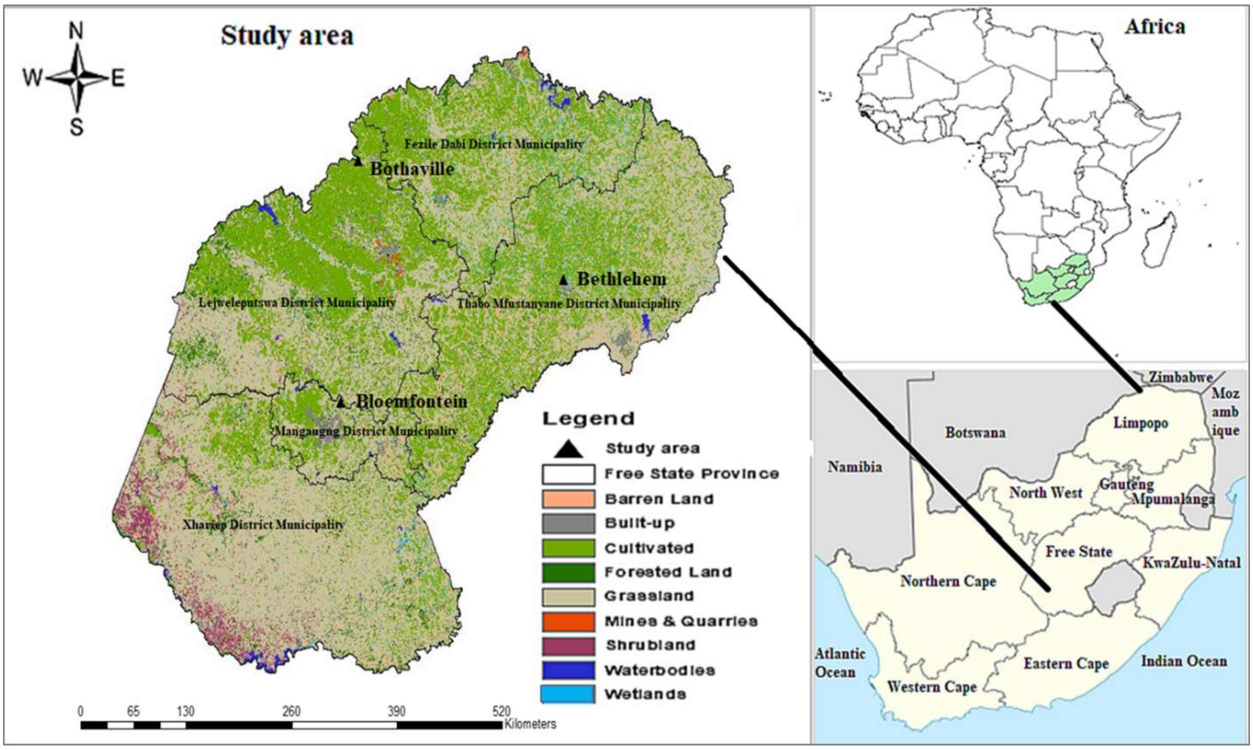


Figure 3.1. Geographical location, land cover and the spatial dissemination of the selected study areas in the Free State Province.

Table 3.1. Details of the climate and soil in the study areas
Adapted from Crespo *et al*. (2012) report.

Attributes	**Bethlehem (BTM)**			**Bloemfontein (BFN)**			**Bothaville (BTV)**		
Optimal planting window	Oct 15 – Nov 30			Nov 15 – Dec 15			Nov 15 – Dec 15		
Climate variables:									
Annual average rainfall (mm)	845			545			565		
Annual average temperature (°C)	18.87			21.04			21.02		
Annual ET$_O$ (mm)	1915			2099			1824		
General soil properties:									
Thickness of the topsoil horizon (m)	0.30			0.30			0.35		
Thickness of the subsoil (m)	1.5			1.9			0.9		
Dominant soil textural class	Sandy clay loam			Sandy loam			Sandy clay loam		
Clay content (%)	10-15			8-14			10-20		
Soil profile description :									
Horizon	A	B1-3	C	A	B1-5	C	A	B21	B22
Depth (cm)	0-30	30-95	95-180	0-30	30-140	140-220	0-30	35-90	90-120

3.2.2 Data acquisition

3.2.2.1 Climate data

Historical monthly average rainfall (RF) and temperature (T) data between 1990 and 2020 was acquired from the Agricultural Research Council-Natural Resource and Engineering (ARC-NRE) archive database for all the study areas. The agrometeorological stations selected for this study had 30 years and more of climate data with over 90% data efficiency (i.e., less than 10% missing daily values) (Table 3.2). The missing data was rigorously assessed, and any missing values were substituted with the mean values obtained from the agrometeorological stations in close proximity (Tan *et al*., 2015; Pei *et al.*, 2020). Table 3.2 below shows the selected agrometeorological climatic data used in the study.

Table 3.2. Selected agrometeorological climatic data used in the study.

Name of Station	Latitude	Longitude	Altitude (m)	Geographical area	Date Range	Climate variables
Bethlehem (Lochlamond)	-28.1626	28.2953	1631	Eastern	1990-2020	RF, T
Bloemfontein (Glen)	-28.9500	26.3333	1304	Central	1990-2020	RF, T
Bothaville (Balkfontein)	-27.4000	26.5000	1280	Northern	1990-2020	RF, T

Note. RF denote Rainfall T-Temperature

3.2.2.2 Maize yield

The long-term historical maize yield data from 1990 to 2020 (Appendix 3) for Bloemfontein, Bethlehem, and Bothaville was obtained from the Crop Estimates Committee (CEC) (2021) of the Department of Agriculture, Land Reform and Rural Development. The data was captured and visualized in Microsoft Excel 2016 with location, years, and yield values.

3.2.3 Seasonal agro-climatic variability analysis

In this study, the long-term monthly rainfall and temperature data were organized based on the agricultural year, which runs from July to June of the following year, allowing for a continuous record of the growing season from October to March (Moeletsi *et al*., 2011; Bello *et al*., 2020). The variability of agro-climatic variables was analyzed on a seasonal basis for the rainfed maize growing season, specifically for the period 1990-2020. The seasons were generated from 3-and 6-month intervals: October-December (OND), November-January (NDJ), December-February (DJF), January-March (JFM) and October-March (ONDJFM). The analysis was performed between October and March because rainfed maize is grown during these months. The statistical approach utilized for analysis was the mean ($\overline{x}$), standard deviation (σ) (Martinez and Bartholomew, 2017) and coefficient of variability (CV) (Naheed and Rasul, 2011). The CV was interpreted as CV < 20% - low variability, 20 < CV < 30% - moderate variability, CV > 30% - high variability, CV > 40% - very high variability and CV > 70% - extremely high variability (Panda and Sahu, 2019). The methods are represented in Equations 1, 2 and 3.

$$\overline{x} = \frac{\sum x}{n} \tag{1}$$

$$\sigma = \sqrt{\frac{\sum(x-\bar{x})^2}{n}} \tag{2}$$

$$CV = \left(\frac{\sigma i}{\bar{x}i}\right) \times 100 \tag{3}$$

Where:

x denotes the values of the data, sigma ($\sum$) represents the "sum of", n is the number of observations, and $\bar{x}$ denotes the mean. σ denotes the monthly standard deviation, xi represents the monthly average of a particular variable, and i is the subindex, the particular month/s of the year.

3.2.4 Computation of drought indices

3.2.4.1 Standardized Precipitation Index

Standardized Precipitation Index (SPI) is a normalized index that measures the likelihood of observed rainfall amounts occurring in a particular location compared to typical rainfall patterns over an extended reference period (Bhavani *et al.*, 2017). Additionally, the SPI is suggested by the World Meteorological Organization (WMO) as the primary meteorological indicator to track and investigate drought across various periods (Uwimbabazi *et al.*, 2022). SPI requires only rainfall data as an input parameter (Fuchs, 2012). The SPEI package built-in RStudio software version 4.0.2, which is a free software environment for statistical computing and graphics, was utilized to calculate seasonal SPI values at 3-and 6-month intervals (Vicente-Serrano *et al*., 2010; Beguería *et al.*, 2014; R Core Team, 2017). The 3-month interval was classified into four overlapping seasons: October-November-December (OND), November-December-January (NDJ), December-January-February (DJF) and January-February-March (JFM), while the 6-month interval covered the entire maize growing season, October-November-December-January-February-March (ONDJFM).

3.2.4.2 Standardized Precipitation Evapotranspiration Index

The Standardized Precipitation Evapotranspiration Index (SPEI) is computed similarly to the SPI; however, the SPEI requires monthly rainfall and temperature data as input parameters (Liu *et al.*, 2018). The potential evapotranspiration (PET) needed by the SPEI method was calculated using PET Thornthwaite's calculation method (Thornthwaite, 1948) built in the SPEI package in RStudio software (Vicente-Serrano *et al*., 2010; Beguería *et al.*, 2014; R Core Team, 2017). Thornthwaite's method requires only monthly average temperature data and latitude coordinates of a particular area (Gurrapu *et al.*, 2014), which were readily available for the study areas. The SPEI package in the R program also computed seasonal SPEI values at 3 and 6 timescales. The categorization of drought levels of the SPI and SPEI (McKee *et al*., 1993; Vicente-Serrano *et al*., 2010) is shown in Table 3.3.

Table 3.3. SPI and SPEI categories of drought.

SPI/SPEI values	Moisture category
≥ 2.00	Extreme Wet
1.50 to 1.99	Severe Wet
1.49 to 1.00	Moderate Wet
0.99 to -0.99	Normal
-1.00 to -1.49	Moderate Drought
-1.50 to - 1.99	Severe Drought
≤ -2.00	Extreme Drought

3.2.5 Drought trends

Mann-Kendall Test

Trend analysis is commonly used to detect climatic or hydrologic time series changes (Adamala, 2016). Mann-Kendall test is a non-parametric method and requires the data to be independent (Kendall, 1948; Yue *et al*., 2002). It determines whether there are increasing or decreasing trends with time for different time series (Mann, 1945; Kendall, 1948). Mann-Kendall test is the most preferred method when various stations are tested in a single study (Hamed and Rao, 1998; Douglas *et al*., 2000; Yue *et al*., 2002). The Mann-Kendall test is a reliable, straightforward method commonly used in climatic, environmental, and hydrological research (Renard *et al.*, 2008; Mendes *et al*., 2022). This study used the modified Mann-Kendall test to detect monthly and seasonal trends in the calculated SPI and SPEI values and their significance at 3-month and 6-month intervals for the period 1990-2020. The modifiedmk package built-in RStudio software was used for analysis. The analysis was performed at a 95% ($p<0.05$) significance level. In determining the trends, Z's positive value signifies an increasing trend, while Z's negative value indicates a decreasing trend (Li *et al.*, 2015). The increasing trend of SPI/SPEI shows a positive trend; thus, SPI /SPEI values are increasing over time, which indicates a trend towards wetter conditions. A decreasing trend of SPI/SPEI shows a negative trend; thus, SPI/SPEI values decrease over time, indicating a trend towards drier conditions (Tan *et al*., 2015).

3.2.6 Drought impact on maize yield

Pearson Correlation

The Pearson's correlation coefficient (r) provides the direction and strength of the statistical relationship between two continuous variables (Christensen, 1996; Kader and Franklin, 2008). Moreover, it represents the relationship between two variables measured on the same interval or ratio scale (Kenton, 2022). Specifically, the study employed this method to investigate the direct impacts of drought (SPI and SPEI) on maize yield during various maize growing seasons across three selected study areas. The ggpubr and ggplot2 packages built in RStudio program version 4.0.2 were employed to calculate the correlation coefficients and develop scatter plots with fitted regression lines (Statistical Tools for High-throughput Data Analysis (STHDA), no date). Fitted regression lines represent the relationship between two variables in a scatterplot. They show how the value of one variable (the response variable) changes as the value of another variable (the predictor variable) changes. In our study, the response variable is maize yield and predictor variable is drought indices. The analysis was done at a 95% confidence level to allow a 5% margin of error. The values range from +1 to -1, with +1 indicating a positive linear correlation, 0 indicating no correlation, and -1 indicating a perfect negative correlation (Taylor, 1990; Schober *et al*., 2018).

3.2.7 Maize yield loss calculation

Maize yield losses are influenced predominantly by extreme weather events such as droughts, heatwaves and flooding (Mangani *et al.*, 2018; Wang *et al.*, 2020). Moreover, technological development, such as applying fertilizers and changing cultivars, can also influence maize yield (Song *et al.*, 2020). In this study, drought was the main factor that was considered the primary influence on maize yield loss. Calculating the yield loss rate is essential because it helps determine the strategic measures that can be put in place to avoid losses (Song *et al.*, 2020). The yield loss rate in a given year was computed as a percentage of the maximum (highest) yield over the previous five years, as determined in Equation (4):

$$\mathrm{YL} = \frac{\mathrm{Yi-Ym}}{\mathrm{Ym}} \times 100\% \tag{4}$$

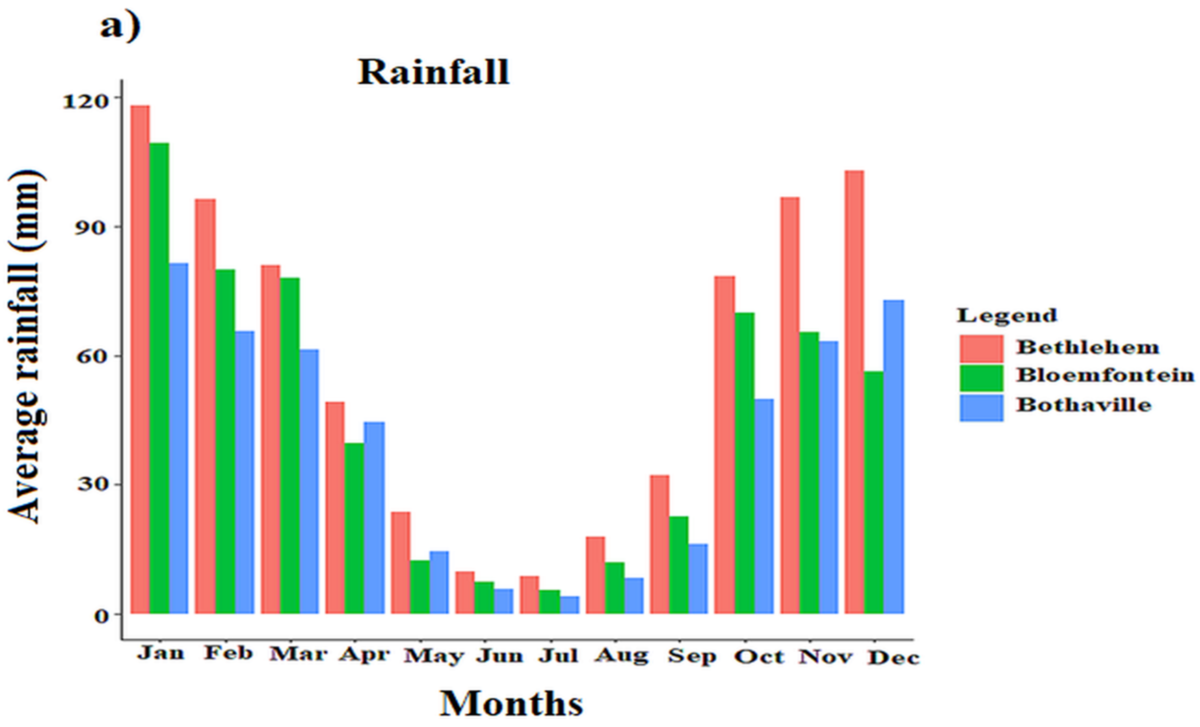
Where:

YL-yield loss is induced mainly by climate events, Yi-yield in a given year, and Ym-maximal yield during the past 5 years (Wang *et al.*, 2020).

3.3 Results

3.3.1 Climate Patterns: Rainfall and Temperature

Figure 3.2 a) and b) presents the historical monthly average rainfall and temperature patterns for Bloemfontein, Bethlehem, and Bothaville from 1990 to 2020. The data reveal that the main rainy season in these areas typically spans from October to April, with peak rainfall occurring between December and February (Figure 3.2 a)). January is consistently the wettest month across all study areas. In contrast, the dry season extends from May to September, with the lowest rainfall recorded between June and August and July being the driest month. Temperature patterns show that the highest temperatures are experienced during the summer months, with January being the warmest (Figure 3.2 b)). The average temperatures for this month were recorded as 19.9°C in Bethlehem, 23.3°C in Bloemfontein, and 22.2°C in Bothaville. Overall, Bethlehem tends to be wetter and colder, while Bloemfontein and Bothaville are generally drier and warmer.



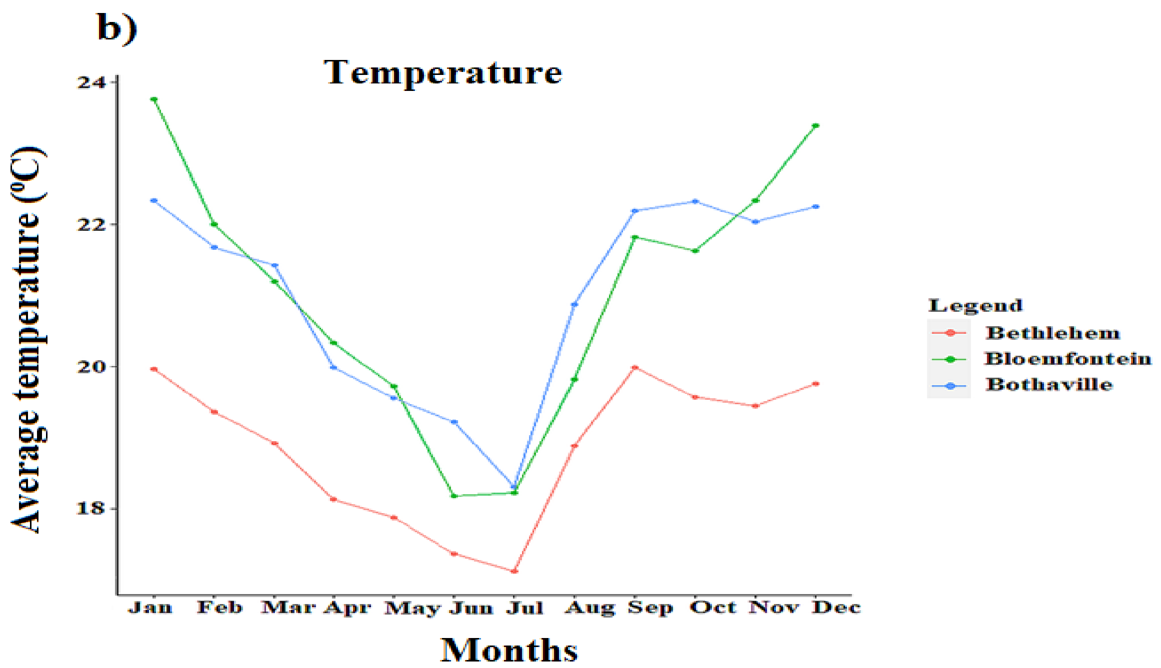


Figure 3.2. Calculated monthly climatology of a) rainfall and b) temperature for Bloemfontein, Bethlehem, and Bothaville from 1990 to 2020.

3.3.2 Seasonal agro-climatic variability during the growing season

3.3.2.1 Rainfall

Table 3.4 shows that Bethlehem had average rainfall ranging from 203.62 to 575.29 mm across seasons, with the highest average in the ONDJFM season. Bloemfontein had average rainfall ranging from 172.66 to 514.53 mm, with the highest average rainfall recorded in the same abovementioned season. Bothaville had average rainfall between 183.38 mm and 526.72 mm, with the highest average rainfall recorded in the ONDJFM season (Table 3.4). Decreasing trends were prevalent across all study areas and seasons, as indicated by the decreasing slope (Figure 3.3). Maize requires 450 to 600 mm of water during its entire growing season (Du Plessis, 2003), which was met across all the study areas. Standard deviations (σ) varied across seasons and all areas, with the highest σ in the JFM season in Bethlehem and Bloemfontein and the OND season in Bothaville (Table 3.4). The coefficient of variation varied across locations and seasons, with low-high variability (CV = 19.91 - 36.19%) indicated in Bethlehem, low-very high variability in Bloemfontein (CV = 18.42 - 46.62%), and low-very high variability (CV = 19.74 – 40.57%) in Bothaville.

Table 3.4. Summary of statistics used to determine average rainfall variability during various seasons across Bethlehem, Bloemfontein and Bothaville for 1990-2020.

Study areas	Seasons	$\bar{x}$	σ	CV (%)
Bethlehem	OND	210.61	73.01	34.67
	NDJ	234.48	73.98	31.55
	DJF	227.10	79.74	35.11
	JFM	203.62	73.70	36.19
	ONDJFM	575.29	114.52	19.91
Bloemfontein	OND	172.66	64.35	37.27
	NDJ	201.69	61.71	30.60
	DJF	210.36	75.88	36.07
	JFM	202.01	94.17	46.62
	ONDJFM	514.53	94.80	18.42
Bothaville	OND	183.38	74.40	40.57
	NDJ	226.59	67.54	29.81
	DJF	230.59	79.83	34.62
	JFM	216.81	83.51	38.52
	ONDJFM	526.72	104.00	19.74

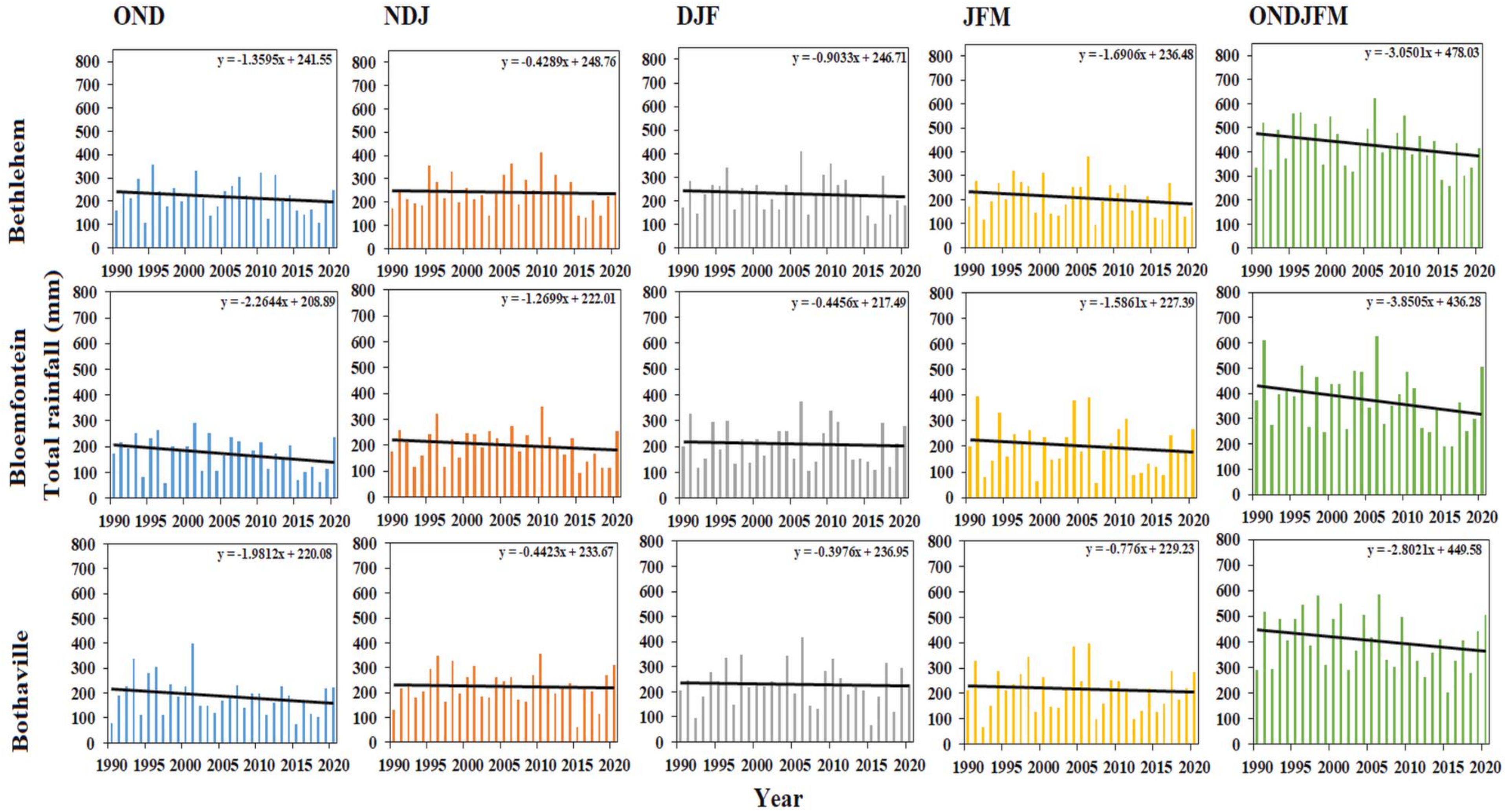


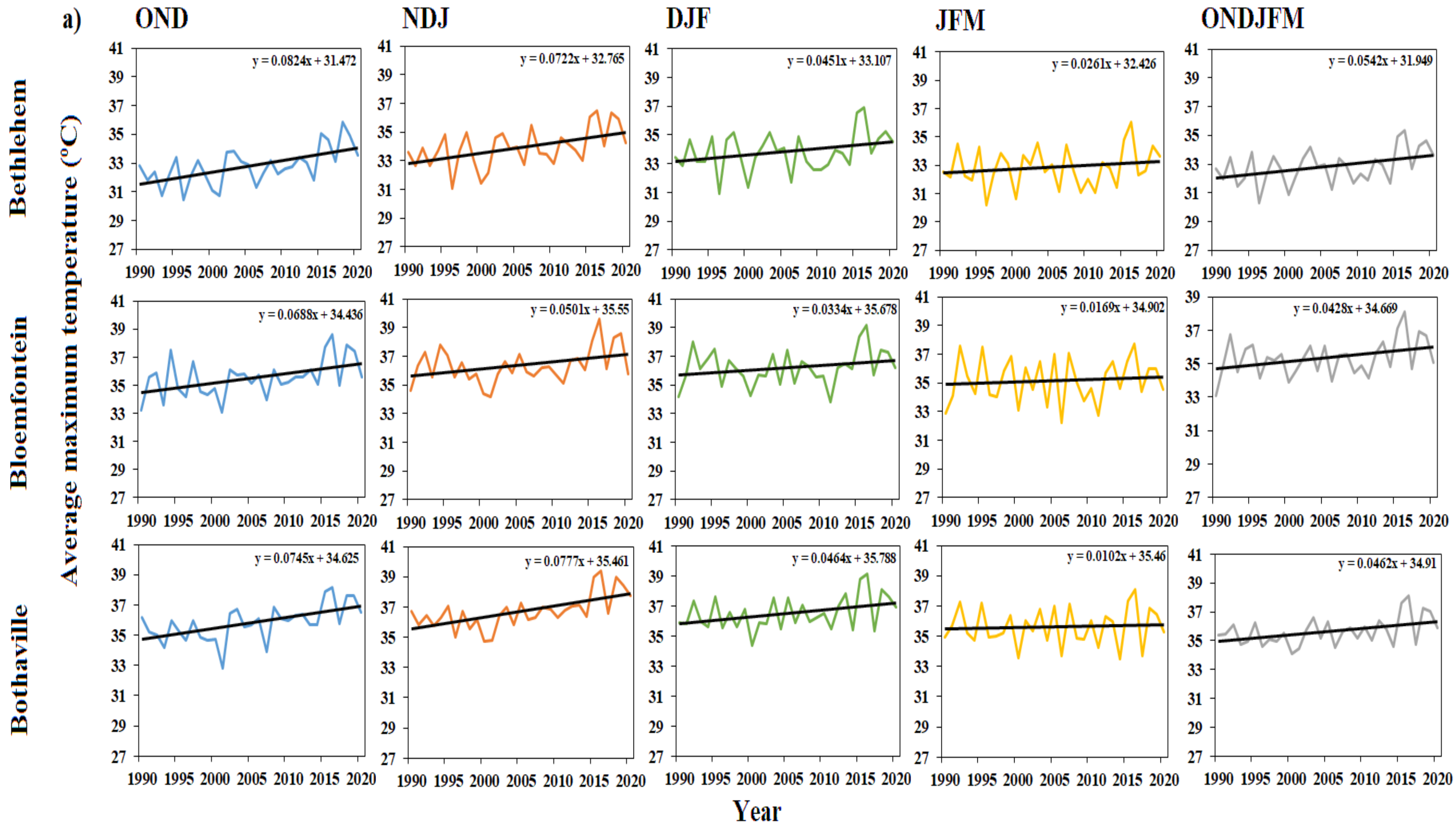
Figure 3.3. Total rainfall trends during maize growing seasons for Bethlehem, Bloemfontein and Bothaville between 1990 and 2020.

3.3.2.2 Temperature

Table 3.5 shows that Bethlehem had an average maximum temperature ranging from 32.67ºC to 33.33ºC, with the highest recorded in the NDJ season. Bloemfontein had an average temperature ranging from 35.15ºC to 36.28ºC, with the highest recorded in the same season mentioned above. Bothaville had an average maximum temperature range from 35.62ºC to 36.71ºC, with the highest recorded in the same season as the two areas (Table 3.5). There were increasing trends across all seasons and study areas, as shown by the increasing slope across, as well as temperature spikes (also known as a sudden increase in temperature) (Figure 3.4 a)). Notable temperature spikes were in 1999 and 2016 (Figure 3.4 a)). Notable temperature decreases occurred in 1993, 1998, 2007 and 2011 (Figure 3.4 a)). The optimum temperature for maize growth is 20-30ºC (Du Plessis, 2003), which was met by all areas. The standard deviation ranged from 3.67ºC to 5.30ºC in Bethlehem, 3.10ºC to 4.74ºC in Bloemfontein, and 0.97ºC to 3.49ºC in Bothaville (Table 3.5). Based on variation, all the areas showed low variability (CV<20%) across all seasons (Table 3.5). The long-term average of minimum temperature ranged from 5.87ºC to 9.41ºC, with the highest recorded in the DJF season in Bethlehem (Table 3.5). In Bloemfontein, the long-term average range was 6.59ºC-10.82ºC, with the highest recorded in the same season (Table 3.5). In Bothaville, the long-term average ranged between 8.54ºC and 12.38ºC, with the highest recorded in the same season as the two areas (Table 3.5). A long-term increasing trend was depicted across all seasons and areas, as depicted by the increasing slope (Figure 3.4 b)). Notable temperature spikes and decreased years are similar to those of maximum temperature. The minimum temperature for maize germination is 10ºC (Du Plessis, 2003), which was met in two seasons in Bloemfontein and four seasons in Bothaville. However, in Bethlehem, the temperatures were relatively low across all seasons. Below the temperature threshold of 10ºC, virtually no germination and the growth is stunted (Du Plessis, 2003). The standard deviation (σ) varied across seasons in each study area. Based on the coefficient of variation (CV), all areas across all seasons accentuated low variability (CV< 20%), indicating relatively consistent patterns or stable conditions, except the OND season in Bethlehem (CV = 22.66% - moderate variability).

Table 3.5. Summary of statistics used to determine temperature variability for Bethlehem, Bloemfontein and Bothaville between 1990 and 2020.

	Tmax				**Tmin**			
Study areas	Seasons	$\bar{x}$	σ	CV (%)	Seasons	$\bar{x}$	σ	CV (%)
Bethlehem	OND	32.97	1.55	4.70	OND	5.87	1.33	22.66
	NDJ	33.33	1.43	4.29	NDJ	7.98	1.48	18.55
	DJF	33.10	1.47	4.44	DJF	9.41	1.34	14.24
	JFM	32.38	1.72	5.31	JFM	9.20	1.21	13.15
	ONDJFM	32.67	1.20	3.67	ONDJFM	7.53	1.07	14.21
Bloemfontein	OND	35.51	1.25	3.52	OND	6.59	1.30	19.73
	NDJ	36.28	1.22	3.36	NDJ	9.05	1.42	15.69
	DJF	36.14	1.33	3.68	DJF	10.82	1.30	12.01
	JFM	35.15	1.66	4.72	JFM	10.31	1.44	13.97
	ONDJFM	35.35	1.10	3.11	ONDJFM	8.45	0.95	11.24
Bothaville	OND	35.82	1.17	3.27	OND	8.54	1.18	13.82
	NDJ	36.71	1.12	3.05	NDJ	10.81	1.38	12.77
	DJF	36.53	1.11	3.04	DJF	12.38	1.33	10.74
	JFM	35.62	1.24	3.48	JFM	11.91	1.23	10.33
	ONDJFM	35.65	0.97	2.72	ONDJFM	10.22	0.93	9.10


a)
OND
NDJ
DJF
JFM
ONDJFM
Bethlehem
Bloemfontein
Bothaville
Average maximum temperature (°C)
y = 0.0824x + 31.472
y = 0.0722x + 32.765
y = 0.0451x + 33.107
y = 0.0261x + 32.426
y = 0.0542x + 31.949
y = 0.0688x + 34.436
y = 0.0501x + 35.55
y = 0.0334x + 35.678
y = 0.0169x + 34.902
y = 0.0428x + 34.669
y = 0.0745x + 34.625
y = 0.0777x + 35.461
y = 0.0464x + 35.788
y = 0.0102x + 35.46
y = 0.0462x + 34.91
Year

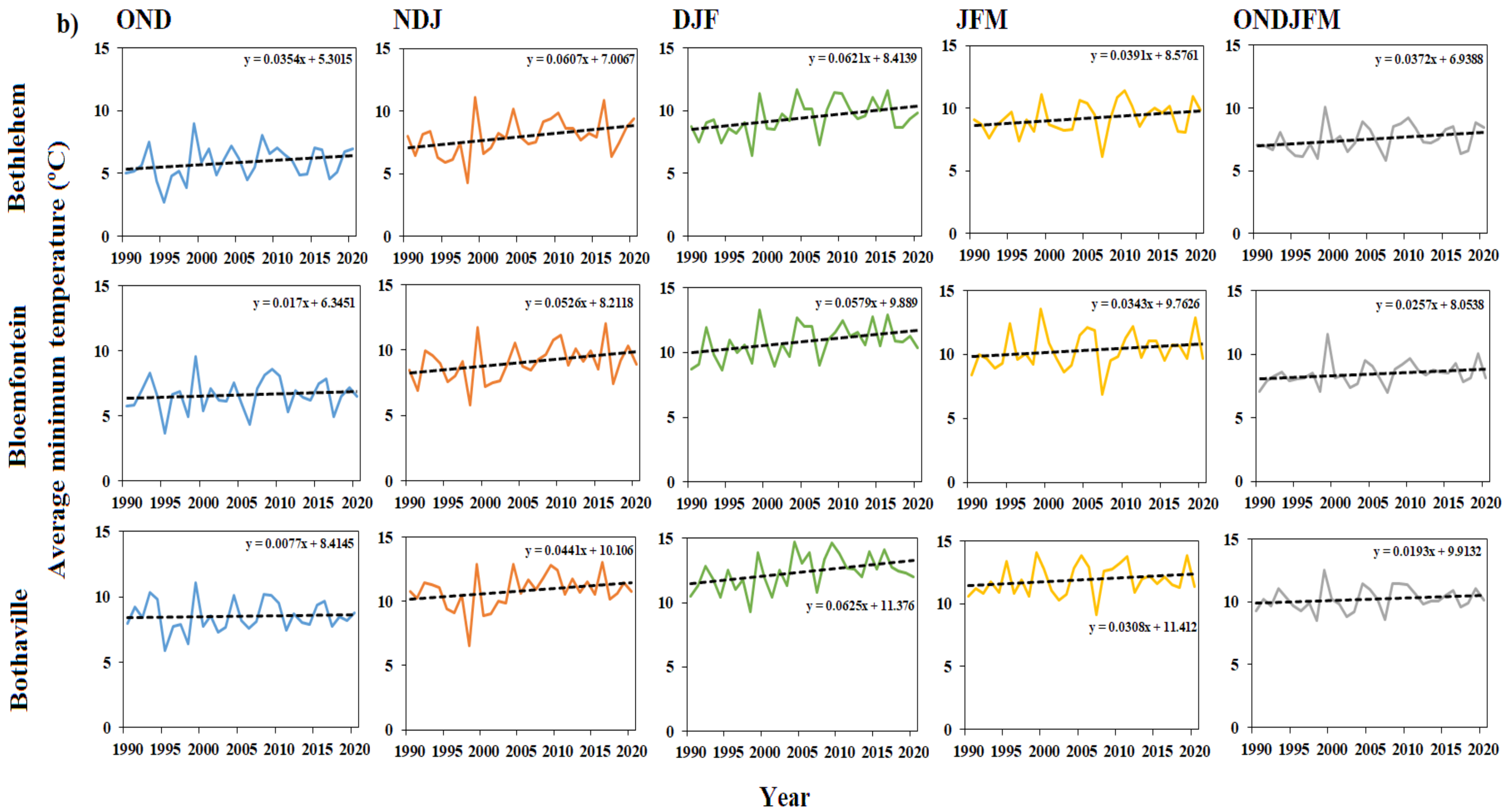
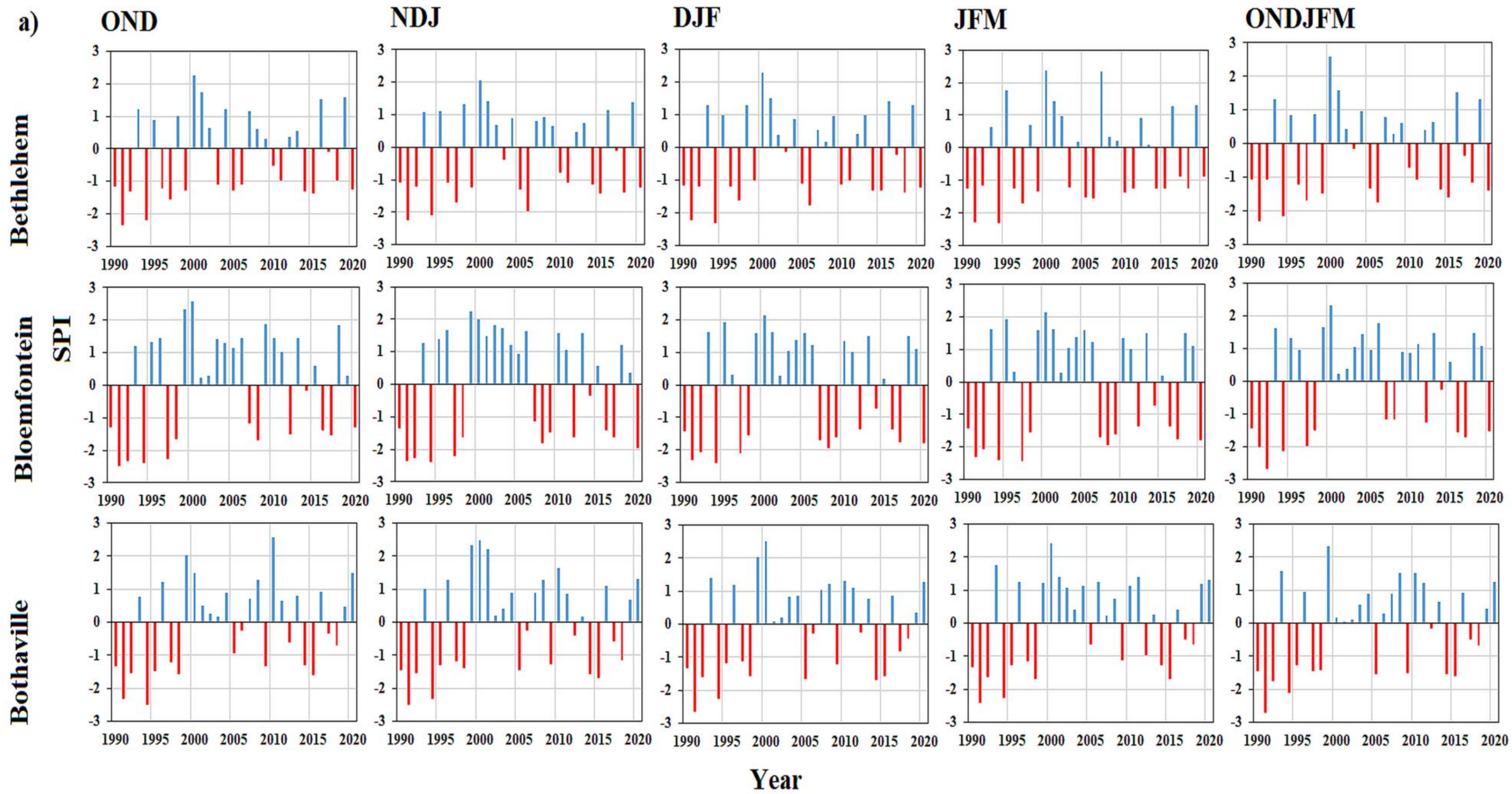


Figure 3.4. Trends in maximum a) and minimum b) temperature during various seasons for Bloemfontein, Bethlehem and Bothaville between 1990 and 2020.

3.3.3 Seasonal variations in drought occurrence

Figure 3.5 a) and b) illustrate the seasonal changes in drought occurrences based on SPI and SPEI over a moving three-month sub-seasonal period and at the seasonal (October-March) during the maize growing season for Bethlehem, Bloemfontein and Bothaville. The results reveal that the frequency of droughts varies depending on the index, season, and region. In Bethlehem, during short-term seasons (OND, NDJ, DJF, and JFM), drought events under SPI were most common in the OND, DJF, and JFM seasons, with drought occurring in 15 of the 30 years studied (Figure 3.5 a)). However, under the SPEI, the DJF and JFM seasons experienced drought in 14 of the 30 study years (Figure 3.5 b)). In Bloemfontein, droughts under SPI often occurred in the NDJ, DJF, and JFM seasons, with 13 of the study years experiencing drought. Conversely, under the SPEI, droughts were most frequent in the OND, NDJ, and JFM seasons, with drought occurring in 10 of the study years (Figure 3.5 b)). In Bothaville, drought events under the SPI frequently occurred in the NDJ season, with 12 of the study years experiencing drought (Figure 3.5 a)). Under the SPEI, however, droughts were most common in the JFM season, with 14 of the study years experiencing recurrent droughts (Figure 3.5 b)). Considering the entire growing season (ONDJFM), Bethlehem experienced frequent droughts in 14 years under the SPI and 17 years under the SPEI. In Bloemfontein, 12 years faced drought under the SPI and 8 years under the SPEI. In Bothaville, both the SPI and SPEI recorded droughts in 11 years of the study period (Figure 3.5 a) and b)). The cyclic nature of these drought occurrences can be observed through the periodic spikes in drought severity, which align with specific years or clusters of years. For instance, the extreme droughts in 1991/92 and 1994/95 and moderate drought in 1990/91, which affected all three locations, suggest the presence of a multi-year drought cycle. These drought occurrences could be due to climate oscillations such as El Niño. This phenomenon is associated with changes in sea surface temperatures in the Pacific Ocean, which can lead to increased drought conditions.



a)
OND
NDJ
DJF
JFM
ONDJFM
Bethlehem
Bloemfontein
Bothaville
SPI
Year

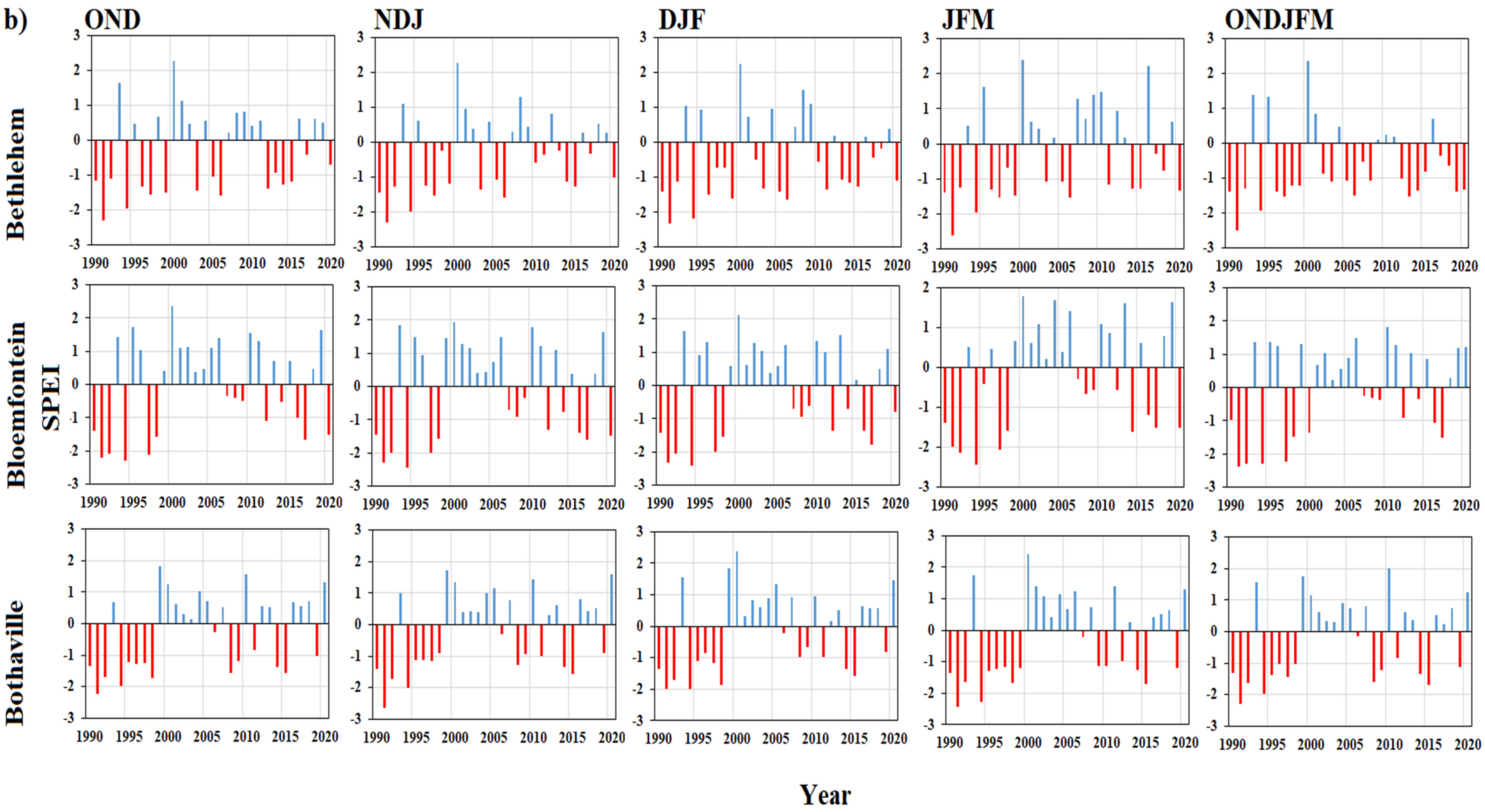


Figure 3.5. Temporal evolution of drought using SPI a) and SPEI b) for Bloemfontein, Bethlehem and Bothaville in various seasons between 1990 and 2020.

3.3.4 Drought severity in the maize growing season based on SPI and SPEI

Table 3.6 shows the drought severity in various seasons: OND, NDJ, DJF, JFM and ONDJFM seasons for the period from 1990 to 2020. The findings indicate that Bloemfontein, Bethlehem, and Bothaville have experienced successions of moderate to severe droughts throughout all seasons since the 1990s. Following the SPI and SPEI, notable moderate droughts for Bethlehem were recorded in 1990/91, 1992/93, 1996/97, 1999/00, 2003/04, 2011/12, 2014/15 and 2015/16 across seasons. Severe droughts occurred in 1997/98 and 2006/07, and extreme droughts occurred in 1991/92 and 1994/95 (Table 3.6). For Bloemfontein, moderate drought was recorded in 1990/91 for both growing seasons. Severe droughts were observed in 1998/99 and 2017/18. Extreme droughts were observed in 1991/92, 1992/93, 1994/95, and 1997/98 (Table 3.6). For Bothaville, moderate droughts were recorded in 1990/91, 1995/96, 1997/98, 1999/00 and 2014/15. Severe droughts in 1992/93 and 2015/16 and extreme droughts in 1991/92 and 1994/95 (Table 3.6). These results suggest that all three locations have been vulnerable to drought conditions over the past three decades, with varying degrees of severity.

Table 3.6. Drought severity during various seasons for Bloemfontein, Bethlehem and Bothaville between 1990 and 2020.

	Drought severity and drought years		
Study areas	Moderate	Severe	Extreme
Bethlehem	1990/91	1997/98	1991/92
	1992/93	2006/07	1994/95
	1996/97		
	1999/00		
	2003/04		
	2011/12		
	2014/15		
	2015/16		
Bloemfontein	1990/91	1998/99	1991/92
		2017/18	1992/93
			1994/95
			1997/98
Bothaville	1990/91	1992/93	1991/92
	1995/96	2015/16	1994/45
	1997/98		
	1999/00		
	2014/15		

3.3.5 Trends during the maize growing season

Table 3.7 a) and b) present an overview of the monthly and seasonal drought trends for Bloemfontein, Bethlehem, and Bothaville. The results show that in Bethlehem, under SPI, on a monthly scale, significant decreasing trends (indicating drier/drought conditions) were observed throughout all the months. On a seasonal scale, decreasing trends were throughout all the seasons, with trends being significant in DJF ($Z = -2.33$, $p = 0.02$), JFM ($Z = -2.60$, $p = 0.008$), and ONDJFM ($Z = -3.20$, $p = 0.0014$) seasons. On a seasonal scale, decreasing trends were throughout all the seasons, with trends being significant in DJF (Z = -2.33, p = 0.02), JFM (Z = -2.60, p = 0.008), and ONDJFM (Z = -3.20, p = 0.0014) (Table 3.7 a)). Under SPEI, on a monthly scale, November-March showed decreasing trends, which were significant in December-March. However, October showed a significant increasing trend (indicating wetter conditions) (Z = 2.55, p = 0.011) (Table 3.7 b)). Bloemfontein showed different trends under the SPI. On a monthly scale, February (Z = -1.91, p = 0.36) and March (Z = -3.33, p = 0.00086) showed decreasing trends, with only March's trend being significant. However, from October to January, there were increasing trends, which were significant in October, November, and December. On a seasonal scale, only the October-November-December (OND) season showed non-significant decreasing trends (Z = -0.05, p =0.96), while NDJ, DJF, JFM and ONDJFM seasons indicated non-significant increasing trends (Table 3.7 a)). Under the SPEI, on a monthly scale, October showed significant increasing trends (Z = 2.55, p = 0.01). However, from November to March, there were decreasing trends, which were significant in only in December (Z = -3.69, p = 0.0002), February (Z = -10.52, p = 0.0031), and March (Z = -12.56, p = 0.0034). On a seasonal scale, all the seasons revealed significant decreasing trends (Table 3.7 b)).)). In Bothaville, under SPI, on a monthly scale, all the months indicated increasing trends, which were significant in October-February. On a seasonal scale, all the seasons indicated significant increasing trends (Table 3.7 a)). However, under SPEI, on a monthly scale, only October (Z = 0.71, p = 0.48) and March (Z = -0.33, p = 0.74) showed decreasing trends that were not significant, while other months showed non-significant increasing trends. On a seasonal scale, all the seasons indicated decreasing trends that were significant in the OND (Z = -2.81, p = 0.004) and NDJ (Z = -1.99, p = 0.04) seasons (Table 3.7 b)). Under SPI drier/drought conditions were prevalent in Bethlehem both on monthly and seasonal scales while under SPEI drought conditions on a monthly and seasonal were dominant in Bloemfontein.

Table 3.7. Monthly and seasonal trends of a) SPI and b) SPEI in Bethlehem, Bloemfontein, and Bothaville from 1990 to 2020.

a) SPI

Months/Seasons	**Study areas**					
	Bethlehem		Bloemfontein		Bothaville	
	Z	P-value	Z	P-value	Z	P-value
OCT	-5.62	0.00018*	3.20	0.0014*	7.03	0.019*
NOV	-6.92	0.00045*	4.62	0.017*	5.69	0.04*
DEC	-4.91	0.00089*	3.62	0.00029*	5.61	0.07*
JAN	-5.99	0.00021*	0.23	0.81	4.33	0.00014*
FEB	-3.52	0.00043*	-1.91	0.36	2.53	0.011*
MAR	-2.93	0.0034*	-3.33	0.00086*	1.15	0.249
OND	-1.58	0.11	-0.05	0.96	2.56	0.01*
NDJ	-1.90	0.06	0.31	0.76	3.62	0.029*
DJF	-2.33	0.02*	1.11	0.27	4.44	0.0091*
JFM	-2.60	0.008*	1.60	0.10	4.90	0.0024*
ONDJFM	-3.20	0.0014*	2.35	0.02	5.20	0.0046*

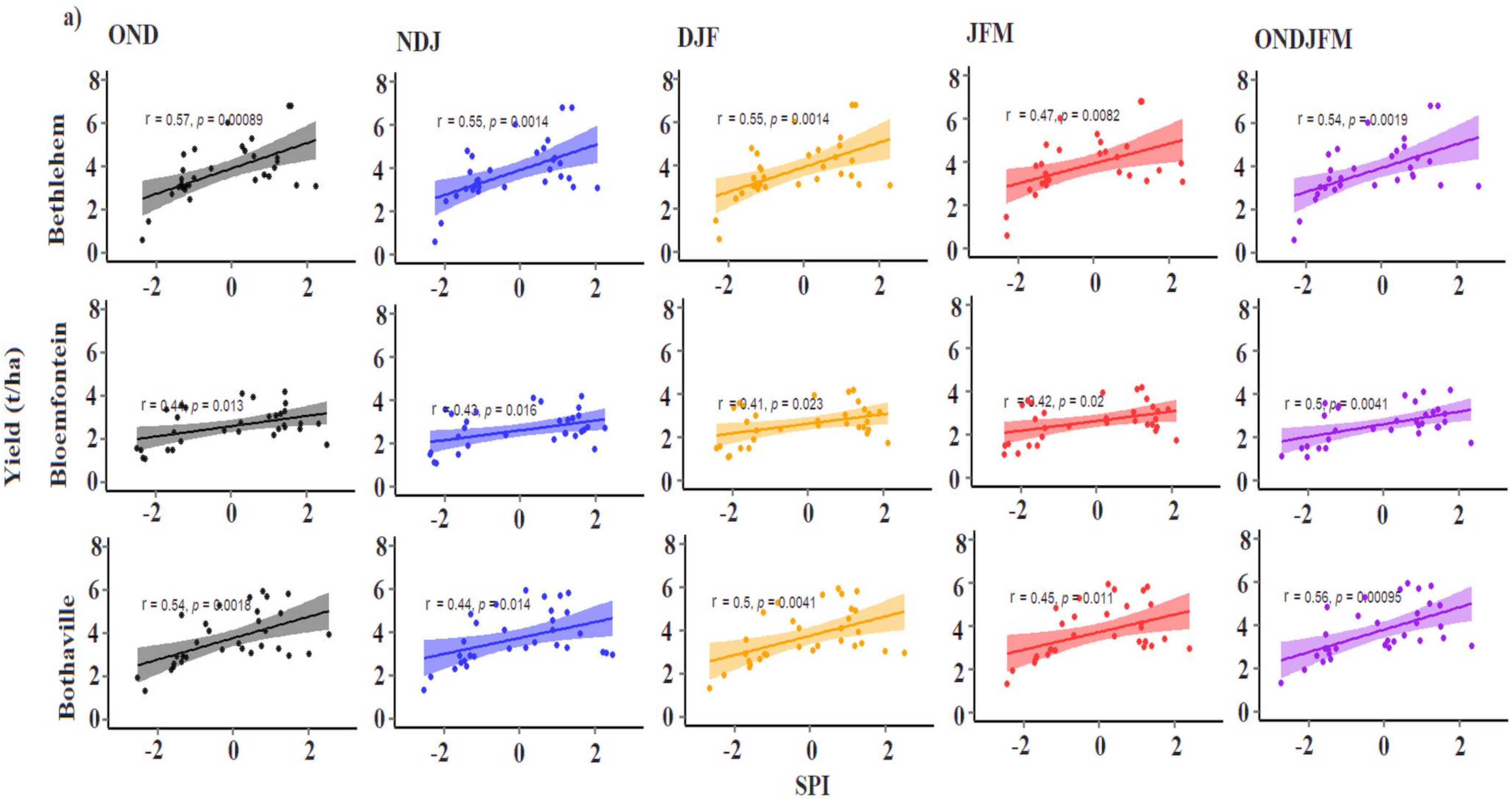
b) SPEI

Months/Seasons	Study areas					
	Bethlehem		Bloemfontein		Bothaville	
	Z	*P*-value	Z	*P*-value	*Z*	*P*-value
OCT	2.55	0.011*	2.55	0.01*	-071	0.48
NOV	-0.33	0.73	-0.33	0.73	0.49	0.62
DEC	-3.69	0.00022*	-3.69	0.0002*	0.50	0.61
JAN	-7.53	0.00054*	-7.52	0.0054	0.59	0.56
FEB	-10.53	0.00031*	-10.52	0.0031*	0.00	1.00
MAR	-12.56	0.00075*	-12.56	0.0034*	-0.33	0.74
OND	-1.95	0.05*	-5.62	0.00018*	-2.81	0.004*
NDJ	-3.25	0.001*	-6.92	0.00045*	-1.99	0.04*
DJF	-4.53	5.90	-4.91	0.00089*	-1.82	0.06
JFM	-4.88	6.02	-5.99	0.00021*	-0.46	0.09
ONDJFM	-4.90	6.24	-3.52	0.00043*	-0.18	0.10

* denote statistically significant at $p<0.05$

3.3.6 Impact of drought on maize yield

Figure 3.6 a) and b) depict the relationship between the calculated seasonal SPI and SPEI values and maize yield for Bloemfontein, Bethlehem, and Bothaville between 1990 and 2020. The shaded area around the regression line in the plot represents the confidence interval, providing information about the precision of the regression estimate. The “r” stands for the correlation coefficient, and “p” shows the significance level at 95%. The results indicate that all the study areas across all seasons revealed a significant positive correlation between the SPI, SPEI and maize yield, with the highest significant positive correlation between SPI and maize yield. Based on short seasons, the highest significant correlation between the SPI and maize yield (r = 0.57, p = 0.0089) was observed in the OND season in Bethlehem, followed by Bothaville in the same season (r = 0.54, p = 0.0018) and Bloemfontein in the same season (r = 0.44, p = 0.013) (Figure 3.6 a)). On the other hand, the highest significant correlation of r = 0.63, p = 0.0016 between SPEI and maize yield was observed in Bloemfontein in the OND season, followed by Bethlehem with a correlation of r = 0.58, p = 0.00059 in the JFM season and Bothaville with a correlation of r = 0.46, p = 0.0093 in the NDJ season (Figure 3.6 b)), which is comparatively low. Regarding the overall season (ONDJFM) under SPI, the highest correlation was observed in Bothaville (r = 0.56, p = 0.00095), followed by Bethlehem (r = 0.54, p = 0.0019) and Bloemfontein (r = 0.50, p = 0.0041) (Figure 3.6 a)). Based on SPEI, the highest significant correlation was observed in Bloemfontein (r = 0.82, p = $1.3e^{-08}$), followed by Bothaville with a correlation of r = 0.38, p = 0.036 and Bethlehem with a correlation of r = 0.29, p = 0.012 (Figure 3.6 b)).



a)
OND
NDJ
DJF
JFM
ONDJFM
Bethlehem
Bloemfontein
Bothaville
Yield (t/ha)
SPI
r = 0.57, p = 0.00089
r = 0.55, p = 0.0014
r = 0.55, p = 0.0014
r = 0.47, p = 0.0082
r = 0.54, p = 0.0019
r = 0.44, p = 0.013
r = 0.43, p = 0.016
r = 0.41, p = 0.023
r = 0.42, p = 0.02
r = 0.5, p = 0.0041
r = 0.54, p = 0.0018
r = 0.44, p = 0.014
r = 0.5, p = 0.0041
r = 0.45, p = 0.011
r = 0.56, p = 0.00095

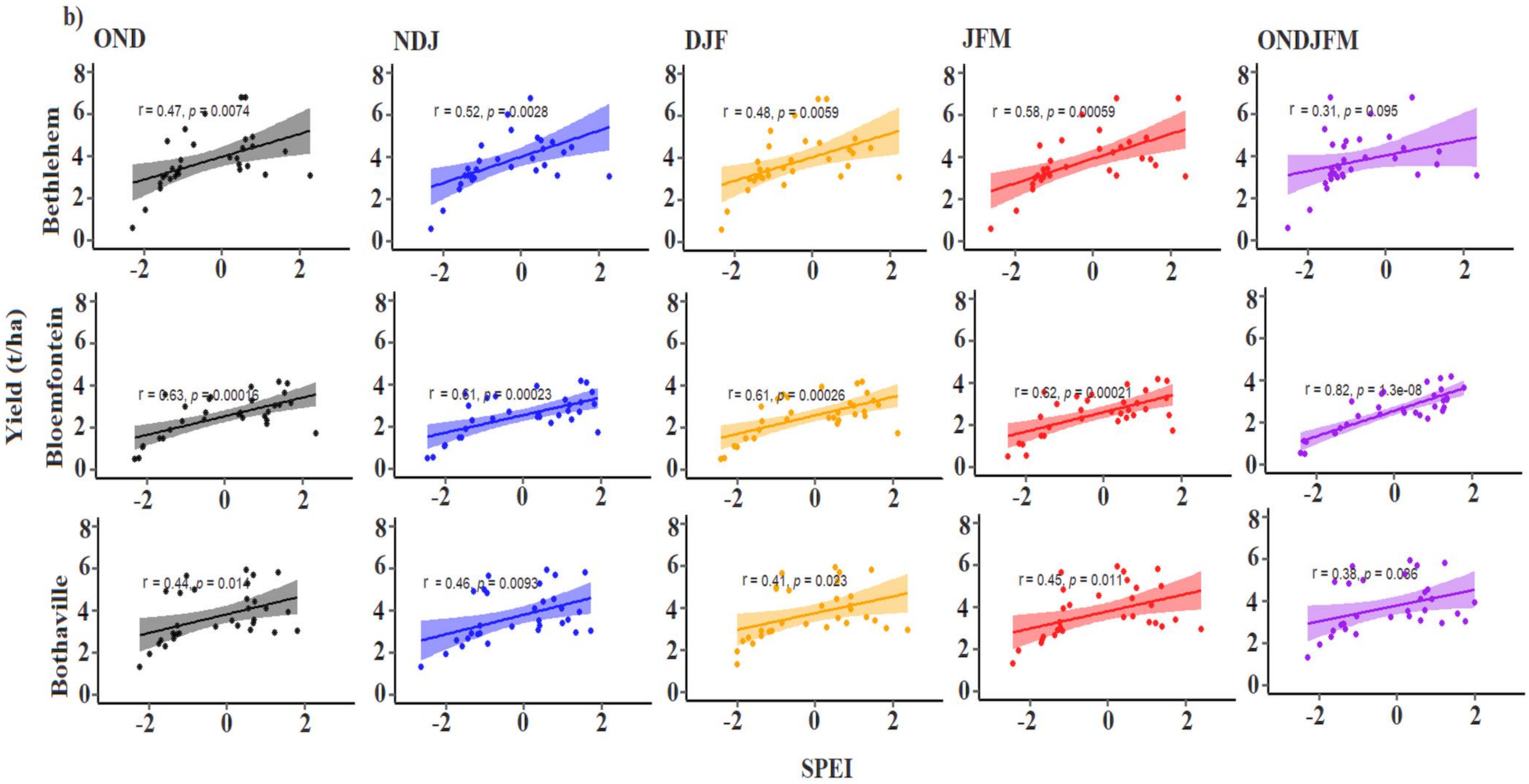


Figure 3.6. Correlation using linear regression between the calculated seasonal SPI a) and SPEI b) values with maize yield for Bloemfontein, Bethlehem, and Bothaville between 1990 and 2020.

3.3.7 Maize yield loss

Table 3.8 shows the percentage loss in maize yield (%) associated with varying degrees of notable droughts. The results show that in moderate drought years, the maize yield loss ranged from -2.02 to -16.71% in Bethlehem and -9.40 to -17.55% in Bothaville. However, in Bloemfontein, there was only one year of moderate drought, which resulted in a yield decrease of -4.67% (Table 3.8). During severe drought years, the yield loss ranged between -22.48 and -29.68% in Bethlehem, -23.23 and -24.74% in Bloemfontein and -20.06 and -28.53% in Bothaville (Table 3.8). In years with extreme drought conditions, the yield loss was even more pronounced, with the yield loss ranging between -59.37 and -83.86% in Bethlehem, -45.88 to -75.26% in Bloemfontein and -40.13 and -58.93% in Bothaville (Table 3.8). Overall, it is evident that the impact of extreme drought on maize yield was significantly greater than that of moderate to severe drought periods across all study areas.

Table 3.8. Maize yield loss relative to drought in Bethlehem (BTM), Bloemfontein (BFN) and Bothaville (BTV) from 1990 to 2020.

Areas	Season	Yield loss (%)	SPI values during different growing seasons					SPEI values during different growing seasons					Drought severity
			OND	NDJ	DJF	JFM	ONDJFM	OND	NDJ	DJF	JFM	ONDJFM	
BTM	1990/91	-11.24	-1.16	-1.08	-1.16	-1.25	-1.08	-1.15	-1.44	-1.42	-1.4	-1.04	Moderate
	1991/92	-83.86	-2.35	-2.25	-2.22	-2.28	-2.29	-2.29	-2.31	-2.32	-2.62	-2.51	Extreme
	1992/93	-9.80	-1.31	-1.21	-1.22	-1.16	-1.08	-1.10	-1.27	-1.11	-1.24	-1.29	Moderate
	1994/95	-59.37	-2.20	-2.08	-2.32	-2.30	-2.15	-2.00	-1.99	-2.18	-2.10	-2.30	Extreme
	1996/97	-16.71	-1.23	-1.10	-1.20	-1.25	-1.22	-1.32	-1.24	-1.48	-1.31	-1.39	Moderate
	1997/98	-22.48	-1.57	-1.69	-1.62	-1.69	-1.67	-1.57	-1.53	-1.71	-1.54	-1.52	Severe
	1999/00	-14.99	-1.29	-1.25	-1.01	-1.35	-1.48	-1.49	-1.19	-1.61	-1.48	-1.23	Moderate
	2003/04	-11.24	-1.11	-1.39	-1.13	-1.23	-1.16	-1.43	-1.35	-1.33	-1.09	-1.11	Moderate
	2006/07	-29.68	-1.09	-1.96	-1.79	-1.54	-1.73	-1.57	-1.74	-1.64	-1.54	-1.50	Severe
	2011/12	-2.02	-1.00	-1.10	-1.03	-1.25	-1.07	-1.02	-1.36	-1.34	-1.15	-1.19	Moderate
	2014/15	-2.59	-1.31	-1.13	-1.32	-1.24	-1.36	-1.26	-1.13	-1.14	-1.27	-1.37	Moderate
	2015/16	-13.83	-1.39	-1.42	-1.32	-1.25	-1.61	-1.19	-1.27	-1.26	-1.24	-1.00	Moderate
BFN	1990/91	-4.64	-1.31	-1.37	-1.43	-1.42	-1.45	-1.38	-1.47	-1.43	-1.39	-1.19	Moderate
	1991/92	-72.68	-2.48	-2.35	-2.32	-2.34	-2.02	-2.20	-2.31	-2.32	-2.00	-2.39	Extreme
	1992/93	-43.3	-2.33	-2.26	-2.07	-2.06	-2.68	-2.08	-2.00	-2.07	-2.15	-2.3	Extreme
	1994/95	-75.26	-2.38	-2.38	-2.41	-2.41	-2.16	-2.31	-2.45	-2.41	-2.44	-2.29	Extreme
	1997/98	-45.88	-2.27	-2.21	-2.10	-2.43	-2.00	-2.10	-2.00	-2.10	-2.06	-2.24	Extreme
	1998/99	-24.74	-1.67	-1.64	-1.55	-1.54	-1.52	-1.57	-1.56	-1.55	-1.59	-1.5	Severe
	2017/18	-24.23	-1.54	-1.63	-1.78	-1.75	-1.71	-1.67	-1.62	-1.78	-1.52	-1.51	Severe
BTV	1990/91	-17.55	-1.35	-1.45	-1.32	-1.35	-1.44	-1.36	-1.42	-1.36	-1.35	-1.32	Moderate
	1991/92	-58.93	-2.31	-2.52	-2.66	-2.43	-2.72	-2.23	-2.63	-2.00	-2.43	-2.29	Extreme
	1992/93	-20.06	-1.56	-1.54	-1.61	-1.65	-1.77	-1.68	-1.72	-1.71	-1.65	-1.62	Severe
	1994/95	-40.13	-2.52	-2.33	-2.27	-2.28	-2.11	-2.01	-2.00	-2.06	-2.28	-2.69	Extreme
	1995/96	-9.40	-1.49	-1.30	-1.20	-1.28	-1.26	-1.21	-1.11	-1.09	-1.28	-1.37	Moderate
	1997/98	-11.29	-1.22	-1.19	-1.14	-1.16	-1.46	-1.27	-1.17	-1.18	-1.16	-1.43	Moderate

1998/99	-24.76	-1.57	-1.39	-1.58	-1.68	-1.42	-1.73	-1.91	-1.85	-1.68	-1.04	Severe
2014/15	-9.40	-1.32	-1.57	-1.69	-1.26	-1.56	-1.37	-1.34	-1.37	-1.26	-1.35	Moderate
2015/16	-28.53	-1.62	-1.71	-1.59	-1.7	-1.61	-1.57	-1.56	-1.58	-1.70	-1.68	Severe

Note. BTM-Bethlehem BFN-Bloemfontein BTV-Bothaville

3.4 Discussion

Drought remains a major threat to food security in many parts of the world, particularly in arid and semi-arid regions. It is a major limiting factor for rainfed crop production in the Free State Province, directly impacting crop growth and anticipated yields. Our study results of agro-climatic variability revealed that during the maize growing season, all three locations (Bethlehem, Bloemfontein, and Bothaville) experienced rainfall variability. The highest coefficient of variability (CV) was observed during the JFM season in Bethlehem and Bloemfontein, and during the OND season in Bothaville, indicating high variability. This high variability indicates a potential unpredictability in rainfall patterns during growing season, which might had implications on maize production. In terms of maximum temperature, both areas exhibited low variability (CV < 20%). However, an exception was noted during the OND season in Bethlehem, where moderate variability (CV = 22.59%) was observed. This suggests potential fluctuations or differences in temperature during the growing season. The variability of rainfall and temperature can be linked to weather patterns such as El Niño-Southern Oscillation (ENSO); this is supported by Moeletsi and Walker (2012) study, which stated that El Niño Southern Oscillation (ENSO) phases play an essential role in the climate variability of most southern African regions including South Africa. The fluctuations of these agro-climatic variables during the maize growing season might have affected crop growth, development and yield. Our findings are relatable to Rowhani *et al.* (2011) whose study assessed climate variability in various crops (including maize) in Tanzania; their study findings indicated that a 20% increase in intra-seasonal rainfall variability reduces agricultural yields of maize by 7.6%. On the other hand, Barnabás *et al.* (2008) reported that temperature variability is a key stress factor with a high potential impact on cereal (including maize) reproduction processes and yield. Bita and Gerats (2013) revealed that temperature changes during the flowering and grain-filling stages of maize affect its growth and reduce the yield quantity and quality by shortening the growing period.

Based on the Standardized Precipitation Index (SPI) and Standardized Precipitation Evapotranspiration Index (SPEI), we observed that all the areas faced droughts across all maize growing seasons; however, Bethlehem (supposedly a wet area) frequently faced worse droughts across all seasons than Bloemfontein and Bothaville (dry areas). Interestingly, Nembilwi *et al.* (2021) assessed the occurrence of drought, impacts, vulnerability and adaptation in Mopani District Municipality, South Africa. Their study revealed that the western bushveld (wetter area) is highly impacted by drought compared to the eastern lowveld (dry area). While it is true that Bethlehem is generally considered a wetter area compared to Bloemfontein and Bothaville, the occurrence of droughts in Bethlehem could be attributed to various factors such as (i) climate variability; droughts are influenced mainly by climate variability and long-term climate patterns. Like other regions, Bethlehem experiences variability in rainfall due to natural climate oscillations such as El Niño and La Niña. These climate phenomena can disrupt normal precipitation patterns, leading to periods of reduced rainfall and increased drought risk. Richard *et al.* (2000) and Moeletsi and Walker (2012) asserted that frequent droughts are related to the high variability of interannual and intra-seasonal rainfall over most parts of southern Africa. (ii) Geographical location, Bethlehem is located in the eastern part of the Free State Province. Its geographical position puts it at a higher elevation and closer to the Drakensberg Mountains. Its proximity to these mountains affects the weather patterns in the area, and it is more exposed to dry, continental air masses coming from the inland areas of the province. These air masses can result in lower precipitation and contribute to drought occurrence. Dubey *et al.* (2023) investigated the role of elevation in governing drought dynamics over the Indus River basin from peaks to plains. They found that droughts prevailed more in high-altitude areas than in low-lying areas.

Regarding drought severity, our findings showed that drought is widespread in Bethlehem, Bloemfontein and Bothaville; however, the severity differed with areas. One of the most notable droughts were recorded in 1991/92 and 1994/95 and were extreme in all areas. Our results are comparable with those of Monyela (2017), who revealed that South Africa faced the worst drought in the 1991/92 season. The severity and impacts of this drought were felt across all sectors and communities, especially in the agricultural sector (Austin, 2008; Mpandeli *et al*., 2015; Nembilwi *et al.*, 2021). In addition, Mbiriri *et al.* (2019) assessed drought severity on a seasonal scale for the Free State Province using SPI; the study found that one of the notable droughts occurred in the OND season in 1991/92 with extreme drought conditions and in the JFM season in 1994/95 with severe conditions. Subsequent seasons saw varying degrees of drought severity: in 1997/98, Bethlehem showed severe conditions, Bloemfontein extreme conditions, and Bothaville moderate conditions. Lyon and Mason (2007) (2009) and Monyela (2017) ascertain that the 1997/98 drought directly impacted South Africa's production, such that crops were severely stressed, particularly in northern and central parts of the country (Food and Agriculture Organization (FAO) & World Food Programme (WFP), 1998). During the 2014/15 season, Bethlehem showed moderate drought conditions, whereas Bothaville and Bloemfontein showed no dry conditions. Archer *et al.* (2017) and Rouault *et al.* (2019) showed that many regions in southern Africa experienced severe drought in 2014/15. The 2015/16 season had moderate drought conditions in Bethlehem, no drought conditions in Bloemfontein, and extreme drought conditions in Bothaville. According to Archer *et al.* (2017), in 2015/16, South Africa saw the worst drought on record. In addition, EM-DAT (https://www.emdat.be/) declared that the Free State Province and other provinces were affected by this drought, which was driven by the El Niño phenomenon. The South African Grain Information Service (SAGIS) indicated that maize production dropped by approximately 30% in this period. The government implemented several measures to support farmers, including financial assistance (Matlou *et al.*, 2021) and programs to promote water conservation and efficiency (Pretorius *et al*., 2022). Only Bloemfontein showed severe drought conditions in the 2017/18 season, while Bethlehem and Bothaville showed no drought conditions. EM-DAT (https://www.emdat.be/) indicated that South Africa faced drought in 2017/18, which lasted for 13 months.

Regarding trends, we observed that monthly and seasonally significant decreasing SPI (drought) trends during maize growing seasons were dominant in Bethlehem and decreasing SPEI (drought) trends in Bloemfontein; the results suggest that drought increased over the months and seasons, which is frightening for maize production. In support of our findings, Cai *et al*. (2015) indicated that drought trends are alarming because they indicate abridged rainfall, which contributes to groundwater in the rainy season, ultimately causing water shortages for agricultural activities, particularly maize production. Mohammed and Yimam (2021) found decreasing drought trends on seasonal and annual scales and indicated an increase in drought frequency. Conversely, significant increasing

SPEI and SPI trends were prevalent in Bothaville; this indicates trends towards wetter conditions, implying that the occurrence of droughts has decreased over seasons, which indicates sufficient water for maize production. Njouenwet *et al.* (2021) assessed drought trends based on SPI during the maize and peanuts growing season in Cameroon; their results showed more moist trends (significantly increasing trend) than dry trends (decreasing trends) in the growing seasons, which showed wetter conditions for maize cultivation. Liu *et al.* (2018) assessed trends during crop (maize) growing seasons in North China Plain; they found a significant wetting trend (increasing trend) during the summer maize-growing season at various timescales. They indicated that their results imply that maize experienced wetter conditions.

Maize is a staple food for most people in South Africa; however, its production is defied by drought. The impact of drought on maize yield can be devastating, not only for farmers but also for consumers who depend on it for their daily sustenance. Based on our impact of drought on maize yield during the maize growing season results; we noted that all areas across all seasons revealed a significant positive correlation between the SPI, SPEI and maize yield. The significant correlation noted in the OND season could imply that drought impacted the germination, emergence and establishment of maize, leading to poor crop stand establishment and lower or no yields. On the other hand, significant correlation in the NDJ and DJF (tasselling and silking stage) could indicate that drought reduced maize growth, and kernel development, resulting in lower yields. In the JFM season (grain filling stage); drought could have reduced photosynthesis and transpiration rates, resulting in lower overall productivity, biomass accumulation, and yields. A significant positive correlation in the ONDJFM season (emergence-grain filling stages) could suggest that it affected growth and productivity, reducing yield reduction. Our findings suggest that maize was susceptible to drought events during growing seasons, as shown by significant positive correlations. In support of our findings, Abubakar *et al.* (2020) indicated that drought during maize germination, silking, pollination, and grain filling could result in lower yields. Mohammed *et al.* (2022) study found a significant positive correlation between drought indices yield residual series during the growing cycle for maize and wheat and suggested that these crops are susceptible to drought events, especially in the tasselling stage of maize, which led to lower yields. Aslam *et al*. (2015) indicated that drought hampers germination, resulting in poor maize standing at the early seedling phase, hindering early maize establishment and reducing yield. Shen *et al.* (2020) indicated that maize yield decreased by 0-40% in western Guanzhong Plain, China, due to drought during the jointing (from the eighth leaf to silking) and heading (from silking to milk) stages of maize. Anami *et al.* (2009) indicated that drought during the grain-filling period leads to low yield due to reduced kernel size.

Drought stress is one of the most significant abiotic stresses affecting maize production, resulting in a substantial reduction in yield, economic losses for farmers and food security. Regarding the maize yield loss, our results showed that the highest maize loss in Bethlehem was -16.71%, 29.68% and -83.86% due to moderate, severe and extreme droughts, respectively. In Bloemfontein, under moderate, severe and extreme droughts, the highest maize yield losses were -4.64%, -24.74% and -75.26%, respectively. In Bothaville, during moderate drought periods, the highest maize yield loss was -17.55%, -28.53% during severe drought and -58.93% during extreme drought. The results showed that while moderate drought has a noticeable impact, severe and extreme droughts have a much more substantial and detrimental effect on maize production. Our results are consistent with those reported by Li *et al.* (2022) in China, whose study found that 30%, 40% and 50% of maize yield losses were induced by moderate, severe and extreme droughts, respectively. Similar conclusions have been reached by Wang *et al.* (2020) in Northeast China, whose study found that maize yield losses of 3.2% and 14.0% were recorded during moderate drought and severe drought, respectively.

3.5. Conclusion

Maize, a key crop in South Africa, is essential for food production and livelihood maintenance as well as for economy stability of the country. However, its susceptibility to water stress makes it highly vulnerable to drought. The regions studied experienced high variability in seasonal rainfall and temperature during growing seasons, which indicated a potential irregularity in rainfall patterns, which might have affected maize production (as maize is sensitive to environmental conditions changes). According to the Standardized Precipitation Evapotranspiration Index (SPEI) and the Standardized Precipitation Index (SPI), droughts were most frequent in Bethlehem, especially in the ONDJFM season, followed by Bloemfontein and Bothaville in the JFM season. Bethlehem predominantly experienced moderate droughts, while severe and extreme droughts were common in both areas and Bloemfontein across all seasons. The SPI and SPEI proved to be valuable tools in our study, allowing us to quantify the severity and duration of drought conditions across different seasons and identify past droughts. This provided important in-sights into the patterns and trends of drought in the areas under study. However, like all tools, the SPI and SPEI have limitations. Both indices assume a normal distribution of precipitation, which may not be accurate in all geographical locations or climatic conditions. Furthermore, while the SPEI does consider evapotranspiration, it may not fully account for the complexity of water demand by vegetation, particularly in regions with diverse ecosystems. Future studies could benefit from incorporating additional indices or models that address these limitations, providing a more comprehensive understanding of drought patterns and their impacts. In terms of trends, significant decreasing trends indicating drier conditions under SPI were more pronounced in Bethlehem and under SPEI in Bloemfontein, while increasing significant trends indicating wetter conditions were more pronounced in Bothaville. The observed trends suggest a shift in climate patterns. The correlations between the SPI, SPEI values, and maize yield showed a significant positive correlation in all seasons and areas, indicating that maize yield was sensitive to drought. Maize yield loss was high during extreme drought, followed by severe and moderate periods. Given the sensitivity of maize yield to drought, it is likely that future drought will impact maize in the study areas. The negative effects of drought on maize yield will be intensified by climate change, which is projected to in-crease the frequency and intensity of drought events. These results suggest that drought is a threat to achieving the second Sustainable Development Goal (SDG-2) of Zero Hunger. Therefore, proactive management strategies will be beneficial in the face of future drought conditions to ensure food security. This study contributes to raising awareness among researchers, policymakers, and decision-makers dealing with drought for preparedness plans and adaptation strategies. Given the importance of agriculture in the Free State Province, further investigation into the impact of droughts on maize yields, specifically during the crop growth stages, is necessary.

CHAPTER 4: ASSESSING AREA-SPECIFIC PLANTING DATES AS A CLIMATE CHANGE ADAPTATION STRATEGY FOR RAINFED MAIZE USING AQUACROP MODEL

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Abstract

South Africa is projected to face dire impacts of climate change due to uncertainties surrounding crop production's responses to the changing climate and its heavy reliance on rainfed agriculture. The study objective was to assess area-specific planting dates as an adaptation strategy for rainfed maize in the Free State Province, South Africa. The AquaCrop model was calibrated and validated before being deemed fit to run simulations. The study utilized ensemble climate projections derived from 11 climate models of CMIP5 to analyze the potential changes in rainfall and temperature patterns under RCP 4.5 and 8.5. The AquaCrop model simulated maize yield for baseline and future periods and evaluated planting dates for mid-century (2040-2069) under Representative Concentration Pathways (RCP) 4.5 and 8.5. The projected climate in the maize growing season indicated an overall increase in seasonal rainfall across all study areas, with the highest overall seasonal rainfall increase under RCP 4.5 (0.42-44.67 mm) and under RCP 8.5 (17.68-33.27 mm) observed over Bloemfontein. The temperature indicated a consistent increase in maximum and minimum temperatures from baseline during the maize growing season across all the study areas under both RCP 4.5 and 8.5. The highest overall seasonal maximum temperature increase was observed in Bloemfontein (0.06ºC to 2.49ºC) under RCP 4.5, and under RCP 8.5 was in Bothaville (1.19-3.51ºC). Conversely, the highest overall seasonal minimum temperature increase was in Bothaville under both RCPs. Thus, 0.90ºC to 2.93ºC (RCP 4.5) and 1.48-4.09ºC (RCP 8.5). The changing climate would increase yield by 20.48-28.72% in Bethlehem under RCP 4.5 and decrease yield by -11.70% to -9.31% under RCP 8.5. In Bloemfontein, the yield would increase under RCP 4.5 by 32.14-44.44% and 28.17-31.75% under RCP 8.5. In Bothaville, yield would increase by 8.38-24.59% and decrease by -20.81 to -18.65% under RCP 8.5, while under RCP 4.5, yield would increase by 1.62-3.78% and decrease by -24.32 to -18.92%. The optimum planting dates as an adaptation strategy under RCP 4.5 for Bethlehem will be 1st November, while under RCP 8.5 will be 15th November (conventional planting date). For Bloemfontein, 29th December will be the optimum planting date under both RCPs, while for Bothaville, 13th December under both RCPs will be the optimum planting date. Our study's findings will aid policymakers, agricultural extension services, and farmers in developing effective

strategies to enhance food security and sustainable agricultural practices in the face of climate change in the Free State Province and similar regions worldwide.

Keywords: Crop model simulation, Model evaluation, Maize yield change, Rainfall and temperature, RCP 4.5 and RCP 8.5 scenarios

4.1 Introduction

Climate change is a global phenomenon that poses significant challenges to agricultural systems worldwide, impacting crop productivity and food security (Misra, 2014; Rao *et al.*, 2022). This is because of variations in temperature, precipitation, carbon dioxide (CO_2) concentration, and solar radiation (Aggarwal, 2003; Mulungu and Ng'ombe, 2019). These factors are bound to have a significant on crop phenology and yield and will induce changes in current agricultural management practices, such as planting dates and choice of cultivar (Alcamo *et al.,* 2007; Duncan *et al.*, 2012; Rao *et al.*, 2022). For instance, due to each degree Celsius increase in global average temperature, maize, soybean, rice and wheat are projected to decrease by 7.4%, 3.1%, 3.2% and 6%, respectively (Zhao *et al.*, 2017). In addition, Jägermeyr et al. (2021) indicated that maize yield is projected to decrease by nearly 24% in the late century on a global scale. The decline is evident in 2030 under high greenhouse gas emissions. It is apparent that maize, compared to rice and wheat, will experience more impacts of climate change (Tripathi *et al.*, 2016).

In developing countries, maize is one of the staple food crops anticipated to face dire consequences of climate change due to high temperatures and reduced water availability required by prolific farms challenging food production (Barnett, 2011; Food and Agriculture Organization (FAO), 2021; Bahta, 2022). In addition, it has been projected that maize demand will escalate in the future, and a large proportion of the increased demand, 72%, will emerge from developing countries (OECD and FAO, 2015). Specifically, South Africa ranks among the top ten leading maize-producing countries globally (Bello *et al*., 2020), and the Free State Province is one of the hubs for rainfed maize production in the country, which is vital for both local consumption and export (Statista, 2022). Among other provinces that produce maize in South Africa, the Free State Province accounts for about 35% of the country's maize production yearly (Bello *et al*., 2020). In general, the ecological conditions in the Free State region are conducive to growing maize crops (Bello *et al*., 2020). However, the changing climate patterns, including shifts in rainfall distribution and rising temperatures, raise concerns about the province's sustainability of rainfed maize production. For instance, the study by Beletse *et al.* (2016) examined the potential climate change impacts on maize production in Bethlehem, central Free State, South Africa. They found that the area will be substantially affected by climate change without any adaptation, such that maize production will drop by 10-16% in the future due to changing climatic conditions. As a result, assessing adaptation strategies locally is essential to ensure the resilience and sustainability of maize production under changing climatic conditions, as suggested by Laux *et al.* (2010) and Waongo *et al*. (2015).

Among various adaptation measures such as new crop varieties, irrigation, nutrient management, crop diversification, mixed cropping, and livestock farming (Hassan and Nhemachena, 2008; Kom *et al.*, 2022), adjusting planting dates has emerged as a viable, cost-effective and effective strategy for rainfed maize production under changing climatic conditions (Ali *et al.*, 2022). Developing new crop varieties and expanding irrigation is expensive and time-consuming (Challinor *et al.*, 2018; Simanjuntak *et al.*, 2022). By selecting appropriate planting dates, farmers can optimize resource allocation, take advantage of favourable climate windows, and reduce exposure to detrimental weather events, ultimately enhancing crop productivity and resilience.

Crop models are support tools for planning, decision-making, yield predictions and evaluating the effects of climate change (Steduto *et al.*, 2009). They are used to develop optimal management and adaptation strategies. Several models have been developed to quantitatively and qualitatively assess the implications of climate change on maize production. They present a plausible explanation of how climate change will impact crop yield. Models like the AquaCrop model have been extensively used to assess planting dates as an adaptation strategy across the world and have proven to be effective using projected climatic data from global climate (Soussana *et al*., 2010; Kephe *et al*., 2021). AquaCrop is a water-driven model, making it well-suited in areas where water is a limiting factor for maize production (Walker *et al.*, 2012). Moreover, the AquaCrop model has been calibrated, validated and used to assess planting dates for rainfed maize under changing climate conditions in other locations to conditions similar to those in South Africa (Mhizha *et al.*, 2014). For the AquaCrop model to be used for a specific crop, it needs to be calibrated and validated using field crop data and weather records (Mubvuma *et al*., 2021). It has been calibrated, validated and used for other crops such as taro, amaranths and sorghum and was found useful (Walker *et al.*, 2012; Mabhaudhi *et al*., 2014; Bello and Walker, 2017; Hadebe *et al*., 2020); however, it has not been calibrated, validated and utilized for maize in South Africa.

Previous studies in the Free State Province have primarily focused on the impacts of climate change on maize production; such studies include Walker and Schulze (2008), Mangani *et al.* (2019) and Cammarano *et al.* (2020), with no or limited research exploring adaptation strategies. Furthermore, there is a lack of area-specific investigations within the province, which are crucial given the diverse agro-ecological zones, varying soil types, topography, and microclimates present in the region. Therefore, our study aims to fill this gap by employing the AquaCrop model to assess the effectiveness of different planting dates as an adaptation strategy for rainfed maize cultivation under local changes in climatic conditions. To achieve the objective, i) we calibrated and validated the AquaCrop model, ii) evaluated projected average monthly rainfall and temperature and its changes from the baseline conditions, iii) simulated maize yield under baseline and future conditions, iv) assessed maize yield changes under different planting dates.

Understanding the role of planting dates as an adaptation strategy, stakeholders, including farmers, researchers, and policymakers, can make informed decisions to safeguard the sustainability and productivity of rainfed maize farming in the face of a changing climate. The insights gained from this study will contribute to the broader discourse on climate change adaptation in agriculture and provide valuable guidance for stakeholders involved in maize production within the Free State Province and similar regions worldwide.

4.2 Materials and methods

4.2.1 Study area

The Free State Province is situated in the central part of South Africa. The province is located at latitudes of 26.6ºS, 30.7ºS, and longitudes of 24.3ºE, 29.8ºE (Moeletsi and Walker, 2012). This province faces challenges in its rainfed agriculture due to erratic rainfall and temperature variations, affecting crop production, particularly maize production (Bello *et al*., 2020; Kephe *et al.*, 2022). Our study focuses on three main areas renowned for maize production in the province: Bloemfontein, Bethlehem, and Bothaville, located in different district municipalities, thus Mangaung, Thabo Matsunyane, and Lejweleputswa, respectively (Figure 4.1). The Lejweleputswa district municipality (where Bothaville is located) is South Africa's top producer of maize, accounting for approximately 21% of the country's maize production (Statistics South Africa (SSA), 2022). Bothaville is often called the "Maize Capital" of South Africa due to its significant contribution to the country's maize production. These selected study areas are characterized by different soil types, with sandy clay loam in Bethlehem and Bothaville and sandy loam soils in Bloemfontein (Johnston *et al.*, 2016), making it suitable for crop production such as maize, wheat, sunflowers, soybeans, sorghum, and potatoes. Following the climate classification by Peel *et al*. (2007), Bethlehem has warm summers and cold and dry winters, Bloemfontein experiences seasonal temperature changes with warm summers and cold and dry winters, and Bothaville has hot summers and warm to cool winters. The long-term annual average rainfall is approximately 788.53 mm, 522.78 mm and 459.39 mm in Bethlehem, Bloemfontein and Bothaville, respectively, which is conducive for maize production.

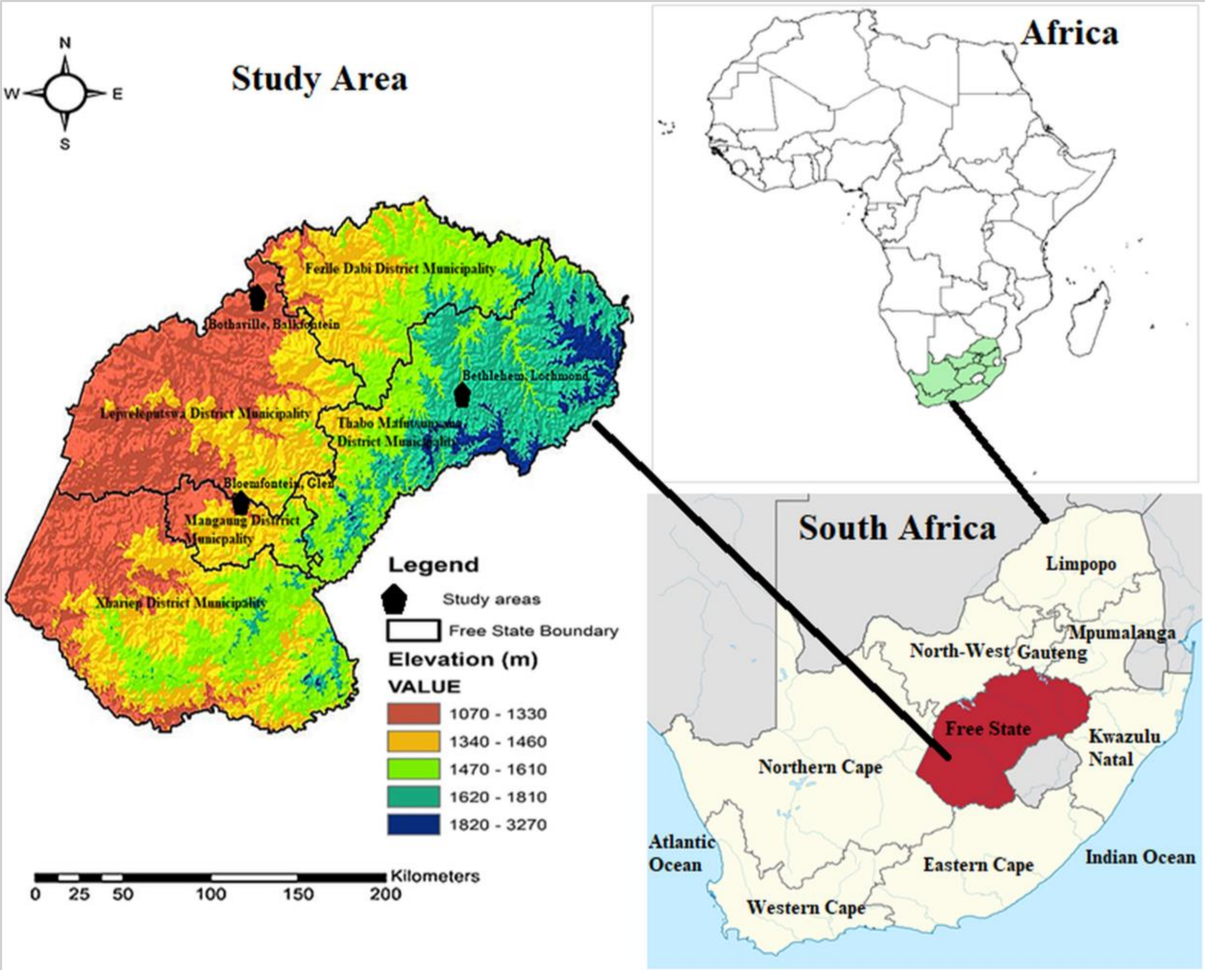


Figure 4.1. Spatial distribution and elevation (m.a.s.l) of the selected study areas in the Free State province.

4.2.2 Data acquisition

4.2.2.1 Agronomic data for model evaluation

The model parameterization, calibration, and validation were based on field experiments conducted at the Kenilworth Experimental Site in Bloemfontein during the 2019/20 and 2020/21 growing seasons under rainfed conditions. These experiments focused on the yield potential and planting dates of maize for commonly grown DEKALB hybrid white maize cultivars (such as DKC77-77BR) in the semi-arid regions of South Africa. Data collected from these trials included weekly recorded growth and development parameters, above-ground biomass, final grain yields, and harvest index. The daily climatic data for the two growing seasons (2019/20 and 2020/21) were obtained from an Automatic Weather Station (AWS) of the Agricultural Research Council-NRE located at the Kenilworth Experimental Site. The specific calendar days and planting dates for each season are presented in Table 4.1. These datasets provided a foundation for our model's parametrization, calibration, and validation processes.

Table 4.1. Datasets summary of maize during the 2019/20 and 2020/21 growing seasons.

Cultivar	Seasons	Planting date	Calendar days
	2019/20	20th November	112
	2019/20	17th December	112
	2019/20	15th January	119
DKC77-77BR	2020/21	15th December	112
	2020/21	17th November	105
	2020/21	18th January	112

4.2.2.2 Baseline and future climate data

The baseline (1991-2021) and statistically downscaled future daily and monthly climate data were obtained from the Climate System Analysis Group (CSAG) of the University of Cape Town Climate Information Portal (CIP) under African merged stations CMIP5 for a mid-century period (2040-2069) under the RCP 4.5 and RCP 8.5 scenarios. The climate data (rainfall and minimum/maximum temperatures) was from 11 Global Climate Models of the Coupled Model Intercomparison Project Phase 5 (CMIP5). The merged set of stations was sourced from the GHCN, WMO and country Met. Services. Time series from stations common to both the WMO and GHCN datasets have been merged provided the data in the overlapping period is identical (http://cip.csag.uct.ac.za). The statistically downscaled projections are based on the CMIP5 models for RCP 4.5 and RCP 8.5 (http://cip.csag.uct.ac.za). The dataset contains both observed and downscaled time series for each station location. Only stations that include all three primary climatic variables (rainfall, min/max temperatures) are included, which is the case for Bethlehem, Bloemfontein and Bothaville stations (http://cip.csag.uct.ac.za). The South African Weather Service (SAWS) and the Computing Center for Water Resources (CCWR) are the two primary sources of the data, which were compiled and quality-checked; thus, bias correction and validated, ensuring the reliability of their climate data before being uploaded to CIP by CSAG (MacKellar *et al*., 2014). The GCMs are part of the CMIP5 project, which was a major international effort that provided a suite of models for studying climate change. The chosen models have been validated against historical observed station climate data in South Africa (http://cip.csag.uct.ac.za), as shown in Appendix 4, as well as worldwide (Su *et al.*, 2013; Xuan *et al.*, 2017; Liess *et al.*, 2022), making them potentially more reliable for simulating climate change impacts. Moreover, they have been extensively used in climate research (Perez *et al.*, 2014; Casas-Prat *et al*., 2018; Navarro-Racines *et al.*, 2020). Using models from the same CMIP phase (CMIP5, in this case) ensures compatibility and allows for comparisons and ensemble analyses. Some of the chosen GCMs have been used in South Africa to assess climate change (Du Plessis and Kalima, 2021; Choruma *et al*., 2022).

4.2.2.3 Soil Data

The soil information was obtained from the Agricultural Research Council-NRE under the soil database archives. Sandy clay loam is the dominant soil type at Bethlehem, sandy loam at Bloemfontein and sandy clay loam at Bothaville (Table 4.2). These soil types have texture classes between 10-30%, with air and moisture regimes that are optimal for healthy maize production (Du Plessis, 2003).

Table 4.2. Soil characteristics in the study areas.

Study areas	Horizons	Soil type	Thickness (m)	PWP	FC (Vol %)	DUL (%)	SAT	Ksat (mm/day)
BTM	A		0.30	20.0	32.0	25.0	47.0	225.0
	B1-3	Sandy clay loam	0.95	10.0	30.0	27.0	50.0	500.0
	C		1.80	10.0	30.0	23.0	50.0	500.0
BFN	A		0.30	10.0	22.0	18.9	41.0	1200.0
	B1-5	Sandy loam	1.40	10.0	30.0	19.1	50.0	500.0
	C		2.20	10.0	30.0	18.9	50.0	500.0
BTV	A		0.30	20.0	32.0	18.8	47.0	225.0
	B21	Sandy clay loam	0.90	10.0	30.0	20.9	50.0	500.0
	B22		1.20	10.0	30.0	21.30	50.0	500.0

Note. BTM denote Bethlehem BFN-Bloemfontein BTV-Bothaville

4.2.3 Generation of ensemble climate data

Prior to computing the ensemble, the rainfall and temperature data were visualized in Microsoft Excel 2016 with relevant metadata, such as the time period and data units. The multi-model ensemble future climate data was generated using the arithmetic mean method for the mid-century (2040-2069) under RCP 4.5 and 8.5 scenarios for three study locations based on 11 Global Climate Models (GCMS), as indicated in Table 4.3. This methodology averages the projections of multiple models wherein the individual models' random errors or inconsistencies tend to cancel out, resulting in a more robust, reliable and accurate prediction (Feng *et al.*, 2011). This helps reduce the influence of any single model's idiosyncrasies and increases the overall reliability of the ensemble mean (Ruan *et al.*, 2019). Moreover, it mitigates the risk of making overly confident predictions based on a single model's output (Khan and Pilz, 2018). The arithmetic mean method has been widely used to calculate an ensemble of climate data from multiple models (Wang *et al.*, 2016; Muhammad *et al.*, 2018; Ruan *et al.*, 2019; Rhymee *et al.*, 2022). The arithmetic mean approach is straightforward and easy to implement (Knutti *et al.*, 2010; Li *et al.*, 2021). The "dplyr" package built-in R Studio software was employed to calculate the ensemble of rainfall and temperature from 11 GCMs for each study area. The Global Climate Models used to generate the ensemble are presented in Table 4.3.

Table 4.3. List of the Global Climate Models (GCMs) used to derive the ensemble of climate data. Adapted from studies by Sung *et al*. (2020) and Irmak *et al*. (2022).

GCMs	Institution	Model Country
BCC-CSM1-1	Beijing Climate Center, China Meteorological Administration, China	China
BNU-ESM	College of Global Change and Earth System Science, Beijing Normal	China
CanESM2	Canadian Centre for Climate Modelling and Analysis	Canada
CNRM-CM5	Centre National de Recherches Meteorologiques	France
FGOALS-s2	Institute of Atmospheric Physics	China
GFDL-ESM2G	NOAA Geophysical Fluid Dynamics Laboratory	USA
GFDL-ESM2M	NOAA Geophysical Fluid Dynamics Laboratory	USA
MIROC5	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	Japan
MIROC-ESM	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and the National Institute for Environmental Studies	Japan
MIROC-ESM2M-CHEM	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and the National Institute for Environmental Studies	Japan
MRI-CGCM3	Meteorological Research Institute	Japan

4.2.4 Climate change projections

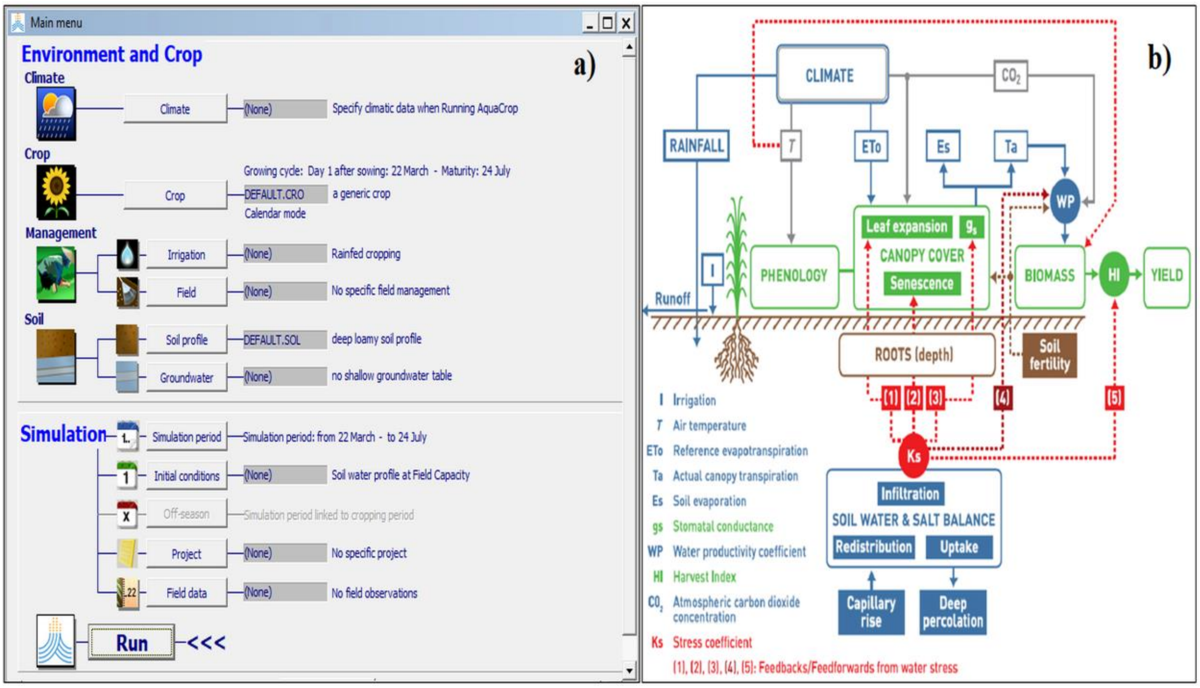
In this study, we employed climate change projections based on RCPs. These RCP scenarios rely on total radiative forcing and encompass four distinct scenarios (RCP 2.6, 4.5, 6.0, and 8.5), each representing a potential future climate outcome. These scenarios are contingent upon the extent of greenhouse gas emissions anticipated in the future (Hamlet *et al.*, 2020). Among the four RCPs (RCP 2.6, 4.5, 6.0 and 8.5), RCP 4.5 and 8.5 were chosen because they represent two contrasting emission pathways, ranging from moderate to high greenhouse gas emissions and radiative forcing. RCP 4.5 is a scenario with significant emissions reductions, while RCP 8.5 represents a high-emission, business-as-usual pathway (Faggian, 2021). Focusing on these two scenarios allows one to evaluate the range of possible climate outcomes under drastically different emission trajectories. Moreover, RCP 4.5 is often seen as a reference point for assessing the potential impacts of emission reduction policies and international agreements like the Paris Agreement (Leiter, 2023; Smirnov *et al.*, 2023). It represents a pathway where significant efforts are made to mitigate emissions and limit global warming to relatively lower levels compared to higher-emission scenarios. RCP 4.5 is a stabilization scenario that stabilizes the radiative forcing at 4.5 W/m^2 before 2100 by employing various technologies and strategies for reducing greenhouse gas emissions (Riahi *et al.*, 2011; Wayne, 2014). On the other hand, RCP 8.5 helps policymakers understand the potential consequences of inaction or inadequate mitigation efforts (Ayele *et al.*, 2016). RCP 8.5 pathway is the concentration of carbon that delivers global warming at an average of 8.5 W/m^2 across the planet. It delivers a temperature increase of about 4.3ºC by 2100 relative to preindustrial temperatures (San José *et al.*, 2016; Lowe *et al.*, 2018).

4.2.5 AquaCrop model

4.2.5.1 Model description

AquaCrop is a water-driven crop model that can be used to plan and make decisions about semi-arid crops like maize. It requires fewer input parameters than other models (Steduto *et al.*, 2009). It normalizes water productivity based on climate factors such as ETo and atmospheric CO_2 (Foster *et al.*, 2017). The model calculates crop biomass (B) and yields (Y) with a focus on splitting evapotranspiration into crop transpiration (Tr) and soil evaporation (E) (Steduto *et al.*, 2012). This is particularly useful during crop establishment when soil evaporation can be significant (Bodner *et al*., 2007). AquaCrop uses a canopy growth model to calculate transpiration (Tr) and soil evaporation (E), and the final yield is determined by biomass (B) and harvest index (HI), allowing functional linkages between the environment and biomass production, as well as the environment and HI, to be separated (Figure 4.2 b)) (Steduto *et al.*, 2009). The model considers four main categories of crop interactions with water stress: canopy growth, senescence, transpiration, and harvest index (Figure 4.2 a)).

This study used the AquaCrop model because AquaCrop simulates the yield response of herbaceous crops (such as maize) to water (Steduto *et al.*, 2009). This makes it especially relevant for conditions where water is a key limiting factor in crop production, such as rainfed agriculture (Walker *et al.*, 2012). Additionally, according to Irmak *et al*. (2022), the AquaCrop model is distinguishable from other crop models due to its unique features: 1) It exclusively concentrates on water. 2) It employs canopy cover instead of leaf area index to simulate crop growth, development, and water usage, which is more accessible and familiar to users beyond researchers. 3) The water productivity consent model is to be used more in many climates, localities, and seasons. 4) It features a relatively small number of more explicit and intuitive input parameters than other models. 5) It is open-source software with a user-friendly interface and comprehensive documentation, and 6) AquaCrop strikes a fine balance between accuracy, simplicity, and robustness.



Adapted from Raes et al. (2009) study.

Figure 4.2. a) shows the database system for the AquaCrop model interface, and b) shows the main components of the soil–plant–atmosphere continuum and the parameters driving phenology, canopy cover, transpiration, biomass production, and final yield.

4.2.5.2 Model Calibration and Validation

Since this study solely focuses on the medium-growing cultivar, the DKC77-77BR cultivar was selected for calibration and validation purposes. As articulated by Crop Science South Africa (https://www.cropscience.bayer.africa/za/en-za.html), the cultivar chosen is highly prolific, with strong seedlings and good vigor. Further, it does not require irrigation and produces an excellent yield. Moreover, it is disease resistant, such as common rust, foliar disease, northern leaf blight, ear rot, and maize streak virus. Three different planting dates were selected from two seasons (2019/20 and 2020/21) to calibrate and validate the model (Table 4.4). The measured variables considered were yield (Y), biomass (B) and harvest index (HI).

4.2.5.2.1 Model calibration

According to Farahani *et al*. (2009), model calibration is the process of modifying model parameters to match measured values in a specific area. The non-conservative parameters were fine-tuned to field experiments and the local agronomic conditions (Table 4.4). The 2019/2020 season trial measurements were used for model calibration. The maximum rooting depth was adjusted to 1.80 m, and plant density was 18 000 plants/ha. The days to emergence, maximum canopy, senescence stage, maturity period, flowering, harvest index (HI) and duration of the flowering stage were determined by the calendar days based on each planting date. The water productivity normalized for ETo and CO_2 was 33.7 g/m^2, suitable for C4 crops such as maize. The three crop parameters analyzed for model calibration were final biomass (B), yield (Y), and harvest index (HI).

Table 4.4. Experimental and agronomic information used in AquaCrop model calibration (2019/20) and validation (2020/21).

Parameters	Growing seasons					
	2019/20			2020/21		
Plant density (plants/ha)	18 000	18 000	18 000	18 000	18 000	18 000
Date of sowing (DAP)	20th November	17th December	15th January	15th December	17th November	18th January
Emergence (DAP)	7	7	7	7	7	7
Flowering (DAP)	56	56	63	56	49	56
Senescence (DAP)	98	98	105	98	91	98
Maturity (DAP)	112	112	119	112	105	112
Planting days to Maximum rooting depth	60	60	67	60	53	60
Maximum effective rooting depth (m)	1.8	1.8	1.8	1.8	1.8	1.8

Note. DAP denate days after planting

4.2.5.2.2 Model validation

Model validation refers to the process of assessing the performance and accuracy of the crop model. This involves comparing the model's predictions or outputs against observed data from field experiments or real-world conditions (Bitri and Grazhdani, 2015). The field data used to validate the model was from the 2020/21 cropping season. The descriptive statistical metrics: Root Mean Square Error (RMSE*)*(Zeleke *et al.*, 2011), Willmott's Index of Agreement (*d*) (Willmott, 1982) and coefficient of determination (R^2) (Chicco *et al.*, 2021) as represented in Equations 1, 2 and 3 were utilized assess how well the AquaCrop model predictions align with real-world observations for both calibration and validation datasets. The deviation between measured and simulated parameters for both calibration and validation datasets was calculated using Hsiao *et al.* (2009) and Muluneh (2020) methodology as indicated in Equation 4. Two crop parameters analyzed for model validation were final above-ground biomass and maize yield.

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{n}}\sum_{i=1}^{\mathrm{n}}(\mathrm{M}i - \mathrm{S}i)^2} \quad (1)$$

$$d = 1 - \frac{\sum_{\mathrm{i}=1}^{\mathrm{n}}|\mathrm{M}i - \mathrm{S}i|^2}{\sum_{i=1}^{\mathrm{n}}|\mathrm{M}i - \overline{\mathrm{M}}| + |\mathrm{S}i - \overline{\mathrm{M}}|^2} \quad (2)$$

$$\mathrm{R}^2 = 1 - \frac{\mathrm{SSR}}{\mathrm{SST}} \quad (3)$$

$$\text{Deviation (\%)} = (\text{simulated} - \text{measured}) \times \frac{100}{\text{measured}} \quad (4)$$

Where:

M*i* is the measured value at data point *i*, S*i* is the simulated (predicted) value at data point *i*, respectively, n is the total number of observations, $\overline{\mathrm{M}}$ is the mean of the measured values, and the summation ($\sum$) runs from *i*=1 to *n*, representing the summation over all data points. SSR is the sum of squared residuals (the sum of the squared differences between the measured values and the predicted values). SST is the total sum of squares (the sum of the squared differences between the measured values and the mean of the dependent variable). RMSE measures the overall or mean deviation between measured and simulated values. According to Heng *et al.* (2009), the RMSE value closer to zero, the better the model simulation performance. d denotes the degree to which anticipated and measured values similarly deviate from the measured mean. It has no dimensions and ranges from 0 to 1, with 0 denoting complete model disagreement and 1 denoting perfect model agreement (Willmott, 1982). The R^2 describes the proportion of the total variance explained by the model (Akumaga *et al*., 2017) and is interpreted as 0- no model prediction, 0-1- partial model prediction and 1- Perfect model prediction (Turney, 2022). The RMSE metric was chosen because it focuses on the magnitude of errors and helps one understand how far off predictions are from the actual values. Willmott Index of Agreement (d) goes beyond error magnitude; it considers both bias and variability on observed and simulated data, making it more robust to outliers. The coefficient of determination (R^2) helps one understand how well the model explains the variability in the data.

4.2.5.3 Model simulations for adaptation under climate change

The AquaCrop model requires four compartments, namely climate, crop, management and soil, to run simulations.

4.2.5.3.1 Model input data and parameters

4.2.5.3.1.1 Climate file data

The climate file requires input files of maximum and minimum air temperatures (*.TMP), rainfall (*.PLU) and reference evapotranspiration (*.ETo). The daily rainfall and minimum and maximum temperature to create a climate file for baseline (1991-2021) were collected from the Climate Systems Analysis Group's (CSAG) Climate Information Portal (CIP) for all the study areas. On the other hand, the downscaled daily ensemble climate data from 2040 to 2069 was obtained from the portal mentioned above for all the study areas. The ETo needed to create climate files was calculated using the FAO ETo calculator version 3.2 (http://www.fao.org/nr/water/eto.html) for historical and future periods. The atmospheric concentration for the baseline period (1991-2021) was obtained from the default CO_2 concentrations of Mauna Loa Observatory readily available in the AquaCrop model. Similarly, the projected CO_2 concentrations for IPCC RCPs 4.5 and 8.5 scenarios were acquired from the AquaCrop database for the mid-century (2040-2069).

4.2.5.3.1.2 Crop file data

The model crop file (*.CRO) requires input parameters such as planting date, plant density, maximum canopy cover, harvest index (HI), crop cycle length (time to crop emergence, flowering, the start of canopy senescence, and maturity), and rooting depth are all crop parameters. For the historical period, the sowing dates were set based on conventional planting dates for all study locations. For future data, the sowing dates were set based on two weeks intervals proportional to the conventional planting dates (i.e., two weeks, four weeks before and after conventional planting dates). Maize.CRO file was chosen for this study from the Aqua Crop data bank, which contains non and conservative parameters of maize (Hsiao *et al.*, 2009). Other non-conservative parameters were adjusted based on the selected areas, cultivar and management practices (Table 4.5).

Table 4.5. Adjusted crop parameters of AquaCrop for maize simulation.

Crop parameters/variables	Default	Adjusted	Sources
Type of Crop	Maize	Maize	
Carbon cycle	C4	C4	
Type of planting method	Sowing	Sowing	
Base temperature (°C)	8	8	Hsiao *et al.* (2009)
Upper temperature (°C)	30	30	Hsiao *et al.* (2009)
Canopy cover per seedling (cm²/plant)	6.50	6.50	Hsiao *et al.* (2009)
Maximum rooting depth (m)	2.40	1.60	Lievens (2014)
Plant density (plants/ha)	185 000	43 000	Du Plessis (2003)
Maximum canopy cover (%)	90	96	Nzimande (2021)
Planting days to maximum root depth	100	67	Gadédjisso-Tossou *et al*. (2020)
Sowing to emergence (days)	5	7	Biazin and Stroosnijder (2012)
Sowing to maximum canopy (days)	50	65	Biazin and Stroosnijder (2012)
Sowing to senescence stage (days)	110	95	Biazin and Stroosnijder (2012)
Sowing to maturity (days)	125	120	Biazin and Stroosnijder (2012)
Sowing to flowering (days)	70	60	Biazin and Stroosnijder (2012)
Length building up HI	50	48	
Duration of the flowering stage	10	15	Biazin and Stroosnijder (2012)
Reference Harvest Index (HIo) (%)	50	48	Zizinga *et al.* (2022)
	Response to stresses		
	Water Stresses		
Canopy expansion	Moderately tolerant to water stress	Extremely sensitive to water stress	
Stomatal closure	Moderately tolerant to water stress	Extremely sensitive to water stress	
Early canopy expansion	Moderately tolerant to water stress	Extremely sensitive to water stress	
Aeration stress	Moderately tolerant to waterlogging	Extremely sensitive to waterlogging	

4.2.5.3.1.3 Soil file data

The dominant soil types are sandy clay loams in Bethlehem and Bothaville and fine sandy loams in Bloemfontein). The AquaCrop soil file (*.SOL) requires input parameters such as saturation (SAT), field capacity (FC), the permanent wilting point (PWP), and hydraulic conductivity (K_{sat}) of various soil depths. The areas have different soil types, ranging from sandy loam to sandy loam clay. The soil information was obtained from the Agricultural Research Council-NRE soil database and used to create the model's soil file (*.SOL). The soil was set as a sandy loam for Bloemfontein and a sandy clay loam for Bothaville and Bethlehem according to land type data based on the typical soil of the study areas.

4.2.5.3.1.4 Field management

Information about irrigation was not considered since the maize is rainfed.

4.2.5.3.2 Maize yield simulations

AquaCrop model version 6.1 was utilized to simulate maize yield from 1991 to 2021 (baseline) and between 2040 and 2069 (mid-century) under climate change for medium-growing cultivar (DKC77-77BR). In addition, the simulation of maize yield for mid-century was run under RCPs 4.5 and 8.5 scenarios. Based on historical data, the planting dates for simulation were selected based on conventional planting dates of all the areas. The conventional dates for planting in Bethlehem and Bothaville were 15th November, while for Bloemfontein it was 15th December. Thus, 3 study areas × 3 conventional planting dates. On the other hand, the planting dates for simulating maize yield under RCP4.5 and 8.5 were selected proportional to the conservative planting dates at 2 weeks intervals, thus two weeks and four weeks before and two weeks and four weeks after conventional planting dates. Thus, 3 study areas × 4 planting dates × 3 GCMs). Like other models, the AquaCrop model needs user-defined input files for climate (*.CLI), crop (*.CRO) and soil (*.SOL) to run. Each growing cycle assumes that other factors (field management) do not affect crop growth stages. Since the study aims to assess prospective yield and planting dates, other data, such as fertilizer treatment and irrigation, were not considered because they require substantial investments (money).

4.2.6 Changes in rainfall and temperature

The long-term average rainfall and temperature changes were computed using the difference method adopted from the Strzepek *et al.* (2011) report, as indicated in Equations 5 and 6.

$$\Delta T = T_{projected} - T_{baseline} \quad (5)$$

$$\Delta P = P_{projected} - P_{baseline} \quad (6)$$

Where:

ΔT represents the change in temperature. $T_{projected}$ is the projected future temperature. The $T_{baseline}$ is the temperature during the baseline period. ΔP represents the change in precipitation, in this case, rainfall. The $P_{projected}$ is the projected future rainfall. $P_{baseline}$ is the rainfall during the baseline period. Positive values indicate an increase in temperature or rainfall, while negative values indicate a decrease. The abovementioned methods were chosen because they provide a straightforward way to quantify changes in temperature (ΔT) and rainfall (ΔP) over time; thus, they are relatively simple and intuitive. In addition, they are effective for detecting anomalies or deviations from the historical climate.

4.2.7 Maize yield change

The projected yield change (%) from baseline was calculated using the method represented in Equation 7, adapted from the Sorecha *et al.* (2017) study. The study used long-term average yield for both baseline and projected periods to assess the changes.

$$\Delta Y\,(\%) = \left(\frac{(Yp - Yb)}{Yb}\right) \times 100 \qquad (7)$$

Where:

ΔY- Yield change, Yp-projected yield (the expected maize yield in the future period for which you are projecting) and Yb -baseline yield (the maize yield during the baseline period - the reference period you are comparing against). If the result is positive, it indicates an increase in yield, while a negative result indicates a decrease compared to the baseline.

4.2.8 Planting dates as adaptation strategies

The planting dates were evaluated as potential adaptation strategies to reduce the loss of maize production over the mid-century era (2040-2069). Five planting dates across all the study areas were used to determine the optimum planting dates under climate change (Table 4.6). Thus, one planting date was set for the baseline, and four planting dates were used as alternative planting dates from the baseline. The simulations for the future period were run under RCPs 4.5 and 8.5 for each study area. In light of the increase in rainfall and temperature, RCP 4.5 and RCP 8.5, respectively (San José *et al.*, 2016), the planting dates were delayed by 2 weeks and 4 weeks before conventional planting dates and advanced by 2 weeks and 4 weeks after conventional planting dates (Table 4.6). The planting date/s with the highest maize yield from the baseline was selected as the optimum planting date/s. The conventional planting date for Bloemfontein was 15th December, while Bethlehem and Bothaville's was 15th November (Table 4.6).

Table 4.6. Adaptation strategies based on planting dates under RCPs 4.5 and 8.5.

Scenarios	Period	Planting dates	Study areas
Baseline	1991-2021	15th November	Bethlehem
RCP 4.5 & 8.5	2040-2069	1st November	
		9th October	
		29th November	
		13th December	
Baseline	1991-2021	15th December	Bloemfontein
RCP 4.5 & 8.5	2040-2069	1st December	
		17th November	
		29th December	
		12th January	
Baseline	1991-2021	15th November	Bothaville
RCP 4.5 & 8.5	2040-2069	1st November	
		9th October	
		29th November	
		13th December	

4.3 Results

4.3.1 Model calibration and validation

Figure 4.3 a) b) and c) show the measured and simulated final above-ground biomass, grain yield and harvest index for the calibration dataset for three planting dates, respectively. The results show that the model could predict final above-ground biomass, grain yield and harvest index with RMSEs of 2.06 t/ha, 0.0.02 t/ha and 8.79%, respectively. The good predictions of these parameters by the model were evident with the coefficient of determination (R^2) of 0.73, 0.99 and 0.46 and Wilmott agreement (d) index of 0.95, 0.99 and 0.92 for the final biomass, maize yield and harvest index, respectively (Figure 4.3 a), b) and c)). Table 4.7 shows deviations between measured and simulated final above-ground biomass, maize yield and harvest index under three different planting dates. The results indicated that the simulated final biomass deviated from measured values by the range of 2.17% and 24.32%, while the maize yield simulations deviated from the measured within a range of -0.23% and -0.60%, and the harvest index deviation ranged between 1.57% and 34.60% (Table 4.7). Overall, the results of this study were satisfactory.

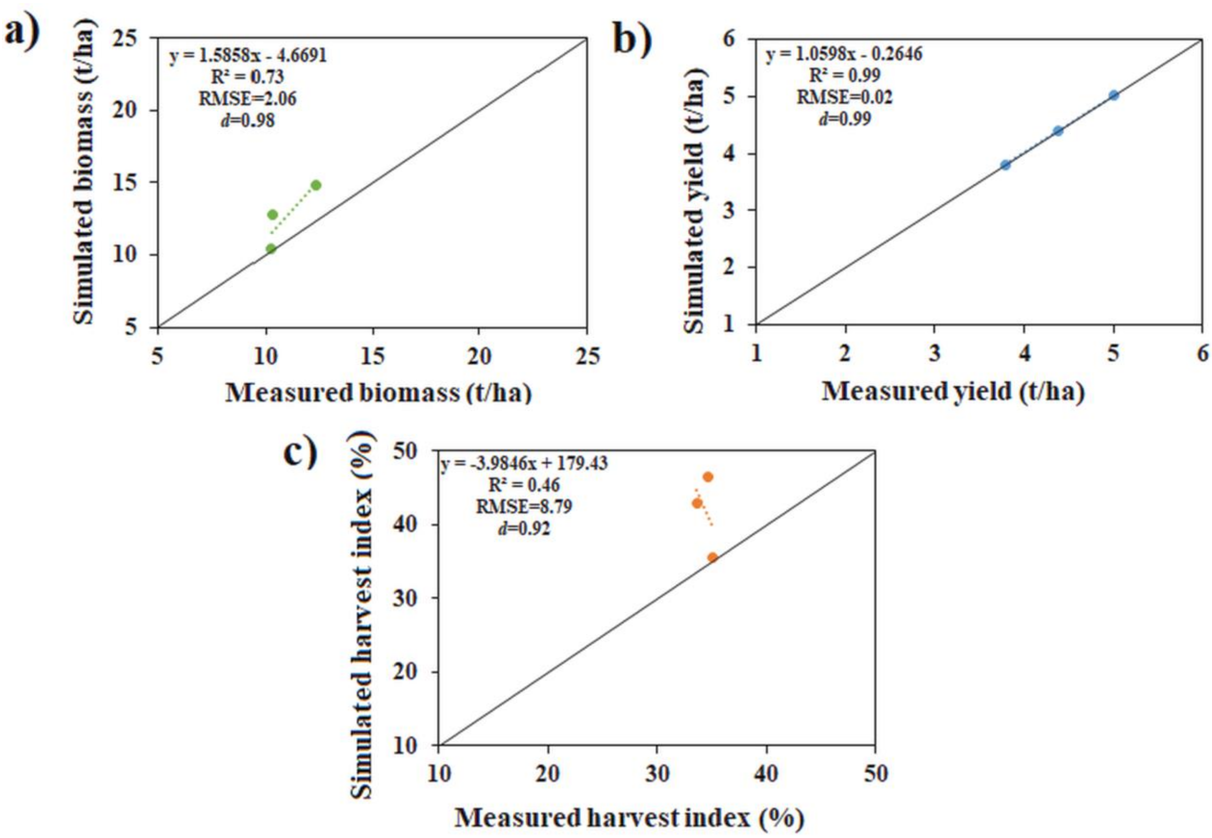


Figure 4.3. Simulated versus measured final above-ground biomass a), yield b), and harvest index c) for three planting dates of the 2019/20 growing season.

Table 4.7. Deviations between measured and simulated values of the final above-ground biomass, maize yield and harvest index under three different planting dates for the 2019/20 growing season.

Growing season: 2019/20	Crop parameters								
	Final above-ground biomass (t/ha)			Yield (t/ha)			Harvest Index (%)		
Planting dates	Meas	Sim	Dev (%)	Meas	Sim	Dev (%)	Meas	Sim	Dev (%)
20th November	10.25	10.47	2.15	4.39	4.38	-0.23	33.61	43.00	27.94
17th December	10.30	12.80	24.27	5.03	5.00	-0.60	34.60	46.57	34.60
15th January	12.32	14.84	20.45	3.81	3.79	-0.52	35.06	35.61	1.57

Note. Meas, Sim and Dev represent Measured, Simulated and Deviation, respectively.

Figure 4.4 a) and b) shows simulated and measured the final above-ground biomass and maize yield for three planting dates, respectively, for the validation dataset. With low RMSEs of 2.08 t/ha (final-aboveground biomass) and 0.18 t/ha (grain yield), the model performed in simulating final-aboveground biomass and grain yield as supported by R^2 values of 0.82 and 0.99 for final biomass and grain yield, respectively (Figure 4.4 a) and b)). The index of agreement (*d*) revealed a good agreement between simulated and observed, with 0.91 for final above-ground biomass and 0.99 for grain yield. Table 4.8 shows deviations between measured and simulated final above-ground biomass and maize yield under three different planting dates. The results show that the deviation for final above-ground biomass ranged from 17.49% to 37.80%, while for maize yield, it ranged between -6.01% and 1.69% (Table 4.8). The efficiency of the model performance was perfect, accentuating that the AquaCrop model is reliable for simulating crop parameters.

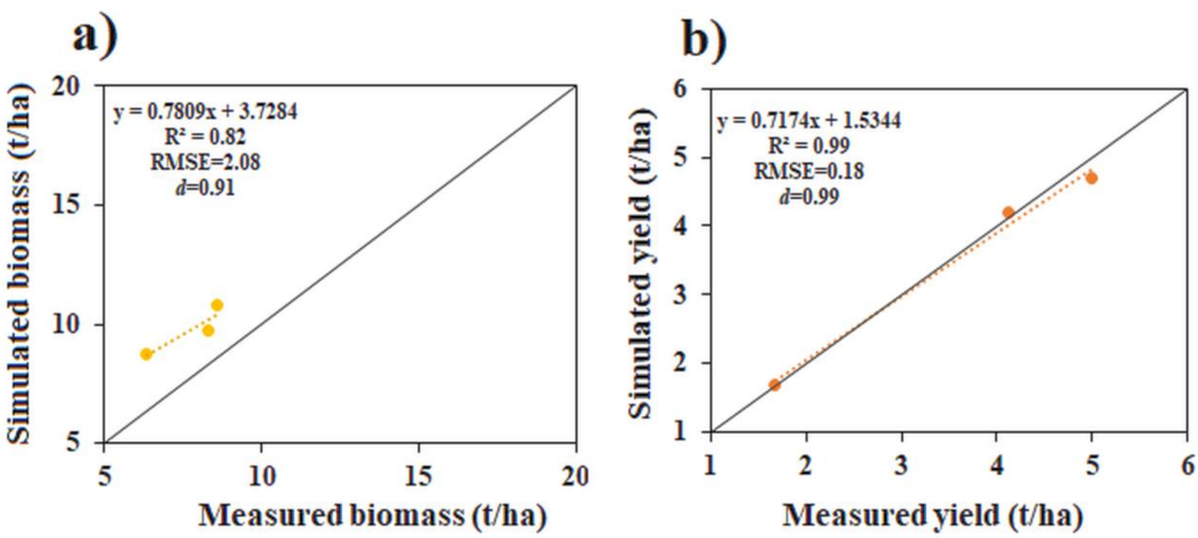


Figure 4.4. Simulated versus measured a) final above-ground biomass and b) maize yield for three planting dates for the 2020/21 growing season.

Table 4.8. Deviations between measured and simulated values of final above-ground biomass and maize yield under three different planting dates for the 2020/21 growing season.

Growing season: 2020/21	**Crop parameters**					
	Final above-ground biomass (t/ha)			Yield (t/ha)		
Planting dates	Measured	Simulated	Deviation (%)	Measured	Simulated	Deviation (%)
17th November	8.57	10.83	26.37	4.13	4.20	1.69
15th December	6.35	8.75	37.80	4.99	4.69	-6.01
18th January	8.29	9.74	17.49	1.68	1.70	1.19

4.3.2 Projected changes in rainfall and temperature

Figure 4.5 a), b) and c) depict the projected ensemble annual long-term average rainfall and temperature (Tmax and Tmin) patterns, respectively, with a focus on maize growing season for Bethlehem, Bloemfontein and Bothaville in the mid-century period (2040-2069) under RCP 4.5 and 8.5 relative to the baseline period (1991-2021). The results indicate that Bethlehem showed an overall increasing trend in seasonal rainfall (maize growing season) under RCP 4.5, with the highest rainfall in March. However, under RCP 8.5, overall seasonal rainfall indicated a decrease relative to the baseline rainfall, except for an increase in October, with the lowest rainfall in November (Figure 4.5 a)). On the other hand, in Bloemfontein, under both RCPs, overall seasonal projected rainfall showed an increasing trend, with exemptions, such that in February, rainfall decreased. The highest rainfall was in March under both RCPs (Figure 4.5 b)). In Bothaville, the projected seasonal rainfall indicated an overall increase under both RCP 4.5 and 8.5 relative to baseline rainfall. However, there are exceptions such that rainfall decreased under both RCPs in January and March. The highest rainfall was in November for both RCPs (Figure 4.5 c)). The highest overall seasonal rainfall change relative to baseline under RCP 4.5 was observed over Bethlehem (0.42-44.67 mm), and under RCP 8.5 was observed over Bloemfontein (17.68-33.27 mm) (Figure 4.5 a)). The rainfall increased more under RCP 4.5 than under RCP 8.5. Based on temperature, the results indicate a consistent increase in seasonal maximum and minimum temperatures during the maize growing season across all the study areas relative to baseline under both RCP 4.5 and 8.5. The highest overall seasonal maximum temperature change under RCP 4.5 was in Bloemfontein (0.06ºC to 2.49ºC), and under RCP 8.5 was in Bothaville (1.19-3.51ºC) (Figure 4.5 b)). Conversely, the highest overall seasonal minimum temperature change was in Bothaville under both RCPs. Thus, 0.90ºC to 2.93ºC (RCP 4.5) and 1.48-4.09ºC (RCP 8.5) (Figure 4.5 c)). Temperatures increased more under RCP 8.5 than under RCP 4.5. These climatic changes highlight the uncertainty in future rainfall and temperature patterns, which can have significant implications on planting and harvesting timing and yield variability, necessitating implementing adaptation and mitigation strategies.

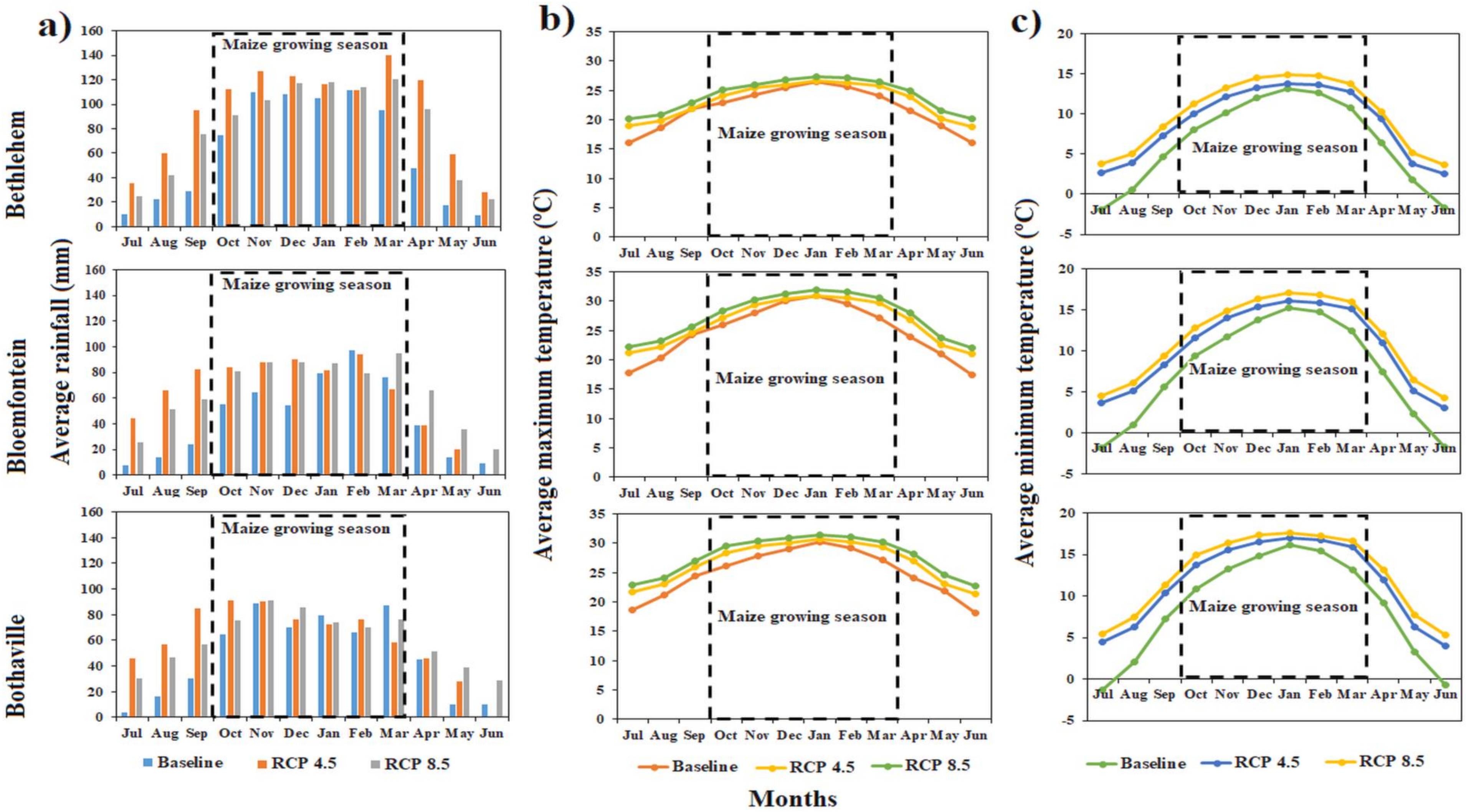


Figure 4.5. Long-term projected ensemble average monthly a) rainfall, maximum b) and c) minimum temperature for Bethlehem, Bloemfontein and Bothaville under RCP 4.5 and 8.5.

4.3.3 Simulated maize yield and changes

Figure 4.6 a), b) and c) represent simulated maize yield in the mid-century (2040-2069) at different proposed planting dates under RCPs 4.5 and 8.5 relative to the baseline yield (1991-2021) for Bethlehem, Bloemfontein and Bothaville, respectively. The simulations for the baseline period used conventional planting dates, while mid-century simulations employed proposed planting dates under RCP 4.5 and 8.5. The conventional planting date for Bethlehem is 15th November, for Bloemfontein 15th December and for Bothaville 15th November. The proposed planting dates for Bethlehem are 19th October, 1st November, 29th November, and 13th December. For Bloemfontein, the proposed planting dates are 17th November, 1st December, 29th December and 12th January, and Bothaville's proposed dates align with those of Bethlehem. Figure 4.7 a), b) and c) shows the maize yield changes under different planting dates in the mid-century period for Bethlehem, Bloemfontein and Bothaville.

The results showed that in Bethlehem, under RCP 4.5, yield increased, while under RCP 8.5, yield decreased across all proposed planting dates relative to baseline yield (Figure 4.6 a)). Thus, the magnitude of yield increment under RCP 4.5 was 20.74%, 28.72%, 21.28%, and 20.48% on the 19th October, 1st November, 29th November, and 13th December planting dates, respectively (Figure 4.7 a)). Under RCP 8.5, the yield reduction magnitude was by -9.31% on 19th October, -10.64% on 1st November, -10.37% on 29th November and -11.70% on 13th December (Figure 4.7 a)). On the other hand, in Bloemfontein, under both scenarios (RCP 4.5 and 8.5), yield increased from baseline yield across all proposed planting dates (Figure 4.6 b)). The yield increase magnitude was 40.08% on 17th November, 42.86% on 1st December, 44.44% on 29th December and 32.14% on 12th January under RCP 4.5 (Figure 4.7 b)). Nonetheless, under RCP 8.5, the yield increased by 28.17% on 17th November, 30.95% on 1st December, 31.75% on 29th December and 25.79% on 12th January (Figure 4.7 b)). In Bothaville, the yield increased on two proposed planting dates with a decrease on the other two proposed planting dates under both scenarios relative to baseline yield (Figure 4.6 c)). Such that under RCP 4.5, the yield increment was 8.38% and 24.59% on 19th October and 13th December, respectively and yield reduction magnitude was -20.81% and -18.65% on 1st November and 29th November (Figure 4.7 c)). Under RCP 8.5, the yield increase was 1.62% on 19th October, 3.78% on 13th December, and a decrease was -24.32% on 1st November and -18.92% on 29th November (Figure 4.7 c)). The highest yield increase under both RCPS was observed over Bloemfontein. The yield increased more under RCP 4.5 than under RCP 8.5. Overall, the changes in maize yield could be attributed to the changing climate as represented by different RCPs, as maize is a crop sensitive to changing environmental conditions.

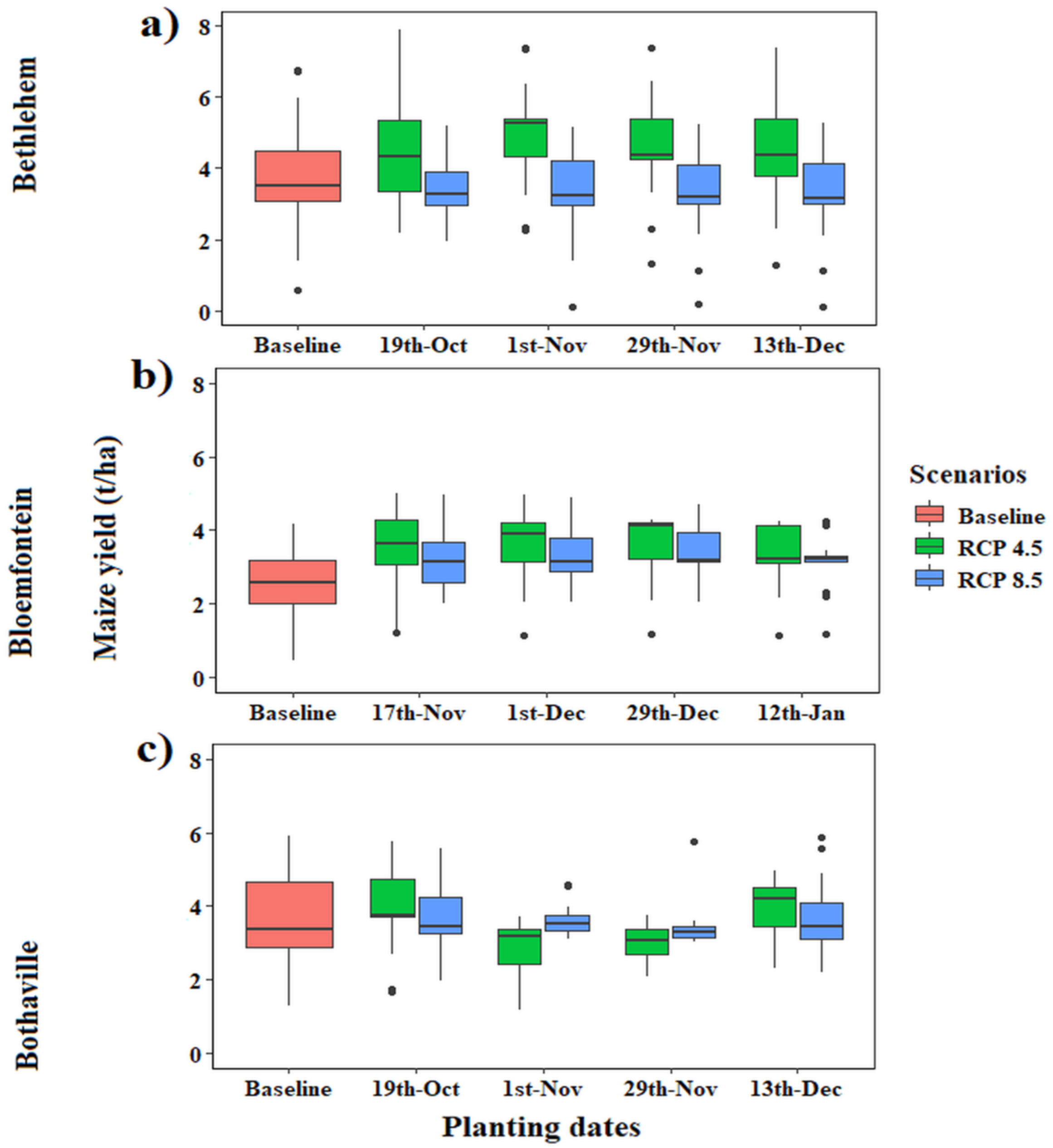


Figure 4.6. Simulated maize yield under different planting dates for mid-century (2040-2069) under RCPs 4.5 and 8.5 relative to baseline yield (1991-2021) for a) Bethlehem, b) Bloemfontein and c) Bothaville.

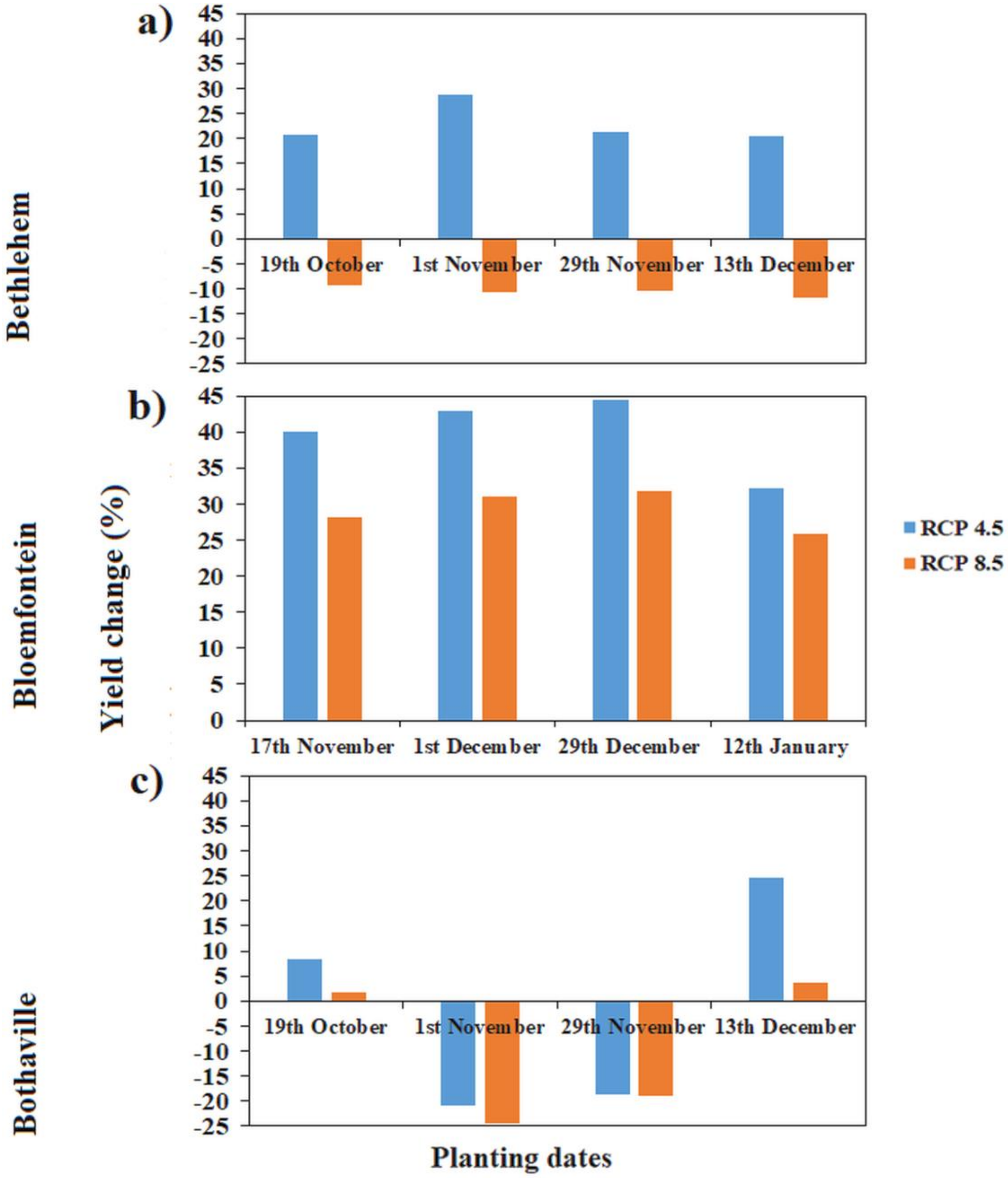


Figure 4.7. Maize yield changes over different planting dates under RCP 4.5 and 8.5 for a) Bethlehem, b) Bloemfontein and c) Bothaville.

4.3.4 Planting dates as adaptation strategies under RCP 4.5 and RCP 8.5 for 2040-2069

Table 4.9 shows different planting dates and the long-term average maize yield for the mid-century period (2040-2069) under RCP 4.5 and 8.5, together with the long-term baseline average yield. The results show that all the proposed planting dates in Bethlehem under RCP 4.5 are optimum for planting maize as yield; nonetheless, the optimum planting date will be 1st November due to the substantially higher average yield than other planting dates (Table 4.9). On the other hand, under RCP 8.5, the yield decreased drastically across all the proposed planting dates; therefore, the conventional planting date (15th November) will be optimum (Table 4.9). For Bloemfontein, the results show that all the proposed planting dates under both scenarios are optimum. However, the recommended planting date will be 29th December under both RCPs due to substantively higher average yield than other planting dates (Table 4.9). In Bothaville, the 19th October and 13th December planting dates under RCP 4.5 and 8.5 are optimum for planting maize; 13th December will be optimum planting date for both RCPs due to the highest average yield (Table 4.9). Overall results demonstrate that the change in rainfall and temperature will shift planting dates under RCP 4.5 and 8.5 across all the areas. The specific planting dates identified as optimum vary depending on future climate projections and the specific conditions of each location.

Table 4.9. Optimum planting dates for mid-century under RCP 4.5 and 8.5.

Study areas	Time frame	Planting dates	Average yield (t/ha)	
			RCP 4.5	RCP 8.5
Bethlehem	1991-2021	15th November (Baseline)	3.76	
	2040-2069	19th October	4.54	3.41
		1st November	4.84	3.36
		29th November	4.56	3.37
		13th December	4.53	3.32
Bloemfontein	1991-2021	15th December (Baseline)	2.52	
	2040-2069	17th November	3.53	3.23
		1st December	3.60	3.30
		29th December	3.64	3.32
		12th January	3.33	3.17
Bothaville	1991-2021	15th November (Baseline)	3.70	
	2040-2069	19th October	4.01	3.76
		1st November	2.93	2.80
		29th November	3.01	3.00
		13th December	4.61	3.84

4.4 Discussion

Climate change has emerged as a pressing global issue, affecting various sectors, including agriculture, food security, and rural livelihoods. Adapting to changing climate becomes crucial for sustainable crop production in regions heavily dependent on rainfed agriculture, such as the Free State Province in South Africa. Our study calibrated and validated the AquaCrop model prior to simulations, assessed changes in the future climate relative to the baseline period, simulated maize yield under baseline and future conditions, assessed the simulated maize yield changes and evaluated planting dates using the AquaCrop model for all three selected regions in the Free State province of South Africa. Our study used a calibration dataset to assess the AquaCrop model's ability to predict maize yield, final above-ground biomass, and harvest index. The model accurately predicted maize yield, with deviations ranging from -0.23% to -0.60% and a Root Mean Square Error (RMSE) of 0.02 t/ha. However, it overestimated the final above-ground biomass and harvest index, with deviations of 2.17% - 24.32% and 1.57% - 34.60%, respectively, and higher RMSE values of 2.06 t/ha and 8.79%. Despite these overestimations, the model's overall effectiveness is supported by high R^2 values (0.98 for biomass, 0.99 for yield, and 0.92 for harvest index) and the Wilmott agreement index (d) of 0.95, 0.99, and 0.92, respectively. Our findings align with those of Mhizha *et al.* (2014), Stricevic *et al.* (2011), and Mibulo and Kiggundu (2018), who also found the AquaCrop model reliable in simulating yield. However, studies assessing the model's performance in simulating the harvest index for rainfed maize post-calibration are limited. Some studies under irrigated conditions found the model's harvest index estimates imprecise and prone to overestimation. For instance, Ran *et al.* (2020) found the model simulated the harvest index under water stress conditions poorly. Simba *et al.* (2013)discovered the model estimated a slightly higher harvest index than experimental treatments, with a 10% deviation in semi-arid regions of Zimbabwe. Despite this, they deemed the model applicable with an acceptable error margin of -10%. In contrast, Thamer *et al.* (2021) found the AquaCrop model accurately simulated the harvest index after calibration for two seasons, with R^2 values of 0.99 and 0.97, RMSE values of 0.84 and 0.83, and d values of 0.978 and 0.960 for the 2016 and 2017 growing seasons, respectively.

Regarding the validation dataset, we observed that the model accurately estimated maize yield, with deviations between -6.01% and 1.69%, a low Root Mean Square Error (RMSE) of 0.18 t/ha, a high index of agreement (d) of 0.99, and a high R^2 of 0.99. However, the model overestimated the final above-ground biomass, showing higher deviations (17.46% - 37.73%) and a higher RMSE (2.08 t/ha). The model showed that it is efficient in simulating final above-ground biomass as indicated by a higher index of agreement (d) of 0.91 and a higher R^2 of 0.82. These results suggest that while the model precisely simulated yield, it was less accurate in predicting the final above-ground biomass; nonetheless, it is reliable in simulating both parameters (as indicated by higher d-index and R^2). Our findings align with those of Akumaga *et al*. (2017), who reported a good simulation of yield with a deviation from 19% to 30%, an R^2 between 0.82 to 0.99, and a d index ranging from 0.6 to 0.88, indicating a range from moderate to good agreement. Giménez (2019) also found that the AquaCrop model simulated yield well under different water availabilities for maize, particularly under rainfed conditions. Biazin and Stroosnijder (2012) supported our findings, reporting a fairly good agreement between measured and simulated biomass and grain yields of maize using the AquaCrop model under stressful conditions (rainfed and non-fertilized), with a high R^2 of 0.98. Nzimande (2021) evaluated multiple crop models, including AquaCrop, and reported overestimated biomass in AquaCrop with an RMSE of 6.14 t/ha. Contrary to our findings, Mebane *et al.* (2013) observed an accurate simulation of biomass progression over time using the AquaCrop model, with an agreement index value of 0.96 and deviations ranging from 2.4% to 20.7% between simulated and measured final above-ground biomass.

Based on the projected ensemble climate, we observed the overall increase of average seasonal rainfall across the three study areas (Bethlehem, Bloemfontein and Bothaville) under RCP 4.5 and 8.5 in the growing season, with few exceptions in some months that indicated a decrease under both RCPs for all areas. Our findings are relatable to those reported by Mangani *et al.* (2019), who found that future projections of rainfall based on the average ensemble of multiple GCMs indicated that rainfall increased during the maize cropping season in major areas producing maize in South Africa. Interestingly, Tofa *et al.* (2021) reported that ensemble GCMs predicted seasonal rainfall increase ranging from 1.2% to 7% for RCP 4.5 and 0.03-10.6% for RCP 8.5 in the mid-century in Nigeria. Further, we observed that rainfall is projected to increase more under RCP 4.5 than under RCP 8.5. These findings are comparable with those of San José *et al.* (2016), who evaluated the impacts of RCP 4.5 and 8.5 in Madrid, Antwerp, Milan, Helsinki and London and found that rainfall increased more under RCP 4.5 than under RCP 8.5. In contrast to our findings, Gummadi *et al.* (2020) found that the rainfall increase was higher under RCP 8.5 than under RCP 4.5. Regarding the temperatures, we observed an overall increase in maximum and minimum temperatures in the growing season across all areas in the growing season. In corroboration with our findings, a study by Tofa *et al.* (2021) reported that ensemble GCMs predicted temperatures increase between 1.7-2.4°C for RCP 4.5 and 2.2-2.9°C for RCP 8.5 in the mid-century. The observed decrease in minimum temperature during the growing season could affect maize production as it is below 10 °C, virtually no germination or growth takes place below 10ºC (Du Plessis, 2003); this can affect the germination and early growth stages of maize, potentially impacting crop yield and overall productivity. Ramirez-Cabral *et al*. (2017) indicated that low temperatures affect germination, emergence and vegetative growth. Although germination can still occur at temperatures below 10ºC, Getachew *et al.* (2016) have found that the emergence of the maize crop is delayed under such conditions, potentially exacerbating the adverse effects on crop development and leading to reduced yields. Further, we observed that temperature increased more under RCP 8.5 than under RCP 4.5. The United States Agency International Development (USAID) (2015) report supports our findings, indicating that various models project increased temperatures in South Africa during the mid-century for the RCP 8.5 scenario. Similarly, the Department of Environmental Affairs (DEA) (2013) reported that the most drastic temperature rise is projected for the RCP 8.5 scenario, with 5-7°C increases across the South African interior regions. Although temperatures are increasing across all the study areas, they are conducive to maize production as they fall within the recommended range specified by Du Plessis (2003). The temperature has a huge impact on maize production; elevated temperatures can disrupt critical physiological processes, such as photosynthesis, maturing period and yield. This is relatable to Lin *et al*. (2015) findings which indicated that maize's flowering duration and maturity duration will be shortened in the future due to the rise of temperature such that maize yield will reduce by 11-46% in Heilongjiang Province (China). Srivastava *et al*. (2021) reported that an increase of 1ºC in maximum and minimum temperatures reduces the maize yield by 1.55% and 0.88% in the mid-century, under rainfed conditions in Eastern India.

Regarding the simulated maize yield based on the proposed planting dates under RCP 4.5 and 8.5 relative to the simulated yield based on the conventional planting dates, we observed that yield increased across all planting dates under RCP 4.5 in Bethlehem. This suggests that lower emission scenarios will positively affect maize yield regardless of the planting date; however, under RCP 8.5, the yield decreased across all planting dates under RCP 8.5, indicating a negative impact of higher emissions on maize production. In contrast, the yield increased across all planting dates and under both RCPs in Bloemfontein, implying that maize production in Bloemfontein will benefit from the changing climate conditions, regardless of the emission scenario or the planting date. In Bothaville, yield increased across two out of four proposed planting dates and vice versa under both RCPs, suggesting that these dates will increase maize production regardless of the emission scenario. Our findings are comparable with findings reported by Rao *et al.* (2022), who found that maize yield is projected to increase by 5% and 3% in mid-century under RCPs 4.5 and 8.5, respectively, in Dharwad (India). On the other hand, Choruma *et al*. (2022) found that the estimated yield will decrease in the mid-century (2040–2069) under both RCP 4.5 and 8.5 in the Eastern Cape Province (South Africa). Similarly, Tofa *et al.* (2021) indicated that the yield is projected to decline by 9-18% under RCP 4.5 and 14-25% under RCP 8.5 in the mid-century in Nigeria. Further, our results indicated that the yields were higher under RCP 4.5 than under RCP 8.5 across all the study areas, and the yield decreased more under RCP 8.5 than RCP 4.5, which can be due to higher greenhouse gas concentrations and radiative forcing in the RCP 8.5 scenario resulting in more pronounced climate change impacts than RCP 4.5. In support of our findings, Araya *et al.* (2017) reported that maize yield increased under RCP 4.5 compared to 8.5 in

Kansas, implying the positive impacts of CO_2 (possibly by minimizing water losses through the stomata) on maize yield was too small compared to the negative impacts of elevated temperatures. On the other hand, Geethalakshmi *et al.* (2023) observed that the magnitude of the decline in maize crop yield would be greater with RCP 8.5 over RCP 4.5 scenario in the mid-century in Tamil Nadu (India). Similarly, Streefkerk *et al.* (2022) indicated that the magnitude of the mean impact of climate change scenarios on maize yield was consistently higher under RCP 8.5 than under RCP 4.5 in Malawi due to the highest temperatures, which resulted in the highest yield decline.

In the context of agricultural practices, adaptation strategies such as planting dates play a crucial role in ensuring optimal crop growth and productivity. Appropriate planting dates are essential for matching crop growth stages with favourable environmental conditions like temperature and rainfall patterns. Furthermore, adjusting planting dates based on climate change projections can help farmers mitigate the impacts of changing weather patterns and ensure long-term agricultural sustainability. Our results indicated that using all delayed and advanced planting dates will increase yield under RCP 4.5 compared to conventional planting date (baseline) in Bethlehem in the mid-century. On the other hand, under RCP 8.5, delaying and advancing planting dates will decrease yield related to the conventional planting date. In Bloemfontein, we observed that using advanced and delayed planting dates across all the RCPs will increase yield in the mid-century compared to conventional planting date. Conversely, in Bothaville, one out of four advanced and one out of four delayed planting dates will lead to increased yield under both RCPs compared to conventional planting date. Our study findings are comparable with those reported by Moradi *et al.* (2013), who found that planting maize based on common planting dates in the future will reduce maize yield. The study indicated that changing planting dates will best adapt strategies to climate change to sustain maize production. Interestingly, Masanganise *et al.* (2012) found that using traditional static sowing practices in the mid-century will reduce maize yield, while adopting dynamic planting dates will result in the highest yield for short-season cultivars. Srivastava *et al.* (2022) found that shifting planting dates would be effective in the 2050s and 2080s, as they will increase maize yields in Eastern India. Rolla *et al.* (2018) findings showed that under RCPs 4.5 and 8.5, advancing planting dates by 20 and 40 days and delaying by 20 days would positively affect yield increment in central Argentina. Moreover, the maize and wheat yields are projected to increase by about 45%. The study suggested that changing planting dates would be an effective adaptation strategy to climate change. Waongo *et al*. (2015) used an optimized planting dates (OPD) approach under rainfed conditions in Burkina Faso. The results showed that 15% of the potential maize yield will be achieved using the planting dates as an adaptation strategy. Lv *et al*. (2020) study found that in the future, delaying the sowing date would improve the potential maize yield by 0-8.9% in future. This suggests that adjusting sowing dates could be a viable strategy for farmers to adapt to changing climate conditions and maintain crop yields.

4.5 Conclusion

Adopting adaptation strategies to address the impacts of climate change on crop production is essential for preserving economic development and food availability. The study assessed area-specific planting dates as an adaptation strategy for rainfed maize production in the Free State Province of South Africa utilizing the AquaCrop model under different scenarios. The AquaCrop model simulations provided insights into the potential yield variations and helped identify optimal planting dates that will maximize maize productivity in future. Despite the limitations in data availability, our study utilized three distinct planting dates for two seasons to calibrate and validate the AquaCrop model. The model demonstrated commendable performance in simulating crop yield. However, it is important to note that the accuracy of the model could be further enhanced with more comprehensive data. Our projected ensemble climate results showed an overall seasonal rainfall increase across all the study areas; thus, maize will be exposed to wetter conditions. On the other hand, maximum and minimum temperatures are projected to increase across all locations during the growing season, indicating that maize will be exposed to warmer conditions. Although temperatures are increasing, they are conducive to maize production as they are within the ranges determined by Du Plessis (2003). While the projected climate provides valuable insights into future climate conditions and their potential impacts on maize production, it's important to note that these projections are based on Global Climate Models (GCMs), which have several limitations such as limited spatial resolution, uncertainty in projections, complexity and computational demand and uncertainty in feedback mechanisms. The projected maize yield in Bethlehem was positively influenced by RCP 4.5 but negatively impacted by RCP 8.5. Conversely, Bloemfontein showed consistent yield increases under both scenarios, and Bothaville exhibited mixed results depending on the planting dates under both RCPs. Based on planting dates as an adaptation strategy, the optimal planting dates varied across different locations due to variations in climate conditions. By adopting area-specific planting dates, farmers in the designated areas can enhance the resilience of their maize crops to climate change. Adjusting planting dates helps synchronize the critical growth stages of maize with available water, thereby minimizing the risk of water stress during sensitive periods. This adaptation strategy can potentially improve overall maize yields and regional food security. However, it is essential to note that while the AquaCrop model is a valuable tool for assessing planting dates and yield projections, it relies on various assumptions and simplifications. Therefore, validating the model's results through field experiments and local observations is recommended to ensure their applicability in real-world farming conditions. Overall, the study aligns with multiple sustainable development goals (SDGs), including zero hunger (SDG 2), climate action (SDG 13), life on land (SDG 15), responsible consumption and production (SDG 12) and industry, innovation, and infrastructure (SDG 9), contributing to the broader sustainable development agenda. Although there may be uncertainties from the crop and climate models, the findings of this study may offer information about the potential impacts of climate change on maize yield as well as scientific support for practical adaptations that farmers can use to combat the adverse effects of future climate change. Moreover, the findings will serve as a reference point for farmers and policymakers for clear guidance on developing and implementing adaptation strategies. Based on the study's findings, it can be concluded that adjusting planting dates according to area-specific conditions can be an effective adaptation strategy for rainfed maize production under climate change.

CHAPTER 5: OVERALL CONCLUSION, LIMITATIONS AND RECOMMENDATIONS

5.1 Overall conclusion

The study's main objective was to analyze the impacts of drought on potential maize yield in the Free State Province, South Africa. The study investigated the impacts of drought in the major agricultural selected areas of the Free State Province. The study confirms that drought events significantly affect maize yield, posing significant challenges to food security. Maize, being a staple crop, is highly vulnerable to water stress, making it susceptible to drought conditions. The study assessed seasonal rainfall and temperature variability, temporal frequency and severity of droughts, trends, and the impacts of drought on maize yield. The results indicated high seasonal rainfall and temperature variability in the study areas (Bethlehem, Bloemfontein and Bothaville). Seasonal drought events were more frequent in Bethlehem, followed by Bloemfontein and Bothaville, with varying levels of severity across all areas and seasons. The study also found significant positive correlations between drought indices and maize yield, highlighting the sensitivity of maize to drought conditions. Extreme droughts resulted in the highest yield losses, followed by severe and moderate droughts.

Additionally, the study sought to assess the effectiveness of different planting dates as adaptation strategies under the anticipated changes in climate for the mid-century period (2040-2069) under RCP 4.5 and 8.5 using the AquaCrop model. Considering the projected increase in frequency and intensity of drought events due to climate change, the adverse effects on maize yield are expected to worsen in the future, threatening the achievement of SDG-2 (Zero Hunger). As a result, implementing proactive management strategies and adaptation measures is crucial to ensure food security in the face of changing climatic conditions. One of the adaptation strategies explored in the study was planting dates, which proved effective in maximizing maize productivity under different climate scenarios. This strategy can enhance maize crop resilience and yield by synchronizing critical growth stages with available water.

The study's findings contribute to the broader sustainable development agenda, aligning with multiple SDGs, including zero hunger (SDG 2), climate action (SDG 13), life on land (SDG 15), responsible consumption and production (SDG 12) and industry, innovation, and infrastructure (SDG 9). However, it is essential to acknowledge that the AquaCrop model's results are based on certain assumptions and simplifications, necessitating validation through field experiments and local observations to ensure their practical applicability. Adjusting planting dates according to area-specific conditions can be an effective and practical measure to combat the adverse effects of climate change on rainfed maize production. However, continuous monitoring and validation of adaptation strategies are necessary to ensure their efficacy in the context of evolving climate conditions and real-world agricultural practices. The research offers valuable information to farmers and policymakers, guiding them in developing and implementing adaptation strategies to mitigate the impacts of climate change on maize production. By proactively addressing drought impacts and adopting climate-resilient practices, we can work towards achieving the goal of food security while contributing to broader sustainable development objectives.

5.2 Limitations of the Study

- The study did not fully account for non-climatic factors that could influence maize production, such as socio-economic factors and technological advancements.
- The study used a predictive model (AquaCrop model) to assess planting dates as an adaptation strategy; this model is subject to uncertainties and limitations inherent in any predictive model. While it provides valuable insights, the field observations (final biomass, yield and harvest index), deviated from the simulated (final biomass, yield and harvest index), which could be due to unaccounted variables in input data. Moreover, the AquaCrop model relies on simplified crop-water relationship assumptions and does not fully capture real-world agricultural systems' intricacies.

5.3 Recommendations

Based on the findings and conclusions of this study, the following recommendations were put forth to guide policymakers, farmers, and other stakeholders in implementing effective drought monitoring, mitigation and adaptation strategies: Strengthening the monitoring and early warning systems for drought events using drought indices will enable timely responses and proactive planning to mitigate drought impacts. This could help farmers and policymakers to anticipate and prepare for drought events and to implement appropriate mitigation and adaptation measures. Farmers should adopt drought-tolerant maize varieties and improved agronomic practices, such as conservation agriculture, mulching, and intercropping, to enhance soil moisture and reduce water stress on crops. Farmers should have access to reliable and timely weather and climate information and advisory services, which could help them, make informed decisions on crop management and risk reduction. Strengthening institutional and policy support for drought management, such as providing financial and technical assistance, crop insurance, and social protection programs, could help to reduce the vulnerability and enhance the resilience of maize farmers.

5.4 Potential areas for future research

- Investigate climate change over the coming decades, incorporating the most recent projections. This would involve using updated climate models and emission scenarios to better capture potential changes in temperature, precipitation patterns, and extreme events.
- Investigate the potential impacts of changing climate conditions on different maize varieties. Assess which maize varieties might be more resilient to future climate conditions and provide higher yields under various drought scenarios.
- Investigate water use efficiency in maize production systems. This research could assess the impact of different irrigation methods (e.g., drip irrigation, sprinkler systems) and agricultural practices (e.g., conservation tillage, mulching) on maize yield during drought periods. Identifying water-saving techniques and sustainable irrigation practices will be crucial for optimizing water resources and minimizing drought impacts.
- Integrate different models, such as hydrological models and land use models, to better understand the complex interactions between climate, water availability, land use changes, and maize production. This could lead to more comprehensive assessments of drought impacts and adaptation strategies.

- Develop risk assessment tools and early warning systems to predict and monitor regional drought events. This research could integrate climate data, soil moisture monitoring, and remote sensing technology to provide timely information for farmers and decision-makers. Timely warnings could enable better preparation and management during drought periods.
- Investigate the socioeconomic impacts of drought on local communities, including changes in livelihoods, food security, and economic stability. Understanding these aspects can guide the formulation of policies and interventions to support vulnerable populations during drought events.
- Explore the concept of climate-smart agriculture, which aims to improve productivity, enhance resilience, and reduce greenhouse gas emissions. Investigate specific practices, such as conservation agriculture and agroforestry, and their potential for enhancing maize production in the face of climate change.
- Assess the carbon footprint of maize production under different planting dates and drought conditions. This would provide insights into the environmental sustainability of different adaptation strategies.

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APPENDICES

Appendix 1: Best Presented Poster Award at Annual Early Career Researchers Conference

Appendix 2: 2nd Prize Award for the Best Oral Presentation under the Masters' category at the Society of South African Geographers (SSAG) conference

Master's Presenter Award

2nd Prize

This award is presented to

Vuwani Makuya

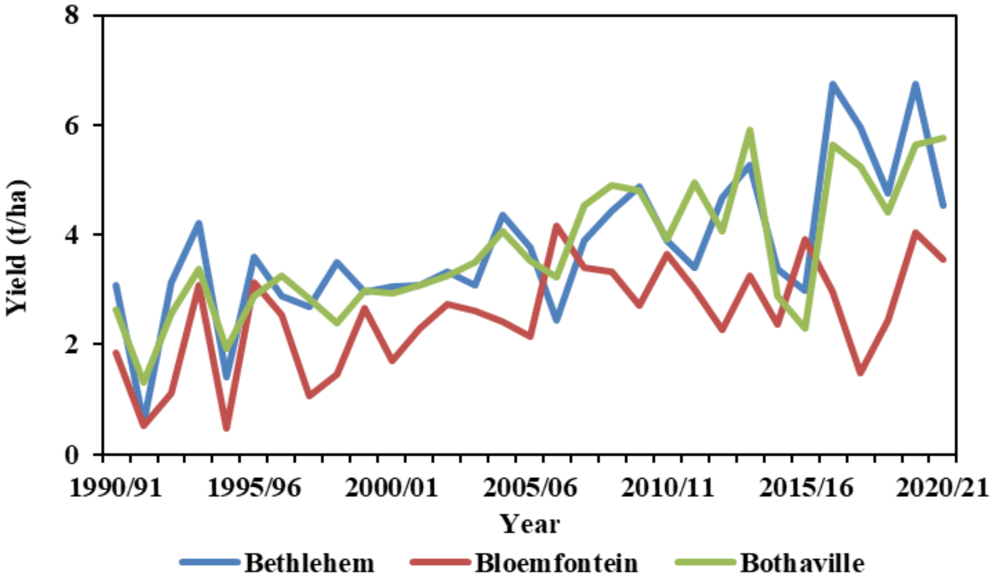
for the presentation of her paper

'Assessing area-specific planting dates as adaptation strategy for rainfed maize under climate change using Aquacrop model in Free State Province, South Africa'

at the Society of South African Geographers (SSAG) Student Conference (SSAG 2023)
held at the Qwaqwa Campus of the University of the Free State
02-04 October 2023

Ntebohiseng Sekhele
Chair: Local Organising Committee
SSAG2023

Appendix 3: Long-term yield between 1990-2020



Appendix 4: Monthly observed station data and historical station GCMs ensemble data for the period 1990-2020